APPLICATIONS OF SOME NEW MULTI-CRITERIA DECISION MAKING TOOLS IN MANUFACTURING ENVIRONMENT

THESIS SUBMITTED BY

SAIKAT CHATTERJEE

DOCTOR OF PHILOSOPHY (ENGINEERING)

DEPARTMENT OF PRODUCTION ENGINEERING
FACULTY COUNCIL OF ENGINEERING & TECHNOLOGY
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JADAVPUR UNIVERSITY
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NAME, DESIGNATION & INSTITUTION OF THE SUPERVISOR:

Dr. SHANKAR CHAKRABORTY
Professor, Department of Production Engineering,
Jadavpur University,
Kolkata –700032, India.

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STATEMENT OF ORIGINALITY

I **Saikat Chatterjee** registered on 28.05.2018 do hereby declare that this thesis entitled **"APPLICATIONS OF SOME NEW MULTI-CRITERIA DECISION MAKING TOOLS IN MANUFACTURING ENVIRONMENT"** contains literature survey and original research work done by the undersigned candidate as part of Doctoral studies.

All information in this thesis have been obtained and presented in accordance with existing academic rules and ethical conduct. I declare that, as required by these rules and conduct, I have fully cited and referred all materials and results that are not original to this work.

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Saikat Chatterjee
....

Signature of the candidate

Date: 29/10/2025

Certified by Supervisor

Shankar Chakraborty 29/10/25
....

(Prof. Shankar Chakraborty)

Thesis Advisor

Department of Production Engineering

JADAVPUR UNIVERSITY

Kolkata-700032

Professor
Production Engineering Department
Jadavpur University
Kolkata - 700 032

CERTIFICATE FROM THE SUPERVISOR

This is to certify that the thesis entitled "**APPLICATIONS OF SOME NEW MULTI-CRITERIA DECISION MAKING TOOLS IN MANUFACTURING ENVIRONMENT**" submitted by Shri **Saikat Chatterjee**, who got his name registered on 28.05.2018 for the award of Ph. D. (Engg.) degree of Jadavpur University is absolutely based upon his own work under the supervision of **Prof. Shankar Chakraborty** and that neither his thesis nor any part of the thesis has been submitted for any degree/diploma or any other academic award anywhere before.

Shankar Chakraborty
29/10/25

(Prof. Shankar Chakraborty)

Thesis Advisor

Department of Production Engineering

JADAVPUR UNIVERSITY

Kolkata-700032

Professor
Production Engineering Department
Jadavpur University
Kolkata - 700 032

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VITA

The author, Mr. Saikat Chatterjee, is currently a research scholar in Department of Production Engineering, Jadavpur University, Kolkata, India. He has almost 11 years of experience in academic sector where the major work focus was on teaching, research and administrative activities. During this tenure, he has taught subjects, like Production and Operations Management, Industrial Engineering, Operations Research etc. He had obtained his Bachelor’s degree in Mechanical Engineering in 2010 from Rajiv Gandhi Proudyogiki Vishwavidyalaya, Bhopal, Madhya Pradesh. He had then obtained his Master’s Degree in 2013 with specialization in Production Engineering from Mechanical Engineering Department, Jadavpur University, Kolkata, India. In the year 2011, he had qualified the Graduate Aptitude Test in Engineering (GATE) examination, conducted by Department of Higher Education, Ministry of Human Resources Development, India. His research interests are the applications of different multi-criteria decision making methods in manufacturing environment-specific problems. He has presented several papers in international and national conferences as well as published numerous papers in international journals of high repute.

Preface

This research work focuses on applying various multi-criteria decision making (MCDM) approaches in the manufacturing environment. Decision analysis is a crucial tool for evaluating significant judgements within the scientific community. When a decision is complex, recurring or important, using a decision making method supports the process by expanding the information framework. MCDM is a key branch of decision analysis, dealing with the methods for incorporating multiple conflicting criteria into the management planning process. The two broad classes are multi-attribute decision making (MADM) and multi-objective decision making (MODM). While MADM compares alternatives within a discrete decision space and pre-specified decisions, MODM focuses on a continuous variables with specific constraints. MADM involves identifying alternatives, evaluating them based on several criteria, indicating preferences and scoring them according to the decision criteria. It selects the best alternative from a limited number of alternatives. MODM, however, employs constraints and continuous variables to develop the best solution with over a single goal.

Evaluating and combining various design and selection goals is essential to the success of manufacturing decision making. It is difficult to assess the overall efficacy of a suggested alternative because different design problems and alternatives call for different areas of knowledge. MADM ranks the feasible alternatives based on different attributes, considering the impact of certain criteria, which may conflict, to optimize the objectives. No single method suits all the decision problems in manufacturing. Different methods fit different problems.

The manufacturing industry is a major economic force worldwide with extensive connections across the industrial and cultural fabric in both the developed and developing countries. The right manufacturing strategies, input materials and machinery etc., must be chosen by the manufacturing organizations in order to address the difficulties of the global economy. The goal of contemporary manufacturing systems is now to increase total performance through efficient use of resources. The intricacy of the variables and forces affecting the system dynamics makes decision-making in a manufacturing environment a strategic challenge. The decision making process can be applied at many phases in an industrial setting as long as managers, engineers, and designers have access to the right tools and methods.

The study of finding and selecting options according to one's own values and preferences is known as decision making. Usually, a variety of criteria can be used to assess these potential alternatives. These criteria frequently contradict one another in some way. There are other possibilities to consider while making a decision, and in this case, the decision maker wishes to identify any viable good options and choose the one that best fits the objective. Making decisions entails reducing uncertainty and confusion about the options, not eliminating them entirely, so that a logical choice may be made.

The general rule that stands out in the eyes of everyone is to suggest the right path in which a particular system to be developed is widely assumed to help the business organizations enhance their decision making processes. This results in a mathematical problem that is well-formulated, meaning that the formulation determines the solution, which is commonly referred to as the optimal solution. The existence and content of the solution, which is typically accomplished by algorithms or heuristics, are thus determined by the formulation of the problem. In many real-time scenarios, implications are so intricate that all the information needed for an extensive comparison of the alternatives cannot be taken into account by an objective (single-criterion) function. One must examine the consequences of each alternative taken into consideration, regardless of how one chooses to respond to the questions posed in order to clarify a choice. The implications are typically numerous and vary greatly in type (e.g. economic, technological, comfort, status etc.).

A number of approaches have been put forth by various behavioural scientists, operational researchers and decision theorists throughout the years to explain how a decision maker might reach a preference judgement when selecting from several feasible alternatives. An ‘act of faith’ (a conviction) underlies every multi-criteria decision making approach, leading one to assume that openly establishing several criteria might benefit the modelling process in some way. A new paradigm for decision aid, i.e. the multi-criteria paradigm, is made possible by this act of faith. Its primary feature (decision assistance) is destined to develop within the context of an ‘ill-formulated’ mathematical problem since it depends on the construction of multiple competing criteria and typically no solution offers the best answer on all criteria at once. It should be noted that a decision problem is not necessarily ‘well formulated’ with respect to the given reality, even it is ‘properly formulated’ mathematically. Instead of looking for an existent reality outside of the stakeholders participating in the process, decision analysis seems to be a discipline with a constructive attitude and focus for learning.

Keeping these in view, this research work aims to apply some newly developed and almost unexplored MCDM tools in the context of manufacturing environment in which the preferences on the alternative’s performances are collected together to reach the final evaluation and decision. This study examines the following eight decision-making techniques for particular manufacturing applications, despite the fact that there are several MCDM techniques that are frequently used in the decision making sector.

a) Mixed aggregation by comprehensive normalization technique (MACONT)
b) Preference analysis for reference ideal solution (PARIS)
c) Evaluation by an area-based method of ranking (EAMR)
d) Collaborative unbiased rank list integration (CURLI)
e) Pareto-Edgeworth Grierson (PEG)
f) Ordering preference targeting at bi-ideal average solutions (OPTBIAS) —
g) Preference ranking on the basis of ideal-average distance (PROBID)
h) Double normalization-based multiple aggregation (DNMA)

MACONT method is a newly developed MCDM approach for making decisions. To derive a reliable result, it employs two mixed aggregation operators, a reference alternative and a thorough normalization technique. It differs from other MCDM techniques, and offers a number of benefits, including simplicity of use, multiple aspects and dependable results across various criteria, and capacity to modify the parameters for personalization. By exploring the effects of altering weights on the results and expanding application to address intricate decision making issues in many domains, more research on MACONT can be carried out to fully realize its potential. PARIS method is a powerful technique for handling difficult decision making situations which is independent of subjective weight assessment. The three normalization procedures and the weighted normalized decision matrix are calculated. The appraisal score of each of the alternatives is subsequently computed. Additionally, the distances from the reference ideal solutions are calculated and the alternatives are ranked according to how close they are to the perfect solutions. EAMR method determines a solution based on both the beneficial and non-beneficial criteria. It can also be used for group decision making and in uncertain conditions where uncertainties are taken into account. In the present research work, this method is compared with other existing MCDM methods and according to the results presented, it has some advantages over the others. CURLI method, introduced in 2016, can rank alternatives using both the qualitative and quantitative criteria, unlike other methods that need only quantitative criteria. This makes it ideal for decision making with qualitative criteria. The CURLI method involves developing a decision matrix, framing and scoring a square matrix for each criterion, combining them into a process scoring matrix and then, rearranging the matrix to highlight the best alternative. The flexibility of this method makes it highly recommended for various decision making scenarios. The application of PEG approach is significant in the MCDM domain, since it can deal with numerous criteria at the same time, requiring no criterion weight information. The steps of the PEG method include determining criteria vectors, arranging criteria vector values in ascending order, determining the aggregate vectors for each criterion, arranging the aggregate vector values in descending order, calculating the shifted vectors and radial shift, computing the PEG functions, calculating the mean squared error (MSE) for each alternative and ranking the alternatives according to the specified rule. OPTBIAS is a novel MCDM method for ordering the Pareto-optimal solutions, fulfilling the comprehensive requirements of simplicity, weight insensitivity, consistency and applicability. The unique aspect of this method is that it considers both the ideal solution and average solution, which decreases the interference of the average solution on the ranking results when the sample size is small. The steps involved in this method include calculating the distances from the Pareto-optimal solutions to the bi-ideal solutions and average solution, and ranking the solutions based on the calculated distances. PROBID is a new method that is reliable and performs at par with the other common MCDM methods. Typically, this approach takes into account a range of ideal solutions (from the most positive to the most negative) as well as the average solutions among them. PROBID is an excellent MCDM method because it provides a broader coverage of the optimal solutions. PROBID follows a systematic six-step process beginning with vector normalization of the initial decision matrix, which is transformed into a weighted matrix. Distinct from the traditional distance-based techniques such as technique for order preference by similarity to ideal solution (TOPSIS) and vlse kriterijumska optimizacija i kompromisno resenje (VIKOR), PROBID employs a unique mechanism to calculate proximity of the alternatives to the ideal references, leading to more precise rankings. It considers non-dominated alternatives, uses diverse normalization methods and integrates objective weights to enhance evaluation accuracy. The final step is ranking the optimal solutions and selecting the one with the highest ranking. DNMA is a utility value-based ranking method that considers double normalization and three aggregation tools. The uniqueness of this method lies in its use of two normalization techniques to overcome the limitations of single normalization methods and avoid biased results. The simple methodological steps involved in the DNMA method are normalization, weight calculation and aggregation. The normalization step involves both target-based linear and vector normalization techniques. The characteristics of this method include its ability to handle both qualitative and quantitative criteria, and capability to provide reliable and consistent results.

The previous researchers have employed a variety of decision making tools for assessing, safeguarding and selecting materials, machines and advanced machining technologies in discrete manufacturing environments. However, all of those approaches are either extremely complex, require time-consuming calculations and occasionally need the assistance of linear programming tools to solve the developed models. Additionally, those methods may produce inadequate results for decision making issues with an extensive range of attributes and a small number of possibilities. In order to provide more accurate and precise rankings of the possible alternatives, the present study investigates the application feasibility and potentiality of eight decision making techniques listed above. To the best of the author's knowledge, these techniques have rarely been used for decision making in a manufacturing settings with only a few successful implementations in business, chemical and other fields. Most of these methods are not applied in manufacturing decision making scenarios. Intense global competition compels the manufacturing organizations to enhance quality of their products and responsiveness cost-effectively. This research work addresses three pivotal areas in the manufacturing environment e.g., material selection, machine selection and dielectric selection (oil) in an advanced machining process, i.e. electrical discharge machining (EDM). These topics are essential because they significantly impact efficiency, quality and sustainability of the manufacturing processes. Selection of the appropriate materials for components, such as nozzles and pistons is crucial as they components must endure high stress and temperature, directly affecting efficiency and lifespan of the machineries. Identifying and solving material selection problems enhances product durability, reduces maintenance costs and improves operational efficiency. The integration of advanced machineries, such as collaborative robots (cobots) and drones transforms modern manufacturing by enhancing productivity and safety, facilitating tasks including inventory management, inspection, and enabling the manufacturers to adopt cutting-edge technologies and streamline operations. Additionally, choice of the dielectric (oil), particularly in EDM, plays a vital role in ensuring precision and quality. EDM oil influences the machining process, tool wear and surface finish of components; selecting the optimal EDM oil achieves higher precision, reduces downtime and ensures product consistency. These combined efforts in materials, machines and EDM oil selection are pivotal in the manufacturing processes, achieving the optimal performance. This research work aims to demonstrate effectiveness of eight MCDM methods for decision making in various manufacturing environments, including:

a) 3D printing nozzle material selection,
b) piston material selection,
c) cobot selection,
d) drone selection, and
e) EDM oil selection.

Focusing on these areas provides comprehensive insights and practical solutions that help the manufacturing industries improve processes, adopt innovative technologies and enhance overall performance. The findings and recommendations from this research drive advancements in manufacturing, leading to more efficient, reliable and sustainable production systems. The purpose of this research work is to address critical decision making problems within the manufacturing environment. By focusing on materials, machines and EDM oil selection, this study aims to provide solutions that enhance efficiency, quality and sustainability of the manufacturing processes, ultimately contributing to the global competitiveness and growth of any industry. Appropriate selection of materials, machine, robots and EDM oil offers significant potential for improving manufacturing performance and achieving the organizational goals. Incorrect selection can lead to productivity and profitability losses. The complexity of the selection processes makes multi-criteria decision making a valuable tool in engineering design.

Table 1 Framework of the considered decision making problems

Problems	Alternatives	Criteria	Nature of the criteria	
			Beneficial	Non-beneficial
3D printing nozzle material selection	8	9	7	2
Piston material selection	8	8	6	2
Cobot selection	13	6	2	4
Drone selection	8	8	7	1
EDM oil selection	10	6	3	3

The decision making issues taken into consideration in this study are listed in Table 1. All the eight MCDM techniques are successfully applied along with eight weighting methods to different manufacturing situations and the derived results are compared for better visualization. Detailed comparative analyses are conducted to assess agreement between the ranking orders obtained by these methods, keeping the performance measures in the evaluation matrices constant. The analyses include: a) comparing rank performance of each of the methods, b) determining the Spearman's correlation coefficient (R_s) to observe rank similarities, c) calculating the weighted Spearman's correlation coefficient (R_w), d) determining ranking similarity coefficients (*WS*), e) computing the number of operations required by each method, and f) conducting sensitivity analysis to demonstrate consistency of these methods. Additionally, the superior weighting and MCDM methods are identified by aggregating the weights and analyzing the results through Pareto analysis.

The organization of this research work is as follows; Chapter 1 introduces the manufacturing environment and its classification, need for decision making and its types, and discusses the MCDM tools, followed by the objectives and scope of the present work. This chapter discusses in detail the commonly used weighting and MCDM methods with their characteristics, merits and demerits. It also provides the reason for application of these methods in this research work. Chapter 2 demonstrates methodology of different objective weighting methods, outlining their principles, steps and contrasting them with subjective approaches. It details several prominent objective techniques, including entropy method, criterion impact loss (CILOS), logarithmic percentage change-driven objective weighting (LOPCOW), symmetry point of criterion (SPC), integrated determination of objective criteria weights (IDOCRIW), method based on the removal effects of criteria (MEREC), criteria importance through intercriteria correlation (CRITIC) and principal component analysis (PCA), highlighting their data-driven nature, mathematical foundations and advantages, such as reduced bias, increased consistency and ability to leverage data insights for more robust and defensible decision outcomes. Chapter 3 illustrates the newly developed MCDM methods by presenting the detailed methodologies of these eight MCDM methods, i.e. MACONT, PARIS, EAMR, CURLI, PEG, OPTBIAS, PROBID and DNMA, which are specifically selected for this study. This chapter outlines the corresponding methodologies of the considered methods, highlighting their uniqueness. Furthermore, it provides the procedural steps and associated mathematical formulations, including normalization techniques and rank determination processes, for these MCDM methods, aiming to enhance decision making accuracy and reliability in the manufacturing applications. Chapter 4 addresses the material selection problem for a nozzle of a 3D printer. Eight alternatives and nine criteria are utilized to construct the decision matrix. Eight MCDM methods are then applied to identify the best alternative. In this problem, tungsten carbide (A_4) emerges as the top-ranked alternative, while brass (A_1) performs poorly in most of the MCDM methods. This chapter also presents a comprehensive comparative analysis of various MCDM methods based on multiple evaluation parameters, including rank comparison under different criteria weighting techniques, evaluating R_s, R_w and WS values, and computational complexity. These findings reveal that alternative A_4 consistently emerges as the top-ranked alternative across most of the weighting conditions, with notable performance from IDOCRIW and CRITIC-combined weighting techniques. Among the MCDM methods, DNMA, PARIS and CURLI demonstrate superior ranking consistency. The R_s and R_w values indicate that DNMA and PARIS exhibit higher correlations under multiple weighting conditions, particularly with entropy method, IDOCRIW and MEREC, while OPTBIAS achieves the highest and most consistent rank correlation values, affirming its reliability. The ranking similarity coefficients further reinforce these findings, with DNMA maintaining very high similarity scores across various weighting conditions. Finally, an analysis of computational complexity highlights

EAMR as the most efficient method, requiring the least number of mathematical operations, whereas, CURLI and MACONT demand significantly higher computations. These results collectively establish DNMA as the most stable and consistent MCDM method, offering superior ranking performance while balancing computational efficiency.

Eight MCDM techniques are used to rank eight material alternatives according to eight assessment criteria in Chapter 5, which addresses the piston material selection problem. According to the results, AISI 4140 steel (A_7) is always the most highly ranked material. In some instances, AISI 8660 steel (A_6), aluminium 4032-T6 (A_2), and aluminium A360.0-F die casting alloy (A_3) also emerge as formidable competitors. The comparative analyses reveal that PARIS and PROBID provide the most stable rankings for A_7 across different weighting methods. The rank correlation studies, including R_s and R_w, highlight that DNMA, PARIS and OPTBIAS exhibit strong correlations across various weighting schemes, whereas, PEG and CURLI demonstrate weak performance. The coefficient of ranking similarity further supports the superiority of DNMA. The computational efficiency analysis results indicate that EAMR requires the least number of mathematical operations. The sensitivity analysis studies highlight the consistency and robustness of PARIS, DNMA and OPTBIAS, especially for the top two alternatives, i.e. A_7 and A_6. This comprehensive study emphasizes strengths of certain MCDM methods in ensuring accurate and stable material ranking for the pistons. Chapter 6 evaluates selection of cobots using eight MCDM methods, focusing on 13 alternatives and six criteria. A_6 (Elfin-P) consistently ranks highest across most the methods, showcasing its robustness and reliability. In terms of rank comparison, A_6 dominates, with DNMA maintaining consistent prioritization of the high-performing alternatives, like A_6 and A_{11} (Techman-TM5-700). The R_s analysis shows that DNMA and PARIS achieve strong correlations across various weightings, often reaching perfect correlation of one while CURLI and PEG perform poorly. The R_w analysis indicates that DNMA and PARIS consistently perform well, reinforcing their reliability in ranking the top alternatives. The *WS* analysis also highlights DNMA and PARIS as the most consistent methods, with frequent *WS* values of 1 or close to 1, while CURLI and PEG are underperformed by the other methods. Computationally, EAMR is the most efficient method, requiring only 221 operations, whereas CURLI needs 1352. Sensitivity analysis study confirms that A_6 remains the top choice in most of the cases, with DNMA standing out as the most balanced and reliable method, outperforming others while maintaining consistent rankings across all the tiers, unlike OPTBIAS and EAMR, which show variability in the middle-tier alternatives. Chapter 7 focuses on the study of a drone selection problem based on eight alternatives and eight criteria, with eight MCDM methods applied to identify the best drone. Power Vision Power Eye (A_2) emerges as the top choice based on the rank comparison. Under equal weight conditions, Autel EVO II Pro V3 (A_6) consistently ranks high, while Aurelia X4 Standard (A_8) remains at the bottom of the list. DNMA prioritizes the top alternative as A_6, while MACONT and PARIS exhibit some variability in the rankings. DNMA and EAMR also show strong performance, with CURLI and PEG being more sensitive to the prioritization criteria. Correlation analysis reveals that DNMA and PARIS show high correlation values, while, the R_w values indicate strong correlation for DNMA-PARIS and OPTBIAS-PROBID. The *WS* values confirm that DNMA, OPTBIAS, PARIS and PROBID perform well across most of the weighting conditions, with some methods occasionally having the corresponding *WS* values over 0.95. In terms of computational efficiency, EAMR method requires the fewest operations (168) to solve the said drone selection problem, followed by OPTBIAS (264), whereas, MACONT (368) and CURLI (640) demand more operations. Sensitivity analysis shows that DNMA is consistent in ranking, maintaining stability and reliability under various weighting conditions. Chapter 8 focuses on selecting the best EDM oil in a manufacturing context, considering ten alternatives and six criteria. The study reveals that Spark SPO-A (A_1) emerges as the top choice. Across different weighting conditions, A_1 consistently ranks highest in most of the methods, with alternatives Diel 7500 (A_2) and EDM-244 (A_6) also performing strongly. In contrast, Exxsol D80 (A_9) often ranks lowest, reflecting its poor performance. DNMA, PARIS and OPTBIAS demonstrate robust and reliable results, while, other methods, such as CURLI and PEG show variability in their rankings. Other methods, including EAMR, also perform well, especially in terms of computational efficiency, requiring fewer operations compared to MACONT and CURLI, which demand higher computational resources. The sensitivity analysis indicates that while some methods are sensitive to changes in the weighting schemes, DNMA provides stable rankings across various conditions, making it the most effective method for ranking of the considered alternatives. Chapter 9 evaluates the most effective weighting technique and MCDM method using an ensemble aggregate ranking approach based on half-quadratic theory, incorporating consensus index and trust level for reliability assessment. The Pareto analysis identifies CRITIC as the most dominant weighting method, contributing the highest cumulative weight share (20.02%) with minimal zero-weight occurrences, followed by LOPCOW (18.55%) and IDOCRIW (16.40%), while entropy method (7.67%) and PCA are least effective. Among the MCDM methods, DNMA and PARIS are the most effective, receiving the highest assigned weight 15 times each, with cumulative weight contributions of 8.959 and 8.802, respectively, whereas PEG and CURLI frequently record zero weights. The Pareto analysis confirms DNMA as the superior method due to its stability, lowest zero-weight occurrences (four times) and highest contribution (36.64%) under equal weighting conditions, outperforming PROBID (34.18%). Chapter 9 also validates these findings under equal weighting conditions, eliminating potential biases from different weighting schemes. DNMA remains the superior MCDM method, securing the highest cumulative weight (1.832) and contribution percentage (36.64%), outperforming PARIS, which ranks second with 34.18% contribution. The DNMA method never records a zero-weight score, reinforcing its robustness. The Pareto analysis further solidifies the dominance of DNMA, confirming its mathematical superiority and reliability across diverse decision making scenarios. These findings validate DNMA as the most effective MCDM method, particularly in high-accuracy ranking applications, with CRITIC as the most suitable weighting technique for robust decision making.

In conclusion, the findings of this research work consistently point to DNMA as the superior MCDM method and CRITIC as the most effective weighting technique for robust decision making. DNMA demonstrates exceptional stability, ranking consistency and computational efficiency across various decision problems, including material selection, drone selection and EDM oil selection, making it the most reliable choice in ensuring accurate solutions. The ability of DNMA to maintain stable rankings, even under varying weighting conditions, is further validated through high R_s and R_w values, particularly when paired with CRITIC, LOPCOW and IDOCRIW weighting techniques. Furthermore, DNMA consistently prioritizes high-performing alternatives and minimizes variability, offering a balanced decision making approach. The Pareto analysis also reinforces the superiority of DNMA, showing that it provides the maximum cumulative weight and contribution with a balanced computational effort. On the other hand, CRITIC emerges as the most stable and influential weighting method, consistently providing reliable weights contribute to its robust performance. This combination of DNMA and CRITIC ensures both ranking stability and computational efficiency, making them the most effective tools for complex decision making scenarios across a range of applications.

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Abbreviations

AHP	Analytical hierarchy process
ANP	Analytic network process
ARAS	Additive ratio assessment
BWM	Best worst method
CCM	Complete compensatory model
CI	Consensus index
CILOS	Criterion impact loss
COPRAS	Complex proportional assessment
COCOSO	Combined compromise solution
CODAS	Combination distance-based assessment
CRITIC	Criteria importance through intercriteria correlation
CURLI	Collaborative unbiased rank list integration
DEMATEL	Decision making trial and evaluation laboratory
DNMA	Double normalization-based multiple aggregation
EAMR	Evaluation by an area-based method of ranking
EDAS	Evaluation based on distance from average solution
EDM	Electrical discharge machining
ELECTRE	Elimination and Choice Translating Reality
EVAMIX	Evaluation of mixed data
FAD	Fuzzy axiomatic design
GRA	Grey relational analysis
HQ	Half quadratic
ICM	Incomplete compensatory model
IDOCRIW	Integrated determination of objective criteria weights
IVPF	Interval-valued Pythagorean fuzzy
LOPCOW	Logarithmic percentage change-driven objective weighting
MABAC	Multi-attributive border approximation area comparison
MACONT	Mixed aggregation by comprehensive normalization technique
MADM	Multiple attribute decision making

MAIRCA	Multi-attributive ideal real comparative analysis
MAUT	Multi attribute utility theory
MCDM	Multiple criteria decision making
MEREC	Method based on the removal effects of criteria
MODM	Multiple objective decision making
MOORA	Multi-objective optimization on the basis of ratio analysis
MOOSRA	Multi-objective optimization on the basis of simple ratio analysis
MSE	Mean square error
MULTI-MOORA	Full multiplicative form of multi-objective optimization on the basis of ratio analysis
NIS	Negative ideal solution
OCRA	Operational competitiveness rating
OPTBIAS	Ordering preference targeting at bi-ideal average solutions
PARIS	Preference analysis for reference ideal solution
PCA	Principal component analysis
PEG	Pareto-Edgeworth Grierson
PIS	Positive ideal solution
PROBID	Preference ranking on the basis of ideal-average distance
PSI	Preference selection index
PROMETHEE	Preference ranking organization method for enrichment evaluation
QUALIFLEX	Qualitative flexible multi-criteria method
RIM	Reference ideal method
SMART	Simple multi-attribute rating technique
SODM	Single objective decision making
SPC	Symmetry point of criterion
SWARA	Stepwise weight assessment ratio analysis
TARO	Technique of accurate ranking order
TODIM	TOmada de Decisao Interativa Multicriterio
TOPSIS	Technique for order preference by similarity to ideal solution
TL	Trust level
UCM	Un-compensatory model

VIKOR	Vlse Kriterijumska Optimizacija I Kompromisno Resenje
WASPAS	Weighted aggregated sum product assessment
WPM	Weighted product method
WSM	Weighted sum method

1. INTRODUCTION

1.1 An introduction to the manufacturing environment

The manufacturing environment is a multi-dynamic and complex ecosystem where parts/components are designed, developed and produced on a large scale. It encompasses various industries and sectors, including automotive, electronics, aerospace, pharmaceuticals, consumer products and many more. It is the starting point of an intricate series of processes that turns raw resources into complete products. The scale and complexity of these industrial facilities range from a few people working in a tiny workshop to enormous factories with thousands of employees. Phases, such as procurement, fabrication, assembly, quality control, packaging and distribution affect the entire production process. To maintain efficacy and efficiency of the manufacturing environment, each phase necessitates use of the suitable equipment, labour and planning. A mass production system is needed to make products in huge quantities and the producers work hard to adapt their products to the ever changing demands of the market. To reduce waste and improve product quality, this scaling frequently necessitates optimal application of automation, robots and changing production practices. Given the existence of dangerous chemicals, gases and procedures, safety is yet another crucial component of any manufacturing environment. Adequate training programmes, protection gear and attention to safety procedures are required to shield employees from these risks. Success of any of the manufacturing industries mostly depends on streamlining the processes, getting rid of the bottlenecks and using the resources more efficiently. Technologies, such as advanced data analytics, artificial intelligence and the internet of things play transformative roles in the industrial operations. Furthermore, industry is prioritizing environmental sustainability more and more these days. It is essential to adopt eco-friendly behaviours, including cutting back on trash, using sustainable energy sources and consuming less energy.

Figure 1.1 presents a holistic view of the manufacturing environment, classifying it based on multiple interrelated dimensions rather than a single factor, highlighting the inherent complexity and diversity of these systems. The figure showcases various dimensions, such as industry type, representing the operational sector with its unique technological, regulatory and product requirements; product type, indicating whether the products are standardized or customized, simple or complex, durable or consumable, thus influencing processes and machineries; production process, encompassing discrete, batch, continuous and process manufacturing, affecting layout, flow and technology choices; production volume, ranging from low-volume customization to high-volume mass production, determining automation levels and economies of scale; flexibility of production, describing adaptability to design or quantity changes, crucial for dynamic markets; and quality and regulatory requirements, pertaining to stringent controls, traceability, documentation and adherence to standards, dictating cleanroom needs and quality protocols. This framework illustrates that the manufacturing environments are rarely uniform, often exhibiting hybrid characteristics, and aids the manufacturers, engineers and managers in comprehensive analysis of the strategic decisions, like facility design and process planning by providing a complete contextual understanding.

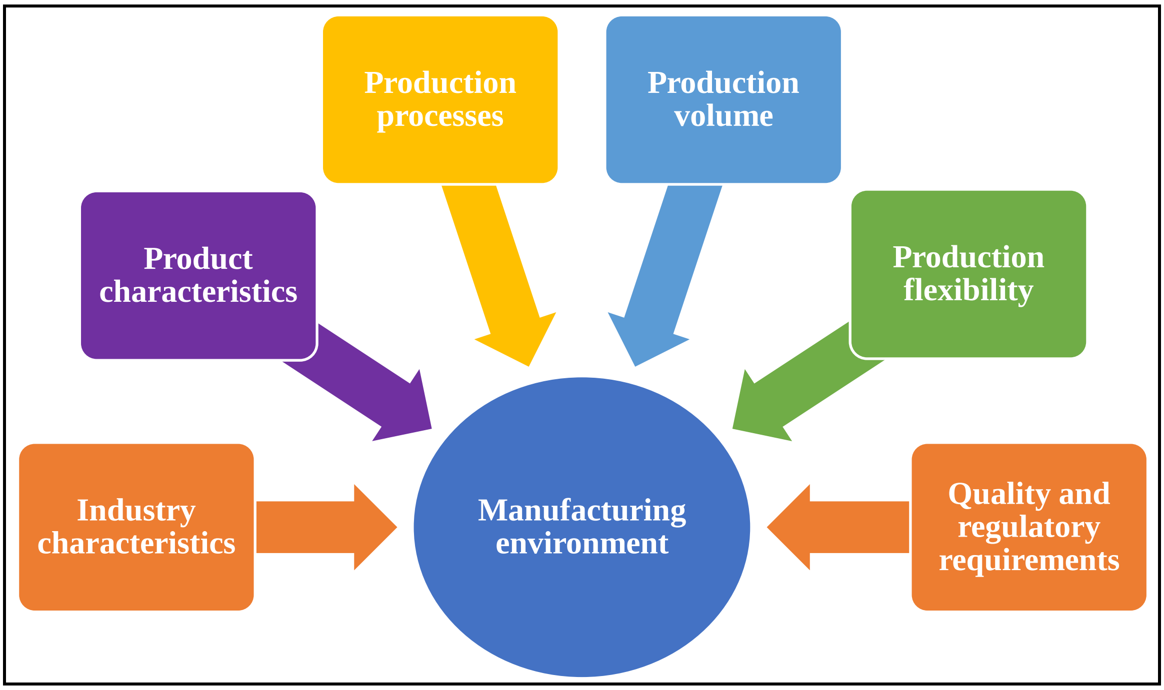


Figure 1.1 Dimensions of the manufacturing environment

Figure 1.2 shows types of the manufacturing environment based on different production processes. Job shop manufacturing, which produces customized or low-volume items using unique methods and setups, caters to a wide range of product types, including machine shops, bespoke furniture makers and specialized fabrication shops [1]. Across diverse sectors, such as food processing, pharmaceuticals and automobile manufacturing, batch production is a typical approach that maximizes resource efficiency by manufacturing comparable items in groups or batches. This enables economical and lean production. The reverse is the continuous manufacturing method, which is a continuous flowing production method applied in areas such as steel production, chemical process and petroleum refining. Automated production employs it as a method for guaranteeing uniformity of output in that it enables materials to flow through various stages continuously without interruption. To produce end products, discrete manufacturing is focused on building and combining parts and is interested in making individual, recognizable items. It is applied most frequently in consumer products, automotive and gadget sectors. Process manufacturing, common for chemical, food, and drink and pharmaceutical sectors, is all about changing the raw material into final products by means of physical or chemical changes. Sturdy industrial environments provide numerous advantages to an organization as well as workers. It improves productivity by refining processes, focusing on quality control and workforce safety through proper training and compliance with regulations [2]. It also promotes employee empowerment and participation, lean manufacturing strategies for waste elimination, and cost reduction and flexibility and responsiveness to meet the needs of the market. In addition, by adopting green practices and reducing carbon emissions, a best practice industrial atmosphere gives high importance to sustainable development. However, sustaining such an environment comes with difficulties, like incorporating technological advancements, obtaining funding, recruiting suitable staff, handling disruptions in the supply chain, adhering to legal requirements, adjusting to changing market demands, competing in a globalized market and attaining ecological sustainability. To overcome these challenges, organizations can implement strategies, such as continuous training, vendor diversification and regulatory compliance control, agility in manufacturing, innovation and sustainable practices. Making informed decisions before taking any action is the key to navigating these obstacles effectively.

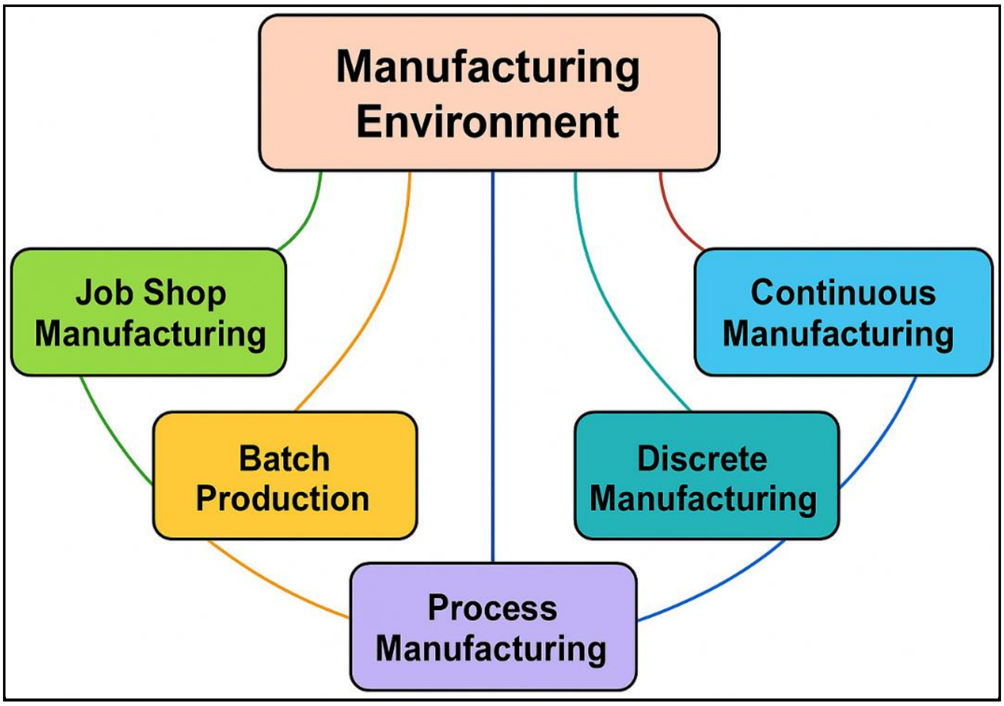


Figure 1.2 Types of manufacturing environment based on the production processes

1.2 Need for decision making in manufacturing

Manufacturing organizations play a crucial role in the economy of every industrialized nation by contributing around 20 to 30% of the value of all the products and services generated [3]. The efficiency of an industrial organization in a country is closely related to the strength of its economy. The transition from traditional economies based on primary activities to contemporary economies powered by high productivity of the industrial sectors occurs dramatically during the last several decades. This change has integrated several scientific and technical domains, and resulted in notable improvements in products and procedures. Manufacturing organizations have the difficult challenge of cutting expenses, improving quality and customising products to satisfy a wide range of customer needs in the present competitive market. The rivalry has only increased because of globalization, forcing these businesses to provide excellent products quickly. Any manufacturing organization that wants to be competitive in an ever-evolving business environment must be able to quickly adjust to the shifting market conditions and maintain premium quality at competitive costs. Global manufacturers need to employ a range of multidisciplinary knowledge to make complex decisions every day to navigate through the labyrinth of operational risks. Every choice that the manufacturing organizations make, from what to create and how to manufacture it to figuring out the production quantities, scheduling and cost considerations, is crucial to their survival and success in the highly competitive world of today. Amongst the countless decisions required in the manufacturing organizations, decisions related to selection of business, locations and layouts, production processes, production technology, materials, suppliers, quality policies etc. are of importance and considerable interest to the management of those manufacturing organizations. To anticipate the impact of huge investments, higher risks and growing competition, management thus needs to be able to make appropriate decisions. Major decisions related to the manufacturing organizations include various areas, such as new business domains, acquisitions and mergers, subsidiaries and affiliates, joint ventures, alliances, portfolios, quality policies, financial institutions, major suppliers, facility locations and layout, new products, service and market development, enterprise resource planning systems, supply chain networks and key personnel selection.

Figure 1.3 presents the five problem areas, shortlisted for the application of MCDM techniques in the manufacturing environment. These areas are selected based on their practical relevance, technological importance and complexity of decision making involved within the modern manufacturing settings. The chosen problems represent a diverse range of decision scenarios across various sub-domains, such as additive manufacturing, mechanical design, automation, logistics and precision machining. Each of these scenarios involves multiple evaluation factors, which make them well-suited for applying MCDM methods that are specifically designed to handle complex, multi-criteria decisions. The selection approach also reflects the current industrial priorities, including integration of Industry 4.0 technologies, use of advanced and sustainable materials, adoption of collaborative automation and enhanced process control. These areas are dynamic and evolving rapidly, making them ideal for exploring the real-world applicability of MCDM approaches in decision support. Moreover, decisions in these domains carry significant implications for performance, safety, productivity, cost-efficiency and environmental compliance. Therefore, by focusing on these specific and practically significant areas, the study aims to highlight the value of MCDM techniques in improving the structure, transparency and reliability of decision making in today’s manufacturing landscape.

In the past decades, numerous researchers have highlighted the significance of material, machine and dielectric oil selection in the manufacturing settings, acknowledging their significant impact on organizational performance. Material selection is most critical in shaping the cost, performance and manufacturing complexities of producing a product. It forms a significant percentage of the overall production costs, making it imperative to exercise careful choice procedures. Poor material selection may result in product rejection and huge financial losses. Therefore, it is important to follow systematic selection procedures. Well-planned material selections, on the other hand, can increase potential of an organization in terms of increased customer satisfaction and competitiveness in the marketplace. Similarly, machinery selection also plays a critical role in determining operational costs, productivity and quality of the product. Selecting the right equipment makes the way for the long-term success of a company through the simplification of processes and elimination of waste [4]. Furthermore, the selection of dielectric oil is also instrumental to the life cycle and functioning of an enhanced machining process, which affects aspects of equipment deterioration, maintenance cost and enhancement in efficiency. Therefore, it is important to make the right choices concerning material, equipment and dielectric oil to promote overall revenue, quality and performance of the production processes. Resolving the issue involved in these decisions is paramount towards promoting organizational development and competitiveness within a contemporary, dynamic market.

Additive manufacturing has increased manifold due to advancements in 3D printing technology and today there are newer ways of making various kinds of products using various processes. For fused deposition modeling, in particular, design and fabrication of the 3D printer nozzle also have a significant role to obtain the optimal product formation. In fused deposition modelling, a motor in the extruder drives the filament towards the hot end, where it melts and is deposited by the nozzle in layers to create the desired shape. Print thickness and resolution depend directly on the shape, size and material of the nozzle. Small nozzle diameters add detail at the risk of clogging the filament and large diameters add speed at the expense of resolution. Nozzle design, particularly the length and width, controls detail and cooling efficiency as well as filament travel time and cooling time. The efficiency of 3D printing also varies with materials selected, i.e. for strength, hardened steel or brass to achieve minimum cost. In the selection of nozzles being used in 3D printing, several factors need to be considered in an attempt to deliver desired print quality and performance.

Another very important element, which is made up of different things to take into account when choosing the best material is piston. When there is a choice to choose the material of the piston, designers must take into account a range of factors like strength, temperature resistance, visibility and even the environmental effect. They must also take into account its machinability and whether it is readily available. Today, it is important that the design is both functional and aesthetic. To design a working piston, there must be a balance of all these elements. Pistons are very important engine and pump components because they transfer force from one point to another. They need to withstand high pressure and temperature but still perform normally. Aluminium silicon alloy is typically used in pistons as they can withstand stress and run in different engines. Sometimes steel is also used, primarily with proper cooling. Piston designs have evolved much over the years to enhance efficiency as well as weightlessness. Heat-resistant and specially engineered pistons that support higher speeds of engine running are used in race cars. Piston manufacturing involves a number of processes like casting and machining to make them exactly suitable for their function.

Assembly cobots bring a great advantage compared to traditional manual assembly, enabling quicker, more efficient factory floor operations that ultimately translate to greater output, better quality and less waste. They are optimal for repetitive or complex work owing to their accuracy and consistency and capacity to work alongside humans for a safe and ergonomic working environment. Cobots are versatile and programmable for various assembly functions, although the initial investment is greater, but return on investment in the long run is high. Cobots, in contrast to industrial robots, are designed to collaborate with humans, include safety sensors and can be readily reprogrammed to accommodate changing production needs. Assembly cobots offer a hands-on way of enhancing the assembly processes due to their compactness, enhanced mobility and suitability in light assembly activities. Cobots, which are separated by design, operation and application, allow the manufacturers to pick the optimal solution to their unique needs, enhancing production, quality and employee safety on the shop floor. Due to their inherent flexibility, mobility and affordability, cobots are a sufficient answer to a vast variety of assembly work. Through cobots, the manufacturing processes are rendered streamlined in order to enable acceleration of operations, thereby, manufacturers enhance productivity, quality and safety in manufacturing plants.

Since, drones prove to be advantageous in comparison to the traditional transport, the drones popularity is increasing among the industrial activities. Drones find it ideal in transporting components, finished goods and raw materials within assembly areas due to the factors of increased flexibility, reduced man-power expense, enhanced safety features and greater efficiency. Drones also make stock management automated, the process of restocking and stock management. This results in greater efficiency waste disposal, repairs and maintenance to attain a greater sustainable industrial economy. Drones greatly increase industrial efficiency by lowering the material transportation costs, and speeding component and product transport. While aerial drones hover over the shop floor, enabling item movement between different regions and conducting inspections, ground-based drones with wheels or tracks perform well in navigating the manufacturing units for material delivery, waste management and inventory control. By smoothly switching between the ground-based and aerial delivery modes, hybrid drones further increase flexibility and meet a greater range of manufacturing needs. In general, drones show themselves to be flexible and effective instruments that are vital to addressing the needs of distribution and transportation in the contemporary manufacturing processes.

Recent developments in non-traditional material removal techniques, notably EDM, have drawn a lot of interest from the industrial sector. In EDM processes, the dielectric fluid, commonly referred to as EDM oil, plays a pivotal role in ensuring quality of the machining operations. It performs a variety of purposes, like permitting regulated electrical discharges, chilling and consolidating the eroded particles, eliminating trash and absorbing heat during the real-time machining operation. An excellent dielectric fluid should have cheap cost, non-toxicity, low viscosity, good wetting characteristics, high flash and fire points to avoid risks, chemical non-corrosiveness, high electric strength, specific gravity, low aromatics and effective quenching behaviour. However, given the intricacy of the components involved, no single EDM oil can fulfil all the criteria concurrently during real-time EDM operations. As a result, selecting the best EDM oil with desirable qualities has become critical for improving the machining performance, particularly during deep-hole drilling of materials, such as aluminium bronze alloy.

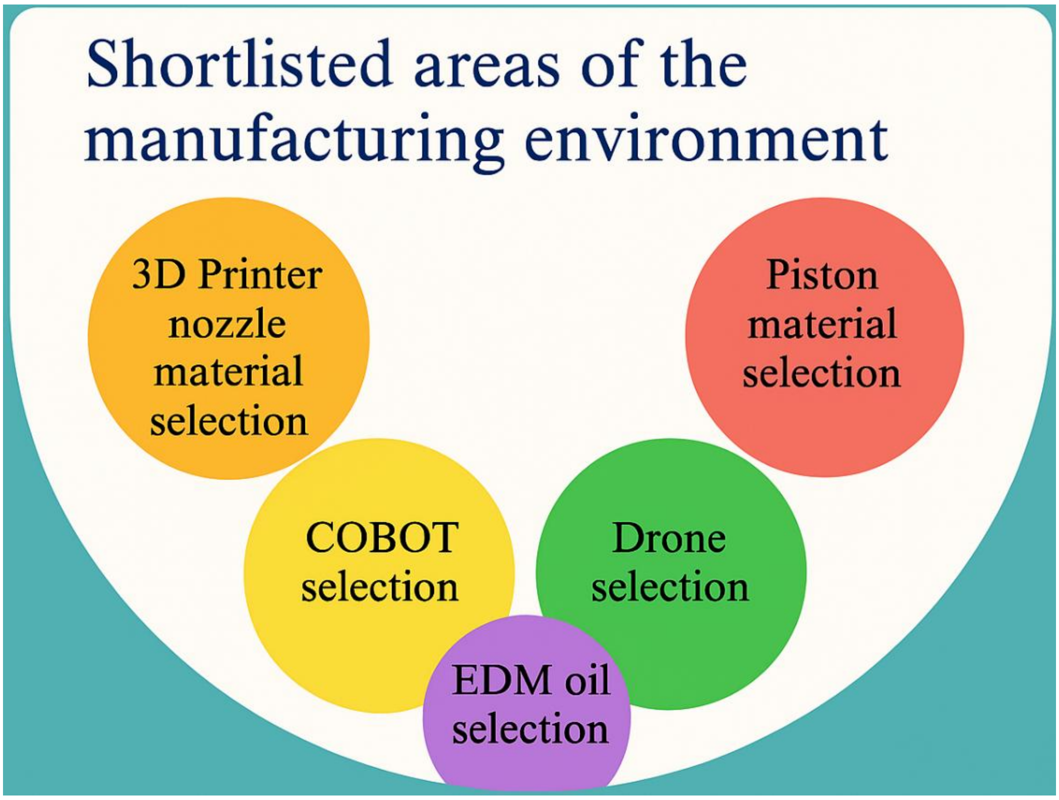


Figure 1.3 Shortlisted areas for application of the MCDM methods

1.3 Multi-criteria decision making techniques

The decision making process in industrial organizations is complex due to many factors, such as unpredictability of data, availability of competing variables and difficulty in determining choices between different factors. Advances in science and technology further complicate the decision making task by introducing new criteria and alternatives. To address these challenges, MCDM approaches provide the most effective analytical measure. In decision making, MCDM tools stand as structured methodologies designed to navigate the complexities of choice and design challenges. They serve as the navigational tools in a sea of competing criteria, offering a systematic way to evaluate and resolve dilemmas. Traditionally, MCDM conundrums present a plethora of potential solutions, yet the ultimate selection hinges on the infusion of preferences of the decision makers into the mix of specified criteria. The overarching aim of MCDM approaches lies in the art of discernment, ranking and picking out the optimal course of action from an array of viable alternatives, each subject to scrutiny against a backdrop of diverse, sometimes conflicting benchmarks. Although MCDM has historical origins dating back to the 18th century, its development does not start to take shape until 1951 when the mathematical concepts are explicitly applied to it. Early research establishes the basis and in the 1980s and 1990s, there is a sharp increase in interest in deciphering complexity. Current research efforts aim to address the complicated problems so as to improve effectiveness and accuracy of the decision making procedures, particularly in modern industry where ambiguity and uncertainty frequently rule supreme. Because of the way its elements are interrelated, there is no definitive way to classify MCDM, no matter how many different approaches are used. However, as shown in Figure 1.4, these methods generally fall into two main categories; i.e. MODM and MADM, each of which is suited to a particular application goal. When sorting among the alternatives, MADM approaches focus on the characteristics that should be prioritized, whereas MODM methods traverse the terrain of compromises under the direction of a hierarchy of objectives and predetermined limitations. MCDM functions as a guiding light of reason, helping the decision makers navigate the maze of alternatives and arrive at decisions that are consistent with their goals and limitations. Because the decision makers are involved in constraint definition, MODM approaches include subjective decision making and are thus ideal for design issues, but MADM techniques are popular for selecting the best choice from the given alternatives.

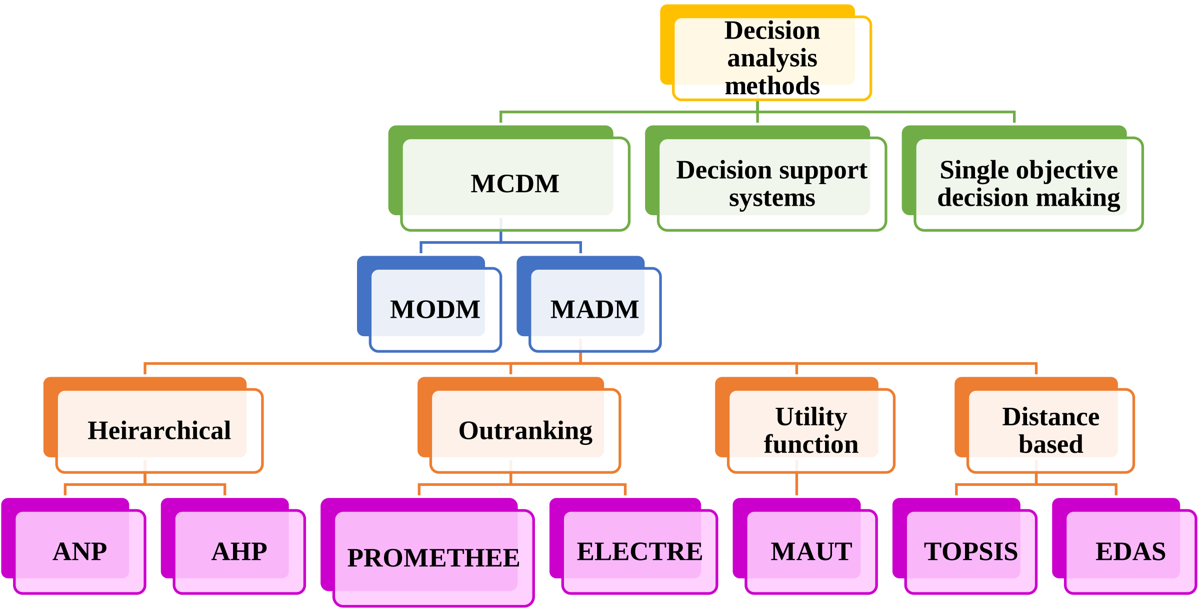


Figure 1.4 Classification of the MCDM methods

The pursuit of efficiency, quality, responsiveness and diversity is an ongoing endeavour in the global manufacturing sector. Production managers are always searching for ways to reduce expenses, produce high-quality products, quickly adjust to the changing consumer demands and expand their product line. Organizations strive for constant improvement in their processes and products in order to achieve world-class performance. Achieving such accomplishments requires a complex combination of planning and control procedures, as well as proper balance of production configurations. Every step matters in this situation because winning here is attaining a significant position in global marketplace and enhancing profitability. At the new manufacturing environment, there is number-one priority and that is maximizing efficiency out of whatever materials are available in order to maximize overall performance. To guarantee optimum results, each stage of the manufacturing cycle, from design through delivery, is precisely calibrated. Conversely, manufacturing decision making is very subtle.

The situation is complex with intricate motivating forces and pressure that all feed into how the production system operates. Having a strategic attitude and having access to a toolbox full of techniques and tools that are specifically designed for the job at hand are needed to work in this environment.

Decisions are made at every stage of the production process, whether they are made by the managers, planners or designers. The availability of appropriate tools and processes allows the decision makers to steer towards the goals that are in line with the objectives of the organization. The art of developing manufacturing plans involves striking a balance between cost, quality, dependability and adaptability. This is where businesses carve out special places for themselves in the market. Cost is the deciding factor for some, pushing choices and procedures in the direction of lean efficiency. For others, however, personalization reigns supreme, inspiring a passionate devotion to adaptability in production scheduling techniques. Fundamental to it all is the understanding that the industrial decision making effectiveness depends on the comprehensive assessment and integration of several goals and attributes, all of which can be easily summed up under the word ‘criteria’. In the intricate world of production, these standards work as guiding lights, shedding light on the way to well-informed and strategic decision making. Requirements may be difficult to meet or even conflicting. In a particular industrial setting, an organization might give the cost criterion more weight and focus its manufacturing efforts on achieving the target, while another organization might value customization more and, consequently, favour a flexible process and emphasize flexibility in its production planning methodologies [5]. The foundation of this research endeavour is to assess and incorporate all design and selection goals, or ‘criteria’, determining success of the industrial decision making problems. Both the goals and characteristics of the problem can be represented by these criteria. These demands can be difficult to meet and sometimes conflicting. Throughout the decision making process, people with varying levels of expertise must be included due to numerous design considerations and alternatives. This makes it challenging to evaluate how widely an alternative is accepted. Numerous intermediate roles may also be determined by the relative weights given to those variables. As mentioned earlier, MADM is a crucial part of modern decision science, helping the decision makers who are faced with a variety of alternatives and evaluation criteria. In addition to a range of real-world issues that call for evaluation of several criteria, practitioners and researchers have been motivated to develop MADM methods in order to suggest better decision making tools based on recent developments in mathematical optimization, scientific computing and computer-based technologies [6, 7]. The prior researchers proposed and adopted a range of MADM tools and other unique mathematical approaches for decision making in the conflicting industrial contexts, according to a thorough literature review and analysis of the earlier works. All those researchers have worked to increase accuracy and dependability of solutions by implementing increasingly relevant and straightforward methods. Such tactics might not work in every situation where decisions need to be made because of the unpredictability of real life. Numerous methodologies have been presented by the earlier academics, but majority of them have not examined how well their suggested methods would work in various decision making scenarios. Among those systems, the primary drawback is their incapacity to manage both the cardinal and non-cardinal data simultaneously.

A variety of real-world manufacturing instances are analyzed and several attempts are made to evaluate, choose and justify the manufacturing processes. Manufacturing organizations face diverse decision making challenges that cannot be fully addressed by a single analytical approach. Depending on the nature of the decision issue and type of the information provided, many strategies may be appropriate. This research aims to help the manufacturing organizations evaluate and select the best alternative for production by introducing sophisticated and multi-advantageous MADM methods that can simplify decision making and increase productivity while minimizing costs and risks. A new generation of MCDM techniques has surfaced in the dynamic field of industrial decision making, ready to take on practical problems head-on. In contrast to their predecessors, these techniques have mainly escaped examination and research. The previous attempts have frequently depended on a variety of decision making strategies, from the complex to the computationally demanding. However, these conventional approaches may not work well in situations where there are many criteria and less alternatives, leading to less-than-ideal outcomes. Taking advantage of this vacuum in the literature, the current study delves into unknown ground by investigating the unrealized potential of the recently established methodologies in providing more accurate and nuanced evaluations of accessible alternatives. Although these methods have not gained much momentum in the manufacturing environment, their potential in other fields has also not been fully investigated. In reality, these methodologies have not yet been applied in industrial decision making. As of right now, very little research has been carried out to examine how MADM techniques function in the discrete manufacturing environments. Furthermore, the previous studies have not succeeded in offering a thorough sensitivity analysis to investigate the stability of MADM ranks in a variety of manufacturing circumstances. Furthermore, the lack of endeavours to synchronize particular industrial decision making situations with appropriate MADM methodologies emphasizes the early phases of research in this field.

The groundwork for this endeavour is laid upon a meticulous curation of choice matrices spanning five distinct domains, each meticulously crafted from technical specifications gathered from a plethora of sources, like catalogues, scholarly journals, online repositories and manufacturing databases. It is through this methodical approach that the study endeavours to shed light on the uncharted terrain of manufacturing decision making, paving the way for a more informed and nuanced approach to tackling the challenges that lie ahead. To address the limitations and contribute to a more robust decision making framework in manufacturing, this research specifically employs entropy method, CRITIC, MEREC, PCA, SPC, LOPCOW, CILOS and IDOCRIW as the weighting methods, and MACONT, PARIS, CURLI, PEG, OPTBIAS, PROBID, DNMA and EAMR as the MCDM methods to solve manufacturing related decision making problem.

The earlier studies have utilized a diverse sets of weighting methods, as outlined in Table 1.1, which summarizes the characteristics, merits and demerits of each of the methods. The selection of entropy method, CRITIC, MEREC, PCA, SPC, LOPCOW, CILOS and IDOCRIW weighting techniques are based on their strong mathematical foundations, ability to extract insights directly from the data and suitability for rigorous decision making scenarios where subjectivity must be minimized. Unlike subjective weighting approaches, such as AHP, Delphi or SWARA, which depend on human judgment, expert opinions or consensus, these objective methods entirely rely on data characteristics, reduce bias, and increase transparency, consistency and repeatability in results. Techniques, such as entropy method calculate weights based on the amount of information or variability in the criteria values, while CRITIC accounts for both intensity of contrast and correlation between the criteria, offering a deeper analysis of interdependencies. MEREC evaluates how elimination of each criterion affects the overall performance, which is useful for understanding the true contribution of each element. PCA reduces the complexity of high-dimensional data by identifying principal components that capture the majority of variations without predefined weights, which helps eliminate human interference. SPC is based on the concept of symmetry point and determines weights through absolute distance of each value from this point, effectively highlighting the influence of each criterion. LOPCOW incorporates performance loss when one criterion is dropped, indicating the extent to which each criterion is critical to the entire decision structure. CILOS overcomes the shortcomings of entropy method by evaluating loss in significance when other criteria reach their ideal maximum or minimum, making it immune to problems caused by homogeneous or negatively skewed data. IDOCRIW brings together the advantages of CILOS and the entropy method into a hybrid, balanced method, which leverages the strength of information dispersion as well as the loss of performance. Compared to other objective methods, such as mean weight, standard deviation or variance-based approaches, which often oversimplify the weighting process and fail to capture complex inter-criteria relationships, these eight methods provide more reliable, accurate and context-sensitive weighting structure. Additionally, IDOCRIW is preferred over other methods because it intelligently combines two complementary perspectives without introducing subjectivity. These methods are particularly effective across a wide range of decision problems, accommodating both the beneficial and non-beneficial criteria, resisting the impact of data scale or negative values and providing a comprehensive representation of the importance of each criterion. Therefore, these eight objective methods are selected due to their superior ability to minimize bias, maximize analytical depth, ensure data-driven insights and uphold consistency across various decision making environments.

Table 1.1 Characteristics, merits and demerits of different weighting methods

Weighting method	Category	Characteristics	Merits	Demerits
Point allocation	Subjective	Distributes a fixed number of points among criteria	Simple, easy to understand	Highly subjective, inconsistent
Direct rating	Subjective	Assigns ratings to criteria based on perceived importance	Simple, flexible	Prone to bias, lacks consistency
Ranking method	Subjective	Ranks criteria in order of importance	Simple, easy to understand	Limited differentiation between criteria
AHP	Subjective	Uses pairwise comparisons to derive weights	Consistent comparisons, hierarchical structure	Time-consuming, potential for inconsistencies
Ratio method	Subjective	Assigns weights based on ratios of importance	Simple, easy to understand	Subjective, limited precision
Swing method	Subjective	Evaluates the ‘swing’ from worst to best performanc	Focuses on practical implications	Requires clear definition of performance ranges
Delphi method	Subjective	Iterative expert consensus	Reduces bias, incorporates expert knowledge	Time-consuming, requires multiple rounds
Nominal group technique	Subjective	Structured group decision making	Encourages participation, reduces dominance	Time-consuming, requires skilled facilitator
SMART	Subjective	Assigns values and weights using linear utility theory	Simple, transparent	Subjective ratings
DEMATEL	Subjective	Analyzes cause-and-effect relationships	Identifies influential factors	Requires expert input, complex calculations
Simos’ procedure/revised Simos’ procedure	Subjective	Uses cards to rank criteria	Visual, easy to use	Subjective
SWARA	Subjective	Experts re-evaluate weights step-by-step by comparing to previous criteria	Stepwise comparison, considers relative importance	Requires expert input
Factor relationship (FARE)	Subjective	Builds factor relationship matrix among criteria	Considers interdependencies between factors	Computationally complex
Kemeny median indicator ranks accordance (KEMIRA)	Subjective	Aggregates rank data using median-based consensus	Aggregates ranks from multiple sources	Computationally intensive for large datasets

Table 1.1 Continued

Weighting method	Category	Characteristics	Merits	Demerits
BWM	Subjective	Compares best and worst criteria against others	Requires fewer pairwise comparisons than AHP	Requires clear identification of the best and worst criteria
Full consistency method (FUCOM)	Subjective	Enforces full consistency while assigning weights	Ensures full consistency in comparisons	Requires strict compliance with the comparison rules
Level based weight assessment (LBWA)	Subjective	Weights based on hierarchical levels of criteria	Focuses on hierarchical level	Requires clear definition of levels
Non-decreasing series at criteria significance levels	Subjective	Prioritizes criteria using non-decreasing significance levels	Emphasizes non-decreasing importance	Requires pre-defined significance levels
Resistance to change method	Subjective	Evaluates resistance to changes in criteria	Focuses on stability and adaptability	Requires subjective assessment of resistance
Mean weight	Objective	Calculates the average weight of criteria based on numerical data	Simple, easy to calculate	Ignores variability and correlation, sensitive to outliers
Standard deviation	Objective	Measures the dispersion of criteria values around the mean, assigning higher weights to criteria with greater variability	Reflects data variability	Ignores inter-criteria relationships, misleading with skewed data
Statistical variance procedure	Objective	Assigns weights based on variance of criteria values, reflecting the degree of data dispersion	Emphasizes criteria with higher variability	Sensitive to outliers, assumes data normality
Ideal point method	Objective	Determines weights by calculating the distance of criteria values from an ideal point (e.g. maximum or minimum)	Focuses on optimal solution, measures deviation from the ideal	Relies on defining an ideal point, which can be subjective
Data envelopment analysis (DEA)	Objective	Derives weights by optimizing the efficiency of decision making units (DMUs) concerning input and output criteria	Identifies efficient DMUs, data-driven and finds optimal weights	Can produce extreme or unrealistic weights, sensitive to input/output selection

Table 1.1 Continued

Weighting method	Category	Characteristics	Merits	Demerits
Multiplication synthesis	Integrated	Multiplies normalized criteria values	Simple, easy to apply	Can obscure individual criterion importance
Additive synthesis	Integrated	Adds normalized criteria values	Simple, easy to apply	Can mask variations in criteria importance
Optimal weighting (sum of squares)	Integrated	Optimizes weights based on sum of squares	Aims for optimal combination	Sensitive to data distribution
Optimal weighting (relational coefficient)	Integrated	Optimizes weights based on relational coefficients	Considers interdependencies between criteria	Complex calculations

Similarly, Table 1.2 presents the characteristics of the commonly used MCDM methods. The traditional MCDM techniques, such as AHP, TOPSIS, VIKOR and PROMETHEE, although widely used due to their structured approach and simplicity, suffer from several well-recognized limitations.These include high sensitivity to normalization methods, dependence on fixed or arbitrarily assigned weights, vulnerability to rank reversal and inadequate handling of high-dimensional or conflicting criteria. Such constraints often reduce their effectiveness in complex, real-world decision making contexts. In this research, selection of the eight advanced MCDM methods, e.g. MACONT, PARIS, CURLI, PEG, OPTBIAS, PROBID, DNMA and EAMR, is deliberate, and grounded in both methodological strength and practical relevance. While no method is entirely free from challenges, these selected approaches are specifically developed to mitigate many of the shortcomings that the traditional models tend to overlook or insufficiently address. Each method offers a unique innovation, contributing to more robust, flexible and meaningful decision making. MACONT improves reliability of rankings by employing a variety of normalization and aggregation strategies, which allow the desired results to remain stable under diverse data conditions. PARIS strengthens decision consistency by offering multiple reference ideals that reduce rank reversal and enhance modelling of the real-world preferences. CURLI facilitates collaborative decision making without requiring predefined weights, making it particularly valuable in group scenarios where consensus on weights is difficult to achieve. PEG applies economic principles, such as Pareto efficiency and Edgeworth equilibrium to ensure fair and balanced rankings, which is essential in multi-stakeholder environments. OPTBIAS addresses the ranking ambiguity through its use of bi-ideal and average reference points, enabling more precise decision making when dealing with numerous interdependent criteria. PROBID blends the strengths of TOPSIS and EDAS while minimizing their respective weaknesses, resulting in improved consistency and risk sensitivity. DNMA enhances decision flexibility by introducing double normalization and adaptable aggregation operators, which effectively accommodate both the beneficial and non-beneficial criteria. Finally, EAMR employs a geometric, area-based analysis to offer clarity on how the alternatives perform across various dimensions, making it easier to interpret the results. These eight MCDM methods represent a broad and complementary mix of decision making philosophies, ranging from economic equilibrium logic in PEG and reference-point modelling in PARIS and OPTBIAS, to collaborative, weight-free decision strategies in CURLI and area-based analysis in EAMR, and robust normalization and aggregation frameworks in MACONT, DNMA and PROBID. This diversity is important because it allows the study to look at decision making from many different angles, which helps to fill the important gaps in the current research. More importantly, these methods are not just mathematically advanced, they are also highly practical. Even though they have not yet been widely used in many industries, they are especially well-suited for solving complex, real-world problems involving many conflicting criteria. In areas, such as 3D printer nozzle and piston material selection, EDM oil evaluation, drone and cobot selection, there are often trade-offs between cost, performance, safety and efficiency. The traditional methods often simplify these situations or fail to capture the true nature of such multi-faceted problems. In contrast, the selected advanced methods can deal with complexity, variability and uncertainty existing in such manufacturing environments. They allow for more flexible input handling, better reflection of real-world priorities and greater stability in the final rankings. This makes them extremely valuable in engineering and industrial settings, where decisions have to be both precise and practical. By using these newer and more adaptable methods, this research takes a big step forward in improving how decisions are made in fields where small errors can lead to big consequences.

Table 1.2 Characteristics, merits and demerits of different MCDM methods

MCDM	Category	Characteristics	Merits	Demerits
AHP	Pairwise comparison / hierarchical	Constructs a hierarchy; uses pairwise comparisons to derive local and global weights; eigenvector method to calculate priorities	No need for additional tool to determine criteria weights	Becomes complicated as the number of criteria and alternatives increase
TOPSIS	Distance-based	Determines the best alternative by minimizing distance to ideal solution and maximizing distance from negative ideal solution; uses Euclidean distance and vector normalization	Simple process; robust to the number of decision criteria and alternatives	Ignores correlation between criteria; requires vector normalization in multi-dimensional problems
PROMETHEE	Outranking	Uses pairwise comparisons and preference functions; calculates preference index and flows (positive, negative, net) for each alternative	Does not require score normalization	Requires separate tools for weight evaluation; preference function must be defined

Table 1.2 Continued

MCDM	Category	Characteristics	Merits	Demerits
ELECTRE	Outranking	Uses concordance and discordance indices to determine outranking relations; includes thresholds; based on pairwise dominance	Can handle missing data; effective for complex evaluations	Computationally intensive without software due to complex procedures
VIKOR	Distance-based/compromise solution	Determines optimal solution, variant of TOPSIS	Updated and flexible version of TOPSIS	Difficult to apply under conflicting decision scenarios
Ashby	Material selection/performance index	Uses material performance indices based on property ratios	Effective for initial material screening	Limited to problems with three decision attributes
COPRAS	Preference ranking, utility-based	Evaluates utility degree based on positive and negative criteria; uses direct importance weights	Simple and effective	Sensitive to data variation, which can affect ranking stability
PSI	Preference ranking, statistical	Determines relative importance based on mean and deviation; eliminates the need for weights	Avoids subjectivity of weight assignment	Requires statistical computation, often involving programming
MAUT	Utility theory/multi-attribute	Converts criteria into utility values and aggregates them using weighted sum; supports risk preferences	Simultaneously evaluates all alternatives	Uncertainty in decision attribute outcomes
WSM	Aggregation -based	Aggregates criteria weights through weighted summation	Simple to compute; can be used without software	Suitable with unidirectional criteria
WPM	Aggregation -based	Similar to WSM but uses multiplication instead of summation	Simple evaluation process without software	Best for decision problems with uniform criteria type
OCRA	Preference ranking	Uses reference alternative for rating; criteria weights included through performance rating scales	Low computation time, simple, high flexibility	Low transparency
ORESTE	Preference ranking	Uses ordinal preferences; constructs preference function matrix; performs linear programming	Moderate computation time, simple, transparent, flexible	None significant
EXPROM2	Preference ranking	Uses preference thresholds; based on preference modelling and outranking relations	Reasonable transparency	High computation time, critical, low flexibility

Table 1.2 Continued

MCDM	Category	Characteristics	Merits	Demerits
EVAMIX	Preference ranking	Combines qualitative and quantitative criteria; establishes dominance matrix	Reasonable transparency, moderate simplicity	High computation time
WASPAS	Hybrid	Combines WSM and WPM by using weighted combination of their outcomes	More robust ranking, balances WSM and WPM advantages	Increased complexity than the elementary methods
EDAS	Distance-based	Calculates positive and negative distances of each alternative from average solution; evaluates based on relative assessment	Computationally efficient, easy implementation	Sensitive to normalization
MABAC	Distance-based	Calculates border approximation area for each criterion; evaluates based on deviation from it	Simple calculation, stable rank reversal	Performance depends on border area
TODIM	Prospect theory	Applies dominance measurement under prospect theory; integrates gains and losses psychology	Considers dominance and human behavior	Computationally complex, requires careful dominance degree determination
ARAS	Preference ranking	Compares normalized performance values with the optimal alternative; includes additive utility function	Simple calculations, high computational efficiency	Sensitivity to normalization
MOORA	Ratio-based	Divides the criterion value by the sum of square’s square root	Simple calculation, applicable to various problems	Ranking depends on normalization

This research exclusively assesses newly introduced MCDM methods based on objective weighting methods. Additionally, it provides a way to identify the most suitable MCDM and weighting methods. In comparison with traditional methods this study examines the performance of new approaches through sensitivity, rank correlation and number of computations. The research narrows the gap with a dependable and resilient framework for sustainable manufacturing decisions.

1.4 Objectives and scope of the present research work

Manufacturing decision making problems, such as material selection, machine selection, EDM oil selection, etc. hold significant importance in ensuring operational efficiency and product quality. The performance, reliability and cost-effectiveness of manufacturing systems are greatly influenced by the choices made at these critical decision points. Inappropriate selection can lead to issues like increased production costs, compromised product quality, reduced system reliability and operational inefficiencies.

To address these challenges and make informed, rational decisions, MCDM methods have been increasingly utilized. These methods are particularly effective in handling complex, multi-criteria problems where conventional decision making approaches often fall short. Considering these requirements, the objectives of the current research are outlined as follows:

a) to employ and explore applicability of eight newly developed MCDM methods, i.e. (MACONT, PROBID, PARIS, OPTBIAS, DNMA, EAMR, CURLI and PEG),
b) to solve real-time decision making problems in the manufacturing environment especially material selection, machine selection and EDM oil selection,
c) to determine the overall ranking results of the eight MCDM methods applied in each of those decision making problems,
d) to investigate and analyze the ranking performance through rank comparison study,
e) to analyze the ranking performance through Spearman's rank correlation coefficient values, weighted Spearman's correlation and rank similarity coefficients between different methods,
f) to compare the computational efficiency of each of the methods by calculating the number of operations required,
g) to evaluate consistency of each method through sensitivity analysis studies, and
h) to identify and validate the most effective MCDM method and weighting technique for robust and reliable decision making.

The future scope of application of this research work is wide-ranging and diverse. These eight MCDM techniques can be investigated in real-time manufacturing scenarios. These consist of the choice of the best location of the plant, the vendor, the automated inspection equipment, the product assembly sequence planning design and the best machining parameters. The study can further develop hybrid decision models that merge these approaches with uncertainty models to manage linguistic and fuzzy variables. Merging with real-time analysis of data can also enhance precision and responsiveness of the adopted practices. Factory experiments in manufacturing can also experiment with their applicability and viability in practice. Compared to such computational approaches with advanced techniques, i.e. machine learning and artificial intelligence could give more insights into their limitation and strength. Besides manufacturing, they could be used in healthcare for hospital resource planning, energy sectors for sustainable consumption and transportation sectors for logistic networks. Overall, MCDM techniques enable formulating policy and strategic planning at government and public administration levels for the areas of urban planning, environmental sustainability and public health. Their incorporation in curricula at training programs and schools can empower decision makers and future engineers. Application of technology using Internet of the Things and blockchain technology could make operations transparent and efficient. There can be development of an expert system to save time. These future visions would provide scope for continuity of research, providing inclusive and adaptable solutions.

2. OBJECTIVE WEIGHTING METHODS

Choosing the right alternative when confronted with several critical aspects is often difficult. Weighting approaches in MCDM solve this problem by assigning a score to each component depending on its value. There are three major weighting approaches, i.e. subjective, objective and integrated scheme. Subjective approaches rely on judgements, allowing the individuals to directly assign weights based on importance of each criterion. This is accomplished through ranking, rating or pairwise comparisons. Objective approaches, on the other hand, are more data-driven, use mathematical formulas and analysis to calculate weights without direct involvement of the decision makers. This reduces bias and ensures that weights reflect the intrinsic properties of each element. Examples include entropy and standard deviation methods. While objective methods eliminate prejudice and increase openness, they may not always reflect the precise context of a decision or personal objectives. Furthermore, they require certain data sets and are not appropriate for all scenarios. However, objective weighing systems provide several additional benefits, such as increased consistency that ensures consistent application across the decision makers and contexts, minimizing the impact of individual biases or inconsistencies and produce repeatable outcomes, which make it easy to compare and analyze various decision making processes. Data driven insights use data analytics to identify hidden patterns or correlations between the criteria, potentially leading to more accurate weight assignments. Reduced manipulation or strategic weight alterations, result in more dependable and defendable decision outcomes. Hence, although the subjective as well as objective weight allocations are found to be utilized, objective methods offer major advantages in terms of minimizing bias, maintaining consistency and using data insights to make more sound decisions. The benefits and drawbacks of the methods under consideration are listed in Table 2.1.

Table 2.1 Advantages and disadvantages of considered weighting methods

Method	Advantage	Disadvantage
Entropy	Depends on degree of disorder in decision matrix, data driven	Sensitivity to scaling and noise
CILOS	Impact sensitive weighting, minimizes entropy bias	Matrix complexity, sensitive to accuracy in loss matrix construction
LOPCOW	Evenly distributed weights due to logarithmic presence	zero or near-zero standard deviations lead to computational issues
SPC	Easy and interpretable	Sensitive to outliers
IDOCRIW	Compensatory mechanism	Double computation and parameter tuning
MEREC	Scale minimized by Logarithmic changes	Computationally intensive
CRITIC	Considers correlation between criteria	Computationally intensive
PCA	Solves redundancy and minimizes noise	Sensitive to scaling and outliers

2.1 Entropy method

It is a stable and common approach to assign weights [8]. The approach is derived from information theory principles and employs the concept of entropy to calculate the degree of randomness or uncertainty of data. In practice, if one criterion differs significantly across alternatives, then that criterion provides more informative information to separate the alternatives and therefore should have a higher weight. One of the most significant strengths of this method is that it never has to base its decisions on human opinion or judgment; rather, it only relies on the data of the decision matrix. This renders the technique highly objective and unbiased. The technique begins by normalizing the data so that all the criteria are on a common scale. It then computes the entropy for every criterion such that it has an idea of how informative that criterion is. Criteria that have higher variability have greater influence on the decision and have a higher weight assigned to them, whereas those with too much similarity among all the alternatives are assigned lower weights. Due to its mathematical simplicity and convenience, entropy method is very effective in difficult cases, with numerous alternatives and factors. Its simplicity, ease of understanding and robust data basis lead to its extensive application across a broad area of disciplines, including engineering, environmental management, economics and operations research. In general, entropy method enhances the decision making process by encouraging objectivity, reducing bias and ensuring that the most impactful criteria get the consideration they merit. Entropy method steps are as follows:

Step 1: Construct the decision matrix

Suppose that there are m alternatives and n criteria. Let x_{ij} be an element of this matrix representing the value of j^{th} criterion corresponding to i^{th} alternative (i =1, 2, ..., m; j = 1, 2, ..., n)

Step 2: Normalize the decision matrix

To remove the effects of different dimensions in the criteria values, the decision matrix must be normalized using Eqs. (2.1) and (2.2)

$$P_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \text{ for beneficial criteria} \tag{2.1}$$

$$P_{ij} = 1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \text{ for non-beneficial criteria} \tag{2.2}$$

Step 3: Calculate the entropy value (e_j) for each criterion

Entropy of j^{th} criterion is determined using Eq. (2.3)

$$e_j = -\frac{\sum_{i=1}^{m} f_{ij}\, ln(f_{ij})}{ln\, m} \; (i=1,2,\ldots,m; j=1,2,\ldots,n) \tag{2.3}$$

where $f_{ij} = \frac{P_{ij}}{\sum_{i=1}^{m} P_{ij}}$

Step 4: Determine the entropy weight (w_j) of j^{th} criterion applying Eq. (2.4):

$$w_j = \frac{1-e_j}{n-\sum_{j=1}^{n} e_j} \tag{2.4}$$

where $0 \leq w_j \leq 1$ and $\sum_{j=1}^{n} w_j = 1$.

2.2 Criterion impact loss

Another potential way to find out the objective weights is CILOS method, which takes into account each criterion significance (impact) loss when one of the other criteria yields the ideal greatest or lowest value [9]. The concept behind using CILOS technique to calculate weights of the criteria is that a criterion should receive a higher weight if the loss it causes is negligible. In contrast, if a criterion results in a substantial loss, the weight is reduced because the criterion significance is smaller than that of the other criteria. The shortcoming of entropy approach is offset by CILOS method. The members of the relative loss matrix approach zero when a criterion has extremely similar values, and the weights of the criteria increase and have a significant impact on the evaluation. When there is homogeneity, all the relative losses and the overall loss (their sum total) equal to zero. This results in the linear system of equations being meaningless because one column of the loss matrix elements becomes equal to zero. Additionally, the relative calculations indicate that a criterion weight is nearly equal to one when it consistently has the same value for all the alternatives. Its application steps are explained as below:

Step 1: Convert the cost-type criteria to profit-type criteria according to Eq. (2.5), $r_{ij} = \frac{\min_i x_{ij}}{x_{ij}}$ (2.5)

Step 2: Create a relative loss matrix *P* based on the square matrix *A*, in which each row corresponds to the row in which the criteria have the highest value, based on Eq. (2.6), $P_{ij} = \frac{A_{ii}-A_{ij}}{A_{ij}}, P_{ii} = 0$ (2.6)

Step 3: Calculate of the F matrix based on the relative loss matrix, using Eq. (2.7)

$$F = \begin{pmatrix} -\sum_{i=m}^{m} P_{i1} & P_{12} & \cdots & P_{1m} \\ P_{21} & -\sum_{i=1}^{m} P_{i2} & \cdots & P_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ P_{m1} & P_{m2} & \cdots & -\sum_{i=m}^{m} P_{im} \end{pmatrix} \tag{2.7}$$

This leads to Eq. (2.8) that results in weights requiring normalization.

$$Fw^T = 0 \tag{2.8}$$

2.3 Logarithmic percentage change-driven objective weighting

It is a recently proposed approach for measuring objective criteria weights, having several advantageous features as compared to its peer ones while providing more acceptable solutions [10]. It avoids huge differences between the criteria values, which are often encountered with other techniques, such as entropy method. It is not affected by negative values of raw data in the decision matrix. In this method, there is no limitation on the criterion type as it can offer a suitable solution for both the beneficial and non-beneficial criteria. It also eliminates the difference caused by the size of the data while expressing the mean squared value of the data as a percentage of their standard deviations. Steps are as follows:

Step 1: Develop the matrix, using the Eq. (2.9)

$$X = [X_{ij}]_{m\times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{2.9}$$

Step 2: Normalize using Eqs. (2.10) and (2.11).

$$V = [v_{ij}]_{m\times n} = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix}$$

where $v_{ij} = \frac{x_{max} - x_{ij}}{x_{max} - x_{min}}$, if j is a non-beneficial criterion (2.10)

$v_{ij} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}}$, if j is a beneficial criterion (2.11)

Step 3: Calculate the percentage value (P_j) of each criterion while taking the natural logarithm of the ratio of the mean squared value of the criterion by its standard deviation and multiplying by 100. It helps in eliminating differences in the size of the data, using Eq. (2.12)

$$P_j = \left| ln \left(\frac{\sqrt{\frac{\sum_{i=1}^{m} {v_{ij}}^2}{m}}}{\sigma_j} \right) \times 100 \right| \tag{2.12}$$

where σ_j is the standard deviation of j^{th} criterion.

Step 4: Compute the objective criteria weights, using Eq. (2.13), $w_j = \frac{P_j}{\sum_{k=1}^{n} P_k}$ (2.13)

2.4 Symmetry point of criterion

SPC measures the contribution of each criterion to the final weight of criteria using its symmetry point [11]. The approach initially determines the midpoint within the maximum and minimum of each criterion. The absolute distance of each criterion value from this symmetry point is then computed to provide an absolute distance vector for each criterion. The modulus of each element in the matrix is derived as the ratio of the averaged absolute distance of the criterion to a value of the criterion element. The symmetry moduli matrix is then formulated. The average values of each column of the symmetry moduli matrix are subsequently computed to develop a new row, with each element representing the criteria modulus of symmetry. Finally, to compute the criterion weight, each average value is divided by the sum of all the values.

Step 1: Develop the initial decision matrix (X) using Eq. (2.14)

$$X = [x_{ij}]_{m \times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{2.14}$$

Step 2: Calculate the SPC_j, using the Eq. (2.15): $SPC_j = c_j = \frac{a_j + b_j}{2}$ (2.15)

where a_j and b_j are the minimum and maximum values of j^{th} criterion among all the alternatives respectively, i.e. $a_1 = \min\{x_{11}, x_{21}, ..., x_{i1}\}^{T}$ and $b_1 = \max\{x_{11}, x_{21}, \ldots, x_{i1}\}^{T}$, c_j is the symmetry.

Step 3: Develop the absolute distance matrix (V), using Eq. (2.16)

$$V = \left\| v_{ij} \right\|_{m \times n} = \begin{bmatrix} |x_{11} - SPC_1| & |x_{12} - SPC_2| & \cdots & |x_{1n} - SPC_n| \\ |x_{21} - SPC_1| & |x_{22} - SPC_2| & \cdots & |x_{2n} - SPC_n| \\ \cdots & \cdots & \cdots & \cdots \\ |x_{m1} - SPC_1| & |x_{m2} - SPC_2| & \cdots & |x_{mn} - SPC_n| \end{bmatrix} \tag{2.16}$$

where v_{ij} is the absolute distance element of matrix V.

Step 4: Formulate the matrix of the moduli of symmetry (S), using Eq. (2.17)

$$S = \left|s_{ij}\right|_{m\times n} = \begin{bmatrix} \frac{\frac{\sum_{i=1}^{m} v_{i1}}{m}}{x_{11}} & \frac{\frac{\sum_{i=1}^{m} v_{i2}}{m}}{x_{12}} & \cdots & \frac{\frac{\sum_{i=1}^{m} v_{in}}{m}}{x_{1m}} \\ \frac{\frac{\sum_{i=1}^{m} v_{i1}}{m}}{x_{21}} & \frac{\frac{\sum_{i=1}^{m} v_{i2}}{m}}{x_{22}} & \cdots & \frac{\frac{\sum_{i=1}^{m} v_{in}}{m}}{x_{2m}} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\frac{\sum_{i=1}^{m} v_{i1}}{m}}{x_{m1}} & \frac{\frac{\sum_{i=1}^{m} v_{i1}}{m}}{x_{m1}} & \cdots & \frac{\frac{\sum_{i=1}^{m} v_{in}}{m}}{x_{mn}} \end{bmatrix} \tag{2.17}$$

Step 5: Evaluate the modulus of symmetry of criterion (*T*), based on Eq. (2.18)

$$T = \left|t_j\right|_{1\times n} = \left|\frac{\sum_{i=1}^{m} s_{i1}}{m} \quad \frac{\sum_{i=1}^{m} s_{i2}}{m} \quad \cdots \quad \frac{\sum_{i=1}^{m} s_{in}}{m}\right|, \forall j \in \{1,2,\ldots,n\} \tag{2.18}$$

Step 6: Calculate the criteria weights vector (*W*), using Eq. (2.19)

$$W = \left|w_j\right|_{1\times n} = \left|\frac{t_1}{\sum_{j=1}^{n} t_j} \quad \frac{t_2}{\sum_{j=1}^{n} t_j} \quad \cdots \quad \frac{t_j}{\sum_{j=1}^{n} t_j}\right|, \text{ } w_j \text{ is the weight} \tag{2.19}$$

2.5 Integrated determination of objective criteria weights

Entropy and CILOS weights are combined to generate the aggregate weights for objective evaluation of the criteria array structure [9]. This is made feasible by the concept of integrating the criteria weights with varying significances into a single overall weight. The relevance of the criteria would decline because of their greater losses in comparison to other criteria, but these weights display the change of individual criteria values, which is a feature of entropy method. The IDOCRIW method aggregates the weights acquired by the execution of CILOS and entropy methods. Then aggregation process is carried out on the basis of the following equation:

$w_j = \frac{q_j q_j}{\sum_{j=1}^{m} q_j W_j}$, where w_j and q_j are entropy and CILOS weight. (2.20)

2.6 Method based on the removal effects of criteria

Ghorabaee et al. [12] developed this weighting approach in 2021. The strategy of MEREC is based on the removal of a criterion and studying its impact on the overall performance. Its application procedures are stated as below:

Step 1: Construct the decision matrix *X*, where the elements are denoted by x_{ij}, and alternatives and criteria are represented by *m* and *n*, respectively: $X = [x_{ij}]_{m\times n}$ (2.21)

Step 2: Normalize the decision matrix *X* using Eqs. (2.22) and (2.23), where the normalized elements are denoted by n_{ij}^{x}

$$n_{ij}^{x} = \frac{min_k x_{kj}}{x_{ij}}, \text{ if } j \text{ is a beneficial} \tag{2.22}$$

$$n_{ij}^{x} = \frac{x_{ij}}{max_k x_{kj}}, \text{ if } j \text{ is a non-beneficial} \tag{2.23}$$

Step 3: Calculate the overall performance (S_i) using Eq. (2.24):

$$S_i = ln(1 + (\frac{1}{n}\sum_j \left|ln(n_{ij}^{x})\right|)) \tag{2.24}$$

Step 4: Compute S'_{ij} using Eq. (2.25): $S'_{ij} = ln(1 + (\frac{1}{n}\sum_{k,k\neq j} \left|ln(n_{ij}^{x})\right|))$ (2.25)

Step 5: Calculate the total sum of absolute deviations E_j applying Eq. (2.26)

$$E_j = \sum_i \left|S'_{ij} - S_i\right| \tag{2.26}$$

Step 6: Evaluate the weight of j^{th} criterion (w_j), $w_j = \frac{E_j}{\sum_k E_k}$ (2.27)

2.7 Criteria importance through intercriteria correlation

The CRITIC method considers the natural conflict and contrast in a decision problem [13]. This kind of correlation technique looks at the data in the criteria as it strives to evaluate the alternatives through an analytical examination of the decision matrix. The CRITIC method uses the decision matrix directly to objectively derive the criteria weights, in contrast to other weighting methods that rely on judgments or pairwise comparisons from the decision makers. It is based on statistical procedures, such as correlation analysis, which emphasize the differences between the criteria. The CRITIC procedure is stated as follows:

Step 1: Formulate the initial decision matrix.

$$X = [X_{ij}]_{m \times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (2.28)$$

Step 2: Utilize the linear max-min normalization technique

$$V = [v_{ij}]_{m \times n} = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix}$$

$v_{ij} = \frac{x_{max} - x_{ij}}{x_{max} - x_{min}}$, if j is a non-beneficial criterion (2.29)

$v_{ij} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}}$, if j is a beneficial criterion (2.30)

where v_{ij} is the normalized component of x_{ij}.

Step 3: Calculate the standard deviation σ_j, for each criterion

Step 4: Compute correlation coefficient (co_{ij}) between i^{th} and j^{th} criteria

Step 5: Evaluate the amount of information (C_j) contained in j^{th} criterion using Eq. (2.31)

$C_j = \sigma_j \sum_{j=1}^{n}(1 - co_j)$, where co_j correlation coefficient between criteria. (2.31)

Step 6: Compute the criteria weights by taking into account the criterion correlation with other criteria as well as its standard deviation using Eq. (2.32). $w_j = \frac{C_j}{\sum_{j=1}^{n} C_j}$ (2.32)

2.8 Principal component analysis

It is a multivariate data reduction statistical technique, identifies a smaller set of variables (principal components) that capture most of the variability in data. This makes it valuable for decision making, effectively simplifying the complex data without sacrificing crucial information. Notably, PCA does not necessitate pre-defining variable weights, thereby reducing subjectivity. Furthermore, it adeptly handles data uncertainty, proving useful in diverse fields. The principle components are generated and used in place of criteria, and the corresponding percentage values are considered as the weights for the criteria. By retaining only the most significant components, PCA reduces dimensionality and improves computational efficiency. Additionally, PCA helps to uncover hidden patterns and correlations within the data, enhancing the overall analysis. The procedural steps are enumerated below [14, 15]:

Step 1: Calculate the covariance matrix

Compute the covariance matrix C to show how each criterion varies with others, using Eq. 2.33.

$$Cov(X_i, Y_j) = \frac{\sum_{k=1}^{n}(X_{ik} - \overline{X}_i)(Y_{jk} - \overline{Y}_j)}{n-1}, \text{ where } \overline{X_i} \text{ and } \overline{Y_j} \text{ are the means of } X_i \text{ and } Y_j. \quad (2.33)$$

Step 2: Decompose the covariance matrix

Break the covariance matrix into eigenvalues λ and eigenvectors υ by solving Eqs. (2.34), (2.35) and (2.36).

$$Cv = \lambda v \quad (2.34)$$

$$det(C - \lambda I)v = 0 \quad (2.35)$$

$$(C - \lambda I)v = 0 \quad (2.36)$$

where I is the identity matrix.

The eigenvectors are placed into a matrix V, which defines the directions of the new axes.

Step 3: Sort the eigenvalues in descending order to prioritize components that capture more variability.

Step 4: Project the data into the new space

Transform the data into the new dataset using Eq. (2.37)

$$Y = X \times V, \text{ where } Y \text{ is new dataset, } X \text{ is original dataset and } V \text{ is eigenvectors.} \quad (2.37)$$

Step 5: Calculate the explained variance

Calculate the variance ratio using Eq. (2.38) to show how much variance is captured by the first k components, $R^2 = \frac{\sum_{i=1}^{k}\lambda_i}{\sum_{i=1}^{n}\lambda_i}$ (2.38)

Step 6: Select the principal components

Select components by cumulative variance. Eigenvector weights show contribution of each criteria.

3. MULTI CRITERIA DECISION MAKING METHODS

MCDM methods play a crucial part in solving multifaceted decision making problems, particularly in manufacturing environments where multiple conflicting criteria must be evaluated. Traditional MCDM methods, such as AHP, TOPSIS and VIKOR, are widely used, but they exhibit several limitations, including subjectivity in weight assignment, sensitivity to normalization techniques and inability to effectively integrate both the qualitative and quantitative criteria. This study explores eight MCDM methods, i.e. MACONT, PARIS, EAMR, CURLI, PEG, OPTBIAS, PROBID and DNMA, with the aim of overcoming these limitations and enhancing decision making accuracy in diverse manufacturing applications. These methods address critical gaps in the traditional techniques, making them highly relevant for solving problems. MACONT integrates three normalization techniques to comprehensively reflect the original values, reducing potential biases arising from using a single normalization approach. It also utilizes a single reference alternative, simplifying comparative evaluations, while the inclusion of operators balances compensatory perspectives, making MACONT a versatile tool for solving manufacturing decision problems where normalization effects significantly impact rankings. The PARIS method eliminates subjectivity in weight assignment, a major drawback of compensatory methods, such as TOPSIS and VIKOR and by allowing both qualitative and quantitative criteria, it ensures a more holistic evaluation of the alternatives. Its novelty in the context of manufacturing presents an opportunity to develop innovative decision frameworks that are more reliable and less dependent on subjective judgments. Table 3.1 shows the strengths and weakness of the considered MCDM methods.

Table 3.1 Advantages and disadvantages of considered MCDM methods

Method	Advantage	Disadvantage
MACONT	Multi normalization, flexible and reliable	Tuning parameters adjustments
PARIS	Multi normalization, multiple rankings	Time consuming
EAMR	Fast, simple and no tuning parameters	Not for solely beneficial / non beneficial
CURLI	Not depended on criteria weights	Time consuming
PEG	Not depended on criteria weights	Complex methodology
OPTBIAS	Minimize single point bias, balances bi-ideal closeness	Complex
PROBID	Balanced evaluation and distance assessment	Parameter sensitivity, scalability issue
DNMA	Multi normalization, adjustable weighting	Tuning parameters adjustments

EAMR exhibits high stability in ranking alternatives, demonstrating resistance to variations in weighting methods, a critical characteristic in the manufacturing settings where fluctuations in weight assignments lead to inconsistent decision making. CURLI eliminates the need for weight assignment, simplifying the decision making process and in manufacturing applications, determining precise weights for criteria is challenging due to uncertainty in the production parameters. The CURLI method facilitates robust decision making without requiring extensive prior knowledge of weight values, making it an attractive alternative for uncertain and complex manufacturing scenarios. PEG is particularly useful in optimizing conflicting objectives without requiring predefined weight values. In manufacturing environments, trade-offs between quality and efficiency are common and PEG ensures that the ranking remains stable across different MCDM approaches, thereby providing reliable solutions that account for inherent trade-offs in the production processes. OPTBIAS enhances the selection of Pareto-optimal solutions by reducing the influence of average solutions, which is a limitation of the traditional MCDM methods. By maximizing distance from average solutions and minimizing distance to bi-ideal solutions, it always prioritizes superior alternatives, which is particularly beneficial in small sample cases, such as selecting the best manufacturing parameters for limited production runs.

PROBID provides a structured method of assessing ideal solutions through averaging distances between positive and negative ideal solutions, improving ranking consistency and decision stability, needed in manufacturing when process and material property variations influence decision outcomes. PROBID is also insensitive to changes in the weightings or alternative sets and thus is an appropriate technique for dynamic production environments. DNMA combines two normalization methods and a collection of aggregation tools to be more adaptable with various data sets. DNMA also guarantees that rankings are consistent regardless of input data variations, thus appropriate for intricate decision making situations in manufacturing. Manufacturing is confronted by a sequence of challenges such as optimizing process parameters, choosing appropriate materials, reducing production costs and enhancing products. The conventional MCDM techniques cannot yield stable and unbiased decision making support because they are sensitive to subjective weighting allocation, normalization and because they are unable to properly address qualitative and quantitative data. The chosen eight MCDM techniques overcome the disadvantages by minimizing subjectivity, increasing stability, decision robustness and managing conflicting objectives. PEG and CURLI remove weight assignment, minimizing human bias, while EAMR maintains rankings robust to different weighting and normalization strategies. MACONT, DNMA and PROBID enhance decision trustworthiness via the employment of various normalization methods and aggregation devices. OPTBIAS and PARIS provide meaningful trade-off analysis, which is essential in the balancing game among cost, efficiency and quality in manufacturing. By integrating these new approaches, this research work builds a complete decision making model that enhances accuracy and reliability of manufacturing related decisions ultimately resulting in enhanced operational efficiency and sustainability. Adoption of these MCDM techniques is necessitated by their capacity to overcome the drawbacks of conventional decision making paradigms in manufacturing environments. By addressing challenges, such as subjectivity, stability, robustness and trade-offs, these methods provide a more effective and adaptable decision support framework, and their integration contributes to the development of more reliable and efficient manufacturing processes, ensuring better resource utilization and optimized operational performance.

3.1 Mixed aggregation by comprehensive normalization technique

Wen et al. [16] introduced the MACONT method for logistics provider selection. Subsequently, Wen and Liao [17] enhanced the MACONT method for pension service institution selection, offering insights into property management improvements. Truong and Li [18] developed a three-technique-based method for optimal investment decisions in transportation agencies. Nguyen [19] combined six normalization techniques with MACONT, thereby improving decision reliability. Simic et al. [20] addressed the sustainability challenge in end-of-life tire management for large freight transportation companies by utilizing MACONT within a two-stage neutrosophic decision support model. Huang and Chen [21] introduced a probabilistic linguistic -MACONT technique for rural vocational education evaluation. Wen and Liao [22] also proposed an innovative approach to multi-criteria decision problems, leveraging MACONT and the deck of card method to address uncertain information. Ulutaş et al. [23] presented an integrated grey-MCDM framework for automotive businesses, incorporating MACONT alongside other methods. Finally, Liang [24] addressed english curriculum reform using the interval-valued pythagorean fuzzy exponential TOmada de Decisao Interativa Multicriterio (TODIM)-MACONT in smart classroom evaluation, focusing on enhancing autonomous learning abilities.

The MACONT method improves decision making by using three different normalization techniques at the same time, which helps reduce errors and increases the reliability of the results. It stands out because it applies linear sum-based, ratio-based and max-min normalization together, making it better at handling different types of data compared to traditional methods. During its working process, MACONT normalizes the data initially to provide the best approximation of the original data, after which it employs two mixed aggregation operators to accumulate the weights of the criteria and compare the performance of each alternative to a reference alternative. Thus, it can rank alternatives appropriately even in a situation that is too complicated for other approaches. MACONT also allows the experts to set parameters according to actual decision cases, thus giving the results a more rational and believable solution. Overall, it has good performance and consistent results with multiple case studies, thus affirming its adequacy in addressing a lot of decision problems. MACONT uses three normalization techniques for a series of criteria. These three derived standardized performance matrices are then combined into a single matrix. Next, a virtual reference alternative is developed as a basis for reference. The distances are then determined. These distances are then processed again by combining them through two mixed aggregation operators, which also take into consideration the weights given to each criterion. Consequently, the final comprehensive scores for each alternative are determined by integrating the subordinate comprehensive scores derived from the two mixed aggregation operators. Ultimately, ranks are based on these final comprehensive scores, providing a clear ordering of their overall performance. MACONT procedure is mentioned below:

Step 1: Construct decision matrix using Eq. (3.1)

$$\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix} \tag{3.1}$$

where *i* = 1, 2,...,*m*, *j* = 1, 2,..., *n*.

Step 2: Normalize the decision matrix

Normalize decision matrix using three different techniques employing the Eqs. (3.2), (3.3) and (3.4) where $\hat{x}_{ij}^1$, $\hat{x}_{ij}^2$ and $\hat{x}_{ij}^3$ denotes the normalized values.

$$\begin{cases} \hat{x}_{ij}^1 = x_{ij} / \sum_{i=1}^{m} x_{ij},\ for \text{ beneficial criterion} \\ \hat{x}_{ij}^1 = \frac{1}{x_{ij}} / \sum_{i=1}^{m} \frac{1}{x_{ij}},\ for\ non-beneficial\ criterion \end{cases} \tag{3.2}$$

$$\begin{cases} \hat{x}_{ij}^2 = x_{ij} / max_i\, x_{ij}, for \text{ beneficial criterion} \\ \hat{x}_{ij}^2 = min_i x_{ij} / x_{ij}, for\ non - \text{beneficial criterion} \end{cases} \tag{3.3}$$

$$\begin{cases} \hat{x}_{ij}^3 = (x_{ij} - min_i x_{ij}) / (max_i x_{ij} - min_i x_{ij}), for \text{ beneficial criterion} \\ \hat{x}_{ij}^3 = (x_{ij} - max_i x_{ij}) / (min_i x_{ij} - max_i x_{ij}), for\ non - \text{beneficial criterion} \end{cases} \tag{3.4}$$

Integrate the three normalized values using Eq. (3.5),

$$\hat{x}_{ij} = \lambda \hat{x}_{ij}^1 + \mu \hat{x}_{ij}^2 + (1 - \lambda - \mu) \hat{x}_{ij}^3, \tag{3.5}$$

where, λ and μ, are balance parameters satisfying $0 \leq \lambda, \mu \leq 1$. Higher value of λ prioritizes overall performance across all alternatives, while a higher value of μ emphasizes the best performance, and lower values of both focus on highlighting the best and worst performance together.

Step 3: Calculate subordinate comprehensive scores

Set a virtual reference alternative by computing the mean of each alternative's normalized performance values on all criteria. Next, compute the subordinate comprehensive scores based on two different aggregation approaches. First, apply the arithmetic-geometric aggregation method as shown in Eq. (3.6):

$$S_2(a_i) = \delta \frac{\rho_i}{\sqrt{\sum_{i=1}^{m} (\rho_i)^2}} + (1 - \delta) \frac{Q_i}{\sqrt{\sum_{i=1}^{m} (Q_i)^2}}, \quad i = 1,2, \ldots ., m, \tag{3.6}$$

where $\rho_i = \sum_{j=1}^{n} w_j (\hat{x}_{ij} - \overline{x}_j), Q_i = \prod_{y=1}^{n} (\overline{x}_j - \hat{x}_{ij})^{w_j} / \prod_{n=1}^{n} (\hat{x}_{ij} - \overline{x}_j)^{x_j},$ w_j represent the weight of criteria and $\sum_{j=1}^{n} w_j = 1. \gamma(\gamma = 1,2, \ldots, n)$ represent the set of criteria that satisfy $\hat{x}_{ij} < \overline{x}_j,$ and $\eta(\eta = 1,2, \ldots, \eta)$ represent the set of criteria that satisfy $\hat{x}_{ij} \geq \overline{x}_j$. In addition, δ (0≤ δ, ≤ 1) adjust the preference towards overall performance.

Second, apply the max-min aggregation method as shown in Eq. (3.7),

$$S_2(a_i) = \vartheta \, {}_{j}^{max} \left(w_j (\hat{x}_{ij} - \overline{x}_j) \right) + (1 - \nu) {}_{j}^{min} \left(w_j (\hat{x}_{ij} - \overline{x}_j) \right), \quad i = 1,2, \ldots, m \tag{3.7}$$

where ϑ (0≤ δ, ≤ 1) is a preference parameter.

Step 4: Compute comprehensive scores $S(a_i)$ and rank alternatives using Eq. (3.8)

$$S_{(a_1)} = \frac{1}{2}\left(S_{1(a_1)} + \frac{S_{2(a_1)}}{\sum_{i=1}^{m}(S_2(a_i))^2}\right), \quad i = 1,2, \dots, m \tag{3.8}$$

Normalize $S_{2(a_i)}$ to ensure dimension consistency with $S_{1(a_i)}$, as values may be negative. Rank alternatives based on descending order of $S_{(a_1)}$.Higher values of $S_{(a_1)}$indicate better alternatives.

3.2 Preference analysis for reference ideal solution

Ardil [25] introduced the PARIS technique in 2020. Subsequently, Ardil [26] employed a combined TOPSIS and PARIS approach for the evaluation of airline quality. Ardil [27] further utilized an integrated PARIS-TOPSIS framework for the selection of trainer aircraft. Le [28] applied the PARIS method in the milling of SNCM439 steel. Ardil [29] implemented the PARIS technique for the selection of suitable unmanned combat aircraft. Giang and Son [30] adopted the PARIS method to address multi-objective optimization (MOO) problems in a turning process. The PARIS method offers several strengths and unique features that distinguish it from conventional MCDM approaches. Its primary advantage lies in the use of three distinct normalization techniques, i.e., vector, linear, and max–min linear normalization, which ensures a comprehensive and unbiased evaluation of alternatives. Using each normalization method, a complete ranking procedure is carried out independently, resulting in one final ranking, which includes two intermediate rankings. In total, nine rankings are generated, with the final three rankings being considered as the outcomes projected by the PARIS method. By explicitly handling both type of criteria, PARIS method ensures a balanced assessment of the diverse decision factors. Its structured, multi-phase process minimizes subjectivity, improves decision accuracy and reduces sensitivity to data anomalies. Additionally, the integration of preference analysis and objective weighting strengthens decision making confidence, making PARIS particularly effective for complex, high-stakes problems across various industries. The procedural steps involved in this method are enumerated as shown below:

Step 1: Construct the decision matrix using Eq. (3.9).

$$x = \begin{bmatrix} x_{11} & x_{12} & x_{1j} & x_{1n} \\ x_{21} & x_{22} & x_{1j} & x_{1n} \\ x_{i1} & x_{i2} & x_{ij} & x_{in} \\ x_{m1} & x_{m2} & x_{mj} & x_{mn} \end{bmatrix} \tag{3.9}$$

where *m* and *n* are the alternatives and criteria, respectively.

Step 2: Normalize the decision matrix based on three normalization approach, using Eqs. (3.10) - (3.15):

First normalization method (vector normalization):

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_i^2}} \quad \text{(beneficial criterion)} \tag{3.10}$$

$$r_{ij} = 1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_i^2}} \quad \text{(non-beneficial criterion)} \tag{3.11}$$

Second normalization method (linear normalization):

$$r_{ij} = \frac{x_{ij}}{x_j^{max}} \quad \text{(beneficial criterion)} \tag{3.12}$$

$$r_{ij} = \frac{x_j^{max}}{x_{ij}} \quad \text{(non-beneficial criterion)} \tag{3.13}$$

Third normalization method ((max – min) linear normalization):

$$r_{ij} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{in}} \quad \text{(beneficial)} \tag{3.14}$$

$$r_{ij} = \frac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}} \quad \text{(non-beneficial)} \tag{3.15}$$

Step 3: Computing the weighted normalized matrix using Eq. (3.16)

$$z_{ij} = \omega_j . r_{ij} \tag{3.16}$$

Step 4: The overall sum of the weighted normalized values is determined by applying the procedure outlined in Eq. (3.17), which combines the weighted results to reflect the cumulative performance across all criteria.

$$\pi_i^{\omega} = \sum_{j=1}^{n} \omega_j . r_{ij} \tag{3.17}$$

Step 5: Rank in the descending order of π_i^{ω} values.

Step 6: The specific components that constitute the reference ideal solution are identified based on the formulation presented in Eq. (3.18), ensuring that the ideal benchmarks for comparison are clearly defined.

$$z_j^* = \{z_1^*, \dots, z_j^*\} = \{max_i z_{ij}, min_i z_{ij}\} \tag{3.18}$$

where $max_i z_{ij}$ is for beneficial criterion and $min_i z_{ij}$ for non-beneficial criterion.

Step 7: The computation of the distance from the reference ideal solution is carried out using Eq. (3.19), allowing for the quantification of how far each alternative deviates from the ideal reference point.

$$\pi_i^* = \sum_{j=1}^{n} (z_j^* - z_{ij}) \tag{3.19}$$

Step 8: Rank in the ascending order of the values of π_i.

Step 9: The distance of each alternative from the ideal solution is calculated according to the methodology described in Equation (3.20), which provides a numerical measure of proximity or divergence from the optimal alternative.

$$R_i = \sqrt{\left(\pi_i^{\omega} - \pi_i^{\omega,max}\right)^2 + \left(\pi_i^* - \pi_i^{\omega,min}\right)^2} \tag{3.20}$$

Step 10: Rank in the ascending order of the value of R_i. Alternative with the smallest R_i value is the best one.

3.3 Evaluation by an area-based method of ranking

The EAMR technique is very effective where careful consideration and precise prioritization are needed to enable wise decision making. EAMR offers increased precision in analyzing the alternatives to distinguish among them even in complicated scenarios where the criteria may contradict each other. Trung and Thinh [31] proved the significance of the EAMR approach in turning operation optimization. Do and Nguyen [32] used the EAMR approach in the hole-turning process to prioritize potential solutions.

Step 1 Develop the decision matrix

Step 2 Normalize the decision matrix using Eq. (3.21), $n_{ij} = \frac{y_{ij}}{\max y_{ij}}$ (3.21)

Step 3 Calculate the weighted normalized values based on using Eq. (3.22), $v_{ij} = n_{ij}.w_j$ (3.22)

Step 4. Compute the normalized points, using Eqs. (3.23) and (3.24)

$$G_i^+ = v_{i1}^+ + v_{i2}^+ + \cdots + v_{m1}^+ \text{, beneficial criterion} \tag{3.23}$$

$$G_i^- = v_{i1}^- + v_{i2}^- + \cdots + v_{m1}^- \text{, non-beneficial criterion} \tag{3.24}$$

Step 5: Determine rank value (RV) based on G_i^+ and G_i^-

Step 6: Evaluate using Eq. (3.25), $S_i = \frac{G_i^+}{G_I^-}$ (3.25)

Step 7: Rank the one with the largest S_i is the best one.

3.4 Collaborative unbiased rank list integration

CURLI, presented in 2016, provided collaborative decision making without weights for criteria [33]. It was able to successfully integrate ranking outcomes and performed well in many applications such as machining [34] and product selection [35]. New improvements were designed to accommodate linguistic variables and delivered strong decision making across a range of fields [36]. This placed importance on the need for a generalized implementation framework, paving the way for larger CURLI use [37]. The CURLI method provides a straightforward solution by doing away with the requirement for criteria weight determination. This aspect prevents the ambiguity that decision makers can have when assigning weights, which typically results in different values of weights and inconsistent ranking outcomes across different methods. The CURLI method increases practicality and effectiveness by its systematic and orderly process. The procedure works by first building a decision making matrix, and then subsequent individual scoring matrices for every criterion. The results are then accumulated to obtain a process scoring matrix, and sorted in a way that all the negative scores are to the left of the principal diagonal. After this has been accomplished, the alternative with the greatest rank is found to be most preferred or the best alternative. This systematic method allows it to consider alternatives in depth based on various criteria and is thus very helpful in cases of hard decision making where clear and unbiased outcomes are needed. The fact that it can address decision making without resorting to subjective weighting assignments makes the CURLI method a powerful and trustworthy tool for MCDM. The steps are as follows:

Step 1: Construct a decision matrix.

Step 2: Develop a square matrix of order *m* for every criteria. Each matrix cell is scored in the manner described below, for instance: if the value of C_j for alternative A_2 is equal to A_m, the cell at column 2 and row *m* receives a score of 0; cells with the same column and row order (the cells on the main diagonal) do not receive any scoring; if the value of C_j for A_1 is greater than that of A_2, the cell at column 1 and row 2 receives a score of 1; if A_2 is less than A_1 in value, the cell at column 2, row 1 will receive a score of -1. This matrix referred as score matrix for each criteria. To put it briefly, there are *n* score matrices.

Step 3: The processing score matrix is generated by adding the scoring matrices for each criterion together.

Step 4: Rearrange the processing scoring matrix's rows and columns so that there are no cells with a positive score (zero) in the upper part of the main diagonal. In an ideal scenario, every negative score would be above the matrix major diagonal. Following reorganization, the alternatives in row 1 is deemed the best.

3.5 Pareto - Edgeworth Grierson

In different studies, researchers have applied PEG to arrive at a decision in various fields. Ali and Smith [38] demonstrated the way, PEG was used to control vibrations in lightweight tensegrity structures by adjusting their self-stress. Korkmaz et al. [39, 40] used it to optimize the control of tensegrity structures, making them better at handling damage. Laory et al. [41] utilized it to decide where and how many sensors should be placed in structural health monitoring systems, helping to detect damage more effectively. Selmi et al. [42] compared it with other methods to see which one worked best in complex decision making tasks. Besharati et al. [43] utilized it to gantry machine tools, improving their performance. Finally, Duc [33] used it to optimize turning processes, finding the best settings. The PEG technique employs adaptive reordering to normalize primary criteria vectors to make them comparable. PEG replicates the Pareto-optimal nature of the initial criteria data set so trade-offs are simple to evaluate. PEG is versatile, extendable to any number of criteria, and computes equilibrium points between primary and aggregate criteria vectors to provide improved decision results. The method guarantees resulting criterion values are a common compromise, balancing competing objectives. PEG operates by first normalizing basic criteria vectors, then aggregating and normalizing aggregate vectors. It applies multi-criteria approaches to these vectors and employs a PEG function for operating on primary criterion values. The method finally identifies trade-offs by examining equilibrium points and compromise designs, deriving a mechanism for balanced decision making that is Pareto-efficient. Its steps of application are explained as under:

Step 1: Determine criteria vectors using Eq. (3.26) and (3.27).

$$X_{ij} = \left(\frac{y_{ij}-min(y_i)}{max(y_i)-min(y_i)}\right) \quad \text{for beneficial criterion} \qquad (3.26)$$

$$X_{ij} = \left(\frac{max(y_{ij})-y_i}{max(y_i)-min(y_i)}\right) \quad \text{for non-beneficial criterion} \qquad (3.27)$$

Step 2: Arrange the values of criteria vector using Eq. (3.28) in ascending order

$$x_j = \left[X_j^{min}, \ldots, X_j^{max}\right]^T = [0, \ldots, 1]^T \qquad (3.28)$$

Step 3: Calculate aggregate vectors using Eq. (3.29)

$$Y_i = \frac{\sum_{k=1}^{m} x_{k,j} - x_j}{m-1} \tag{3.29}$$

Step 4: Arrange aggregate vector values in descending order using Eq. (3.30)

$$Y_j = \left[Y_j^{max}, \dots, Y_j^{min}\right]^T = [1, \dots, 0]^T \tag{3.30}$$

Step 5: Compute shifted vectors using Eq. (3.31) and (3.32)

$$x^* = \frac{x+\delta x}{1+\delta x} \tag{3.31}$$

$$y^* = \frac{y+\delta y}{1+\delta y}\text{, where } \delta x = \delta y = \sqrt{2} - 1. \tag{3.32}$$

Step 6: Calculate radial shift using Eq. (3.33) and (3.34)

$$\Delta x_i = \sqrt{2}\Delta x_j = \sqrt{2}\Delta y_j \tag{3.33}$$

where, $$\Delta x_j = \Delta \mathrm{y_j} = 0.5 - \frac{\left(\mathrm{x}_j^* + \mathrm{x}_{j+1}^*\right)\left(\mathrm{y}_j^* + \mathrm{y}_{j+1}^*\right)}{\mathrm{x}_j^* + \mathrm{x}_{j+1}^* + \mathrm{y}_j^* + \mathrm{y}_{j+1}^*} \tag{3.34}$$

Step 7: Evaluate Pareto-Edge-worth-Grierson function, using Eq. (3.35)

$$f_i^0 = f_i^{max} - (f_i^{max} - f_i^{min}(\Delta r_i + \sqrt{2}/2)) \tag{3.35}$$

Step 8: Calculate mean square error (MSE) for each alternative using Eq. (3.36)

$$MSE_I = \frac{1}{n}\sum\left(\frac{1-f_i^*}{f_i^0}\right)^2. \tag{3.36}$$

Step 9: Assign best rank to the alternative with the highest MSE value.

3.6 Ordering preference targeting at bi-ideal average solutions

The OPTBIAS technique is used to a collection of Pareto-optimal solutions depending on their distance from a group of reference points, such as, mean solution, bi-positive solution and bi-negative ideal solution [44]. It is different from TOPSIS in calculating the reference points and relative distance. OPTBIAS computes bi-positive and bi-negative ideal points by preserving information in the top and bottom third of ideal points, while TOPSIS uses either the best or worst value of each parameter to compute reference points. TOPSIS also considers relative values of distances of Pareto-optimal solutions to reference points using a weighted Euclidean distance, while OPTBIAS uses an ordinary Euclidean distance measure. Lastly, OPTBIAS attempts to minimize computational complexity while making the most of Pareto-optimal solutions, while TOPSIS can be computationally intensive in the case of high-dimensional problems. In this method, ranking of each alternative is dependent upon its distance from the reference points. The nearer a solution to a bi-positive ideal solution, the greater its ranking. Alternatively, the more similar a solution is to an average solution or bi-negative ideal solution, the worse it will rank. The steps to use under OPTBIAS are as follows:

Step 1: Develop the normalized matrix from the initial decision matrix, using vector normalization procedure as provided in Eq. (3.37)

$$R = [r_{ij}]_{m\times n} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \tag{3.37}$$

Step 2: Formulate *Y* using Eq. (3.38)

$$Y = [y_{ij}]_{mn} = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \cdots & w_n r_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ w_1 r_{m1} & w_2 r_{m2} & \cdots & w_n r_{mn} \end{bmatrix} \tag{3.38}$$

Step 3: Identify the corresponding reference points, i.e. bi-positive (*BP*) ideal, bi-negative (*BN*) ideal and average (*A*) solutions using the Eqs. (3.39) - (3.42)

$$SA_{(p)} = \left\{ \begin{matrix} Max(y_{ij}), & \text{beneficial criteria} \\ Min(y_{ij}), & \text{non} - \text{beneficial criteria} \end{matrix} \right\} = \{y_{(p)1}, y_{(p)2}, y_{(p)3}, \dots, y_{(p)n}\} \tag{3.39}$$

$$BP_{(k)} = \begin{cases} SA_{(p)|p=1} & k = 1 \\ \sum_{p=2}^{n/3} \frac{SA_{(p)}}{p} & k = 2 \end{cases} \tag{3.40}$$

$$BN_{(k)} = \begin{cases} SA_{(p)|p=n} & k = 1 \\ \sum_{p=n+1-(n/3)}^{n-1} \frac{SA_{(p)}}{n-p+1} & k = 2 \end{cases} \text{, where } k = \begin{cases} 1 & n < 6 \\ 1,2 & n \geq 6 \end{cases} \tag{3.41}$$

$$A = [\overline{y_j}]_n = [\overline{y_1 y_2} \dots \overline{y_n}] = \left[\frac{\sum_{i=1}^{m} y_{(i)1}}{m} \frac{\sum_{i=1}^{m} y_{(i)2}}{m} \dots \frac{\sum_{i=1}^{m} y_{(i)n}}{m} \right] \tag{3.42}$$

where $SA_{(p)}$ represents the combination of p^{th} best value for each criterion among all the considered alternative. For example, $SA_{(1)}$ consists of the best value for each criterion with respect to all the alternatives (i.e. maximum for beneficial and minimum value for non-beneficial), assigned with rank one ideal solution, also known as the most ‘positive’ ideal solution. Similarly, $SA_{(2)}$ denotes the second-best value for each criterion among all the alternatives and so on. Thus, $SA_{(n)}$ signifies the most ‘negative’ ideal solution (minimum for beneficial and maximum for non-beneficial). On the other hand, Max(y_j) and Min(y_j) represent the p^{th} maximum and minimum values of j^{th} weighted normalized data (i.e. y_j) for each criterion respectively, *k* denotes the first and second positive and negative ideal solutions respectively, (*n*\3) is an integer and $\overline{y_j}$ is the average weighted normalized value for j^{th} criterion.

Step 4: Compute Euclidean distances *RP*, *RN* and *RA* for each alternative using Eqs. (3.43) - (3.45).

$$RP = [RP_i]_m = \begin{bmatrix} RP_1 \\ RP_2 \\ \vdots \\ RP_m \end{bmatrix}, RP_i = \begin{cases} \sum_{k=1}^{2} \sqrt{\sum_{j=1}^{n} \left(y_{ij} - BP_{(k)j}\right)^2} & n \geq 6 \\ \sqrt{\sum_{j=1}^{n} \left(y_{ij} - BP_{(1)j}\right)^2} & n < 6 \end{cases} \tag{3.43}$$

$$RN = [RN_i]_n = \begin{bmatrix} RN_1 \\ RN_2 \\ \vdots \\ RN_m \end{bmatrix}, RN_i = \begin{cases} \sum_{k=1}^{2} \sqrt{\sum_{j=1}^{n} \left(y_{ij} - BN_{(k)j}\right)^2} & n \geq 6 \\ \sqrt{\sum_{j=1}^{n} \left(y_{ij} - BN_{(1)j}\right)^2} & n < 6 \end{cases} \tag{3.44}$$

$$RA = [RA_i]_m = \begin{bmatrix} RA_1 \\ RA_2 \\ \vdots \\ RA_m \end{bmatrix} = \begin{bmatrix} \sqrt{\sum_{j=1}^{n}\left(y_{1j} - \overline{y_j}\right)^2} \\ \sqrt{\sum_{j=1}^{n}\left(y_{2j} - \overline{y_j}\right)^2} \\ \vdots \\ \sqrt{\sum_{j=1}^{n}\left(y_{mj} - \overline{y_j}\right)^2} \end{bmatrix} \tag{3.45}$$

Step 5: Develop the final performance score matrix (*PS*) for each alternative using Eq. (3.46) and (3.47).

$$PS = [PS_i]_m = \begin{bmatrix} PS_1 \\ PS_2 \\ \vdots \\ PS_m \end{bmatrix} = \begin{bmatrix} exp\left(\frac{B_1}{3}\right) + \frac{RA_1}{2n} \\ exp\left(\frac{B_2}{3}\right) + \frac{RA_2}{2n} \\ \vdots \\ exp\left(\frac{B_m}{3}\right) + \frac{RA_m}{2n} \end{bmatrix} \tag{3.46}$$

$$B = [B_i]_m = \begin{bmatrix} B_1 \\ B_2 \\ \vdots \\ B_m \end{bmatrix} = \begin{bmatrix} \frac{RN_1}{RP_1} \\ \frac{RN_2}{RP_2} \\ \vdots \\ \frac{RN_m}{RP_m} \end{bmatrix} \tag{3.47}$$

where *B* is the ratio of the Euclidean distances *RN* and *RP*. The alternatives having the maximum *PS* is selected.

3.7 Preference ranking on the basis of ideal-average distance

The PROBID technique, developed by Wang et al. [45], offers a full and comprehensive approach to decision making by considering both the average and all potential ideal options. This approach combines the benefits of TOPSIS and evaluation based on distance from average solution (EDAS). The most positive ideal solution (PIS), according to this method, is the one that yields the best outcome in terms of the influence of criteria. This approach gives the risk-tolerant decision maker more options by calculating the full spectrum of PIS, i.e., the first, second, third, and most negative PIS (also known as the most negative ideal solution or NIS) in relation to the number of alternatives under consideration. Furthermore, the average solution also takes risk avoider opinions into account. Unlike TOPSIS, it produces steady and consistent results, being free from the rank reversal problem. Several recent studies have highlighted the versatility and applicability of the method in various fields. Wang et al. [45] addressed the need for better methods in ranking non-dominated solutions in MOO within chemical engineering by introducing PROBID for MCDM problems. The research demonstrated that PROBID exhibit sensitivity to changes in objective weights and display ranking consistency, with PROBID showing greater robustness compared to other MCDM methods. Biswas et al. [46] extended the application of PROBID into social science research, specifically in evaluating video conferencing tools within a picture fuzzy environment. In chemical engineering optimization, Wang et al. [47] introduced a machine learning aided MOO-MCDM framework that included PROBID, showcasing its benefits in optimizing complex processes such as in power plants. These works collectively emphasize the significance of PROBID in decision making. The steps are as follows:

Step 1: Normalize using vector normalization procedure as shown in Eq. (3.48)

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, i \in \{1,2,\ldots,m\}; j \in \{1,2,\ldots,n\} \tag{3.48}$$

where r_{ij} is the vector normalized element of x_{ij}.

Step 2: Develop the weighted normalized decision matrix using Eq. (3.49), $z_{ij} = r_{ij} \times w_j$ (3.49)

Step 3: Establish the PIS in the order first (A_1), second (A_2), third (A_3),...,and n^{th} (A_n) (i.e. the first NIS) using Eq. (3.50)

$$A_k = \{(\text{Large}(z_j, k) | j \in J), (\text{Small}(z_j, k) | j \in J')\} = \{(z_{(k)1}, z_{(k)2}, \ldots, z_{(k)m}\} \tag{3.50}$$

$k \in \{1,2,\ldots, m\}$, J = beneficial criteria, J' = non-beneficial criteria. Large(z_j, k) and small(z_j, k) are the k^{th} largest and smallest values in column z_j.

The average of each criterion column is subsequently calculated using Eq. (3.51).

$$\bar{z}_j = \frac{\sum_{k=1}^{m} z_{(k)j}}{m}, j \in \{1,2,\ldots,n\} \tag{3.51}$$

The average solution is now provided applying the following Eq. (3.52):

$$\overline{A} = \{\bar{z}_1, \bar{z}_2, \ldots, \bar{z}_n\} \tag{3.52}$$

Step 4: Determine the average solution and the Euclidean distance.

Therefore, the following Eq. (3.53) is used to calculate the distance of ideal solutions:

$$E_{i(k)} = \sqrt{\sum_{j=1}^{n} (z_{ij} - z_{(k)j})^2}\ i \in \{1,2,\ldots,m\}; k \in \{1,2,\ldots,m\} \tag{3.53}$$

The distance of average solution is then computed using Eq. (3.54) as shown below:

$$E_{i(avg)} = \sqrt{\sum_{j=1}^{n} (z_{ij} - \bar{z}_j)^2} \tag{3.54}$$

Step 5: Calculate the overall positive-ideal distance as Eq. (3.55):

$$E_{i(pos-ideal)} = \begin{cases} \sum_{k=1}^{(m+1)/2} \frac{1}{k} E_{i(k)} & \text{when } m \text{ is an odd number} \\ \sum_{k=1}^{m/2} \frac{1}{k} E_{i(k)} & \text{when } m \text{ is an even number} \end{cases} \tag{3.55}$$

and overall negative-ideal distance as Eq. (3.56):

$$E_{i(neg-ideal)} = \begin{cases} \sum_{k=(m+1)/2}^{m} \frac{1}{m-k+1} E_{i(k)} & \text{when } m \text{ is an odd number} \\ \sum_{k=(m/2)+1}^{m} \frac{1}{m-k+1} E_{i(k)} & \text{when } m \text{ is an even number} \end{cases} \tag{3.56}$$

Here, positive and negative-ideal distance represent the weighted sum of the distance between each solution (criteria value) and the first half and second half of the ideal solution respectively. In case of positive ideal distance, the weight would reduce as the number of ideal solutions increases i.e. k = 1, 2, 3 and so on). However, for negative ideal distance, weight would increase with increase in the number of ideal solutions.

Step 6: Determine the pos-ideal/neg-ideal ratio (*RA_i*) using Eq. (3.57):

$$RA_i = \frac{E_{i(pos-ideal)}}{E_{i(neg-ideal)}} i \in \{1,2,\ldots,m\} \tag{3.57}$$

and performance score (*PS_i*) of each solution, using Eq. (3.58) as: $PS_i = \frac{1}{1+{RA_i}^2} + E_{i(avg)}$ (3.58)

Eq. (3.58) indicates that a value of RA_i closer to 0 implies that the i^{th} solution is closer to PIS_s, resulting in a higher value of PS_i. On the contrary, a high RA_i value signifies that the solution is closer to NIS_s, leading to a lower value of PS_i. Alternative with the highest PS_i value is selected.

3.8 Double normalization-based multiple aggregation

DNMA stands out as an effective tool for making complex decisions [48]. Its capacity to adapt to various data kinds and criteria via flexible normalization (linear and vector techniques) enables it to prioritize solutions that coincide with desired outcomes. This makes it excellent for scenarios involving specific aims. DNMA goes beyond standard methods by taking into account both positive and negative characteristics, allowing for more informed decisions even in the face of conflicting information. Its comprehensive evaluation is facilitated by the integration of three distinct aggregation models, i.e. complete compensatory model (CCM), uncompensatory model (UCM) and incomplete compensatory model (ICM), which enhances its ability to address diverse evaluation contexts and preferences. Its complete evaluation is based on the integration of these three distinct aggregating operations. DNMA strong theoretical base, as well as recent advances such as hesitant fuzzy DNMA and CRITIC weighting [49], demonstrate its adaptability across multiple domains, as proven by its successful applications in finance [50], such as fuel vehicles [51], location selection [52] and beyond. The DNMA procedure is stated as follows:

Step 1: Normalization. Target-based linear and vector normalized using Eqs. (3.59) and (3.60), respectively.

$$\tilde{x}_{ij}^{1N} = 1 - \frac{|x^{ij} - r_j|}{max\{\max_i x^{ij}, r_j\} - min\{\min_i x^{ij}, r_j\}} \tag{3.59}$$

$$\tilde{x}_{ij}^{2N} = 1 - \frac{|x^{ij} - r_j|}{\sqrt{\sum_{i=1}^{m}(x^{ij})^2 + (r_j)^2}} \tag{3.60}$$

where $r_j = \begin{cases} \max_i x_{ij,} if\ c_j\ is\ beneficial\ criterion \\ \min_i x_{ij,} if\ c_j\ is\ non-beneficial\ criterion \end{cases}$

Step 2: Adjusting. To achieve a trade-off between the evaluation criteria, the weight values are adjusted using Eqs. (3.61) - (3.63). $\omega_j^{\sigma} = \frac{\sigma_j}{\sum_{j=1}^{n}\sigma_j}$ (3.61)

In Eq. (3.61), σ_j denotes the standard deviation of j^{th} criterion, calculated using the following Eq. (3.62)

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}\left(\frac{x^{ij}}{\max_i x^{ij}} - \frac{1}{m}\sum_{i=1}^{m}\left(\frac{x^{ij}}{\max_i x^{ij}}\right)\right)^2}{m}} \tag{3.62}$$

Lastly, with the help of Eq. (3.63), weights are adjusted as $\tilde{\omega}_j = \frac{\sqrt{\omega_j^{\sigma}.\omega_j}}{\sum_{j=1}^{n}\sqrt{\omega_j^{\sigma}.\omega_j}}$ (3.63)

Step 3: Aggregation. Eqs. (3.64), (3.65) and (3.66) are used to compute the three types of utility values using three aggregation operators: CCM, UCM and ICM. As a result, three subordinate ranks of the alternatives are determined, in descending, ascending and descending orders of $u_1(a_i), u_2(a_i)\ and\ u_3(a_i)$, respectively.

$$u_1(a_i) = \sum_{j=1}^{n} \tilde{\omega}_j . \tilde{x}_{ij}^{1N} / \max_i \tilde{x}_{ij}^{1N} \tag{3.64}$$

$$u_2(a_i) = \max_j \tilde{\omega}_j \left(1 - \tilde{x}_{ij}^{1N} / \max_i \tilde{x}_{ij}^{1N}\right) \tag{3.65}$$

$$u_3(a_i) = \prod_j \left(\tilde{x}_{ij}^{2N} / \max_i \tilde{x}_{ij}^{1N}\right)^{\omega_j} \tag{3.66}$$

Step 4: Synthesize and rank. Eq. (3.67) calculates the comprehensive utility values. The parameter ω (ω ∈ 0,1) represents the utility value's relative significance, which may be set to 0.5. Furthermore, ω_1, ω_2 and ω_3 are the weights of CCM, UCM and ICM, respectively, resulting in ω_1, ω_2 and $\omega_3 = 1$. A larger weight might be assigned to the CCM if the decision maker is ready to assess the overall performance of the alternative. If the decision maker does not prefer to take any chance, a high-weight value might be set to the UCM. Finally, if the ICM excels in both overall performance and risk-taking, he or she may be granted a high-weight value. Finally, alternatives are ordered in decreasing order, so the alternative with the largest S_i value is preferred.

$$\begin{aligned} S_i = \overline{\omega}_1 . &\sqrt{\varphi . \left(\frac{u_1(a_i)}{\max_i u_1(a_i)}\right)^2 + (1-\varphi) . \left(\frac{m - r_1(a_i) + 1}{m}\right)^2} - \\ &\overline{\omega}_1 . \sqrt{\varphi . \left(u_2(a_i) / \max_i u_2(a_i)\right)^2 + (1-\varphi) . \left(\frac{r_2(a_i)}{m}\right)^2} + \\ &\overline{\omega}_1 . \sqrt{\varphi . \left(u_3(a_i) / \max_i u_3(a_i)\right)^2 + (1-\varphi) . \left(\frac{m - r_3(a_i) + 1}{m}\right)^2} \end{aligned} \tag{3.67}$$

4. 3D PRINTER NOZZLE MATERIAL SELECTION

The development of additive manufacturing has been significantly accelerated by the advancement of 3D printing technology, which makes it possible to create a greater range of goods using several well-established techniques [53]. The quality of the finished result in 3D printing is mostly determined by the design and construction of the component parts. One of the most popular quick prototyping techniques, fused deposition modelling, uses an extruder with a motor to push the filament in the direction of a heated end. There, as illustrated in Figure 4.1, the filament melts and is extruded through a nozzle to create controlled layers of the desired object. After each layer, the platform is lowered or the nozzle is raised to construct the product layer by layer [54]. The last component the filament goes through before extrusion is the nozzle, shown in Figure 4.2, and it needs to be adjustable to meet the demands of different applications. The nozzle is a crucial part of 3D printing systems since its exact design and manufacturing have a significant impact on the quality of the finished product. The nozzle diameter has a direct impact on the printed object's horizontal resolution and layer thickness, so factors like nozzle size, shape, and material need to be carefully addressed. The most commonly used and preferred nozzle bore diameter is 0.4 mm, as it provides an optimal balance between resolution and speed [55]. A larger nozzle diameter results in increased layer thickness, reducing resolution but enhancing printing speed. Conversely, a smaller nozzle diameter decreases layer thickness, improving resolution but slowing down the printing process. Nozzles with smaller diameters enable the production of more precise, smoother and highly detailed products. However, larger diameter nozzles are generally more reliable than their smaller counterparts, as over-extrusion may cause clogging, thereby disrupting the efficient operation of the 3D printer. Conversely, under-extrusion can weaken the bonding between layers of the fabricated object.

The shape of nozzle, including nose length and width, also affects performance. Short-nosed nozzles result in shorter travel distances for the molten filament, leading to inadequate cooling. In contrast, long-nosed nozzles allow for extended travel distances, facilitating proper cooling. A broad nozzle nose can lead to a loss of intricate design details, whereas a narrow nozzle nose may cause bulging of the extruded filament. Pointed nozzles enhance product quality, while flat-head nozzles provide improved sturdiness. The internal design of a nozzle is also limited by the thickness of its conduits. Additionally, the nozzle's material composition significantly influences its performance. Brass is a relatively soft and affordable material that offers excellent thermal conductivity and machinability; however, it tends to wear out quickly when exposed to abrasive filaments. In contrast, hardened steel and stainless steel are more suitable for handling abrasive materials, though they possess reduced thermal conductivity [56]. To improve longevity, other materials like ruby, plated copper, and aluminum alloys are also utilized in nozzle fabrication. However, brass and aluminum weaken considerably at elevated temperatures. A copper nozzle coated with a nickel layer is preferable due to its superior corrosion resistance and thermal conductivity. It is well established that the material properties of mechanical components play a vital role in their design. Given the vast range of available material choices and the specific constraints and criteria set by designers, selecting the most suitable alternative has become an increasingly complex task for manufacturers. The coexistence of several conflicting criteria and a wide range of material alternatives makes it necessary to employ an MCDM approach.

4.1 Review of MCDM in material selection for engineering applications

Previously, researchers investigated the applicability of MCDM methods in a variety of engineering fields, particularly material selection. Chede et al. [57] utilized TOPSIS method for selecting materials in the design of a powered hand truck, while Hasanzadeh et al. [58] employed TOPSIS and MOORA methods for automotive bumper beams. Kumar and Singal [59] applied AHP, TOPSIS, and modified TOPSIS methods for penstock material selection in small hydropower projects and Rastogi et al. [60] used TOPSIS for identifying suitable phase change materials in HVAC systems. Sen et al. [61] adopted COPRAS, MOORA, TOPSIS, VIKOR, and ARAS methods to select materials for connecting rods and Yang et al. [62] implemented fuzzy TOPSIS method for automotive components designed for remanufacturing. Goswami et al. [63] applied ARAS method for general engineering applications, while Dev et al. [64] used VIKOR method for piston materials. Giorgetti et al. [65] proposed VIKOR algorithm for valve seat materials in high-performance engines and Ishak et al. [66] utilized fuzzy VIKOR method for natural fibre-reinforced composites in car front hoods. In addition, Zhang et al. [67] integrated PROMETHEE with AHP and FAHP for pipeline material selection in the sugar industry, whereas Goswami et al. [68] employed fuzzy PROMETHEE for automotive instrument panels and Li et al. [69] applied PROMETHEE II for tool steels. Sharma et al. [70] implemented PSI method for brake friction materials and Yadav et al. [71] applied AHP for selecting natural fiber reinforced polymer composites for automotive applications. Further, Zhang et al. [72] developed a fuzzy MCDM method based on axiomatic design principles for selecting protective coating materials and aluminum alloys for underwater vehicles. Bhattacharyya and Chakraborty [73] explored Q-analysis technique for material selection and Xue et al. [74] applied fuzzy-MABAC approach to automotive instrument panels. Zhang and Liu [75] adopted GRA for material selection considering environmental and economic factors in automotive components, while Saha et al. [76] used TODIM method for engine flywheels and metallic gears. Sahoo et al. [77] proposed a hybrid TOPSIS-PSI approach for marine applications, Singh et al. [78] utilized MAIRCA method for lightweight automotive materials, Cheng et al. [79] applied MAIRCA for piston materials and Wang et al. [80] implemented WSM method alongside FEA simulations for selecting materials for collapsible pot haulers. These MCDM methods have been extensively applied to solve diverse material selection problems.

Review reveals that AHP, MOORA, PSI, TOPSIS, VIKOR and PROMETHEE MCDM methods are commonly used for material selection in various mechanical components. However, no prior research related to selection process of 3D printer nozzle material, has been conducted. To address this issue, newly developed methods are used in this study. The limited use of these newly developed methods in previous studies has inspired an exploration of its potential in addressing the material selection problem for 3D printer nozzles.

4.2 Illustrative example

The nozzle is the outlet through which the melted filament is released from a 3D printer. It is located at the tip of the extruder. The nozzle's material properties have a significant impact on the printed components overall quality and shape accuracy. Therefore, selecting the best nozzle material under the particular conditions has become essential to enhancing the additive manufacturing experience with the end product. As a result, there will be less wear and the molten filament will flow easily and affordably. The developed decision matrix which includes criteria and nozzle material alternatives, is displayed in Table 4.1, where criteria values are collected from the websites [81].

Density (C_1) of the nozzle material is an important criterion as less material in nozzle shape greatly decreases the weight of the print head. Thermal conductivity (C_2) is the ability to conduct heat and it is important to keep a steady extrusion temperature throughout the flow of the molten filament as heat is able to travel up to the tip of the nozzle keeping the molten filament at appropriate temperature. Corrosion resistance (C_3) is the ability to withstand the damage caused by oxidization or other chemical reactions, ensuring lengthening of the life span of the nozzle head. Hardness (C_4) is a measure of resistance to local plastic deformation induced by either mechanical indentation or abrasion. Presence of abrasive particles in filaments makes hardness a crucial criterion while selecting a nozzle material. Wear resistance (C_5) is the ability to minimize the damage of the nozzle caused by the abrasive particles present in the filament material. Few molten filament particles sometimes stick out and scoop out the nozzle from inside. Presence of hard and sharp particles in the filament and higher loading of filament material would also increase the wear rate. Therefore, for abrasive filament, more wear resistant nozzle material needs to be selected. Cost of the nozzle material (C_6) is a major decisive criterion as it ultimately affects the product cost. Yield strength (C_7) is the tension during which the material begins deforming plastically. Hence, yield strength of a nozzle material must be as high as possible, otherwise, the nozzle shape would be distorted due to plastic deformation. Ultimate tensile strength (C_8) is the ability to withstand tensile loading due to the forced flow of high temperature molten filament through the nozzle and must be high for the selected 3D printer nozzle material. Machinability (C_9) of a nozzle material represents the easiness with which it can be machined. Machinability ratings are relative in nature and are compared against the standard rating of 100% assigned to 160 Brinell hardness B1112 cold drawn steel. In Table 4.1, absolute values are expressed for all criteria except corrosion resistance, machinability and wear resistance. To indicate the values of the three qualitative material attributes, a nine-point relative scale is employed, where one represents extremely low, three low, five medium, seven moderate and nine very high. Table 4.1 shows the material alternative for 3D printer nozzle. Brass is mainly an alloy of copper and zinc (Cu 69%, Zn 30%) and is mostly used as a nozzle material for non-abrasive filaments. It is a comparatively good conductor of heat and relatively cheap than most of the other considered materials. Hardened steel is often considered as high carbon steel (Fe 93.6%, C 0.85%, W 4.68%, V 2.53%) and is better with respect to hardness, wear resistance, yield strength and ultimate tensile strength properties in comparison to other material alternatives. Stainless steel (Fe 68.3%, Cr 18.3%, Ni 10.8%, Co 4.37%), though poor in conducting heat, is an excellent corrosion resistant material mainly used for nozzles adopted for manufacturing of medical devices and utensils.

Table 4.1 Decision matrix addressing the problem of selecting the material for the 3D printer nozzle

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Brass (A_1)	8.49	124	1	65.1	1	5.44	255	430	7
Hardened steel (A_2)	7.5	46.9	3	262	3	4.35	810	1010	7
Stainless steel (A_3)	7.81	16.7	9	252	3	3.12	666	939	3
Tungsten carbide (A_4)	15.7	110	7	1006	9	46.17	415	344	1
Titanium alloy (TiAl6V4) (A_5)	4.43	6.7	9	334	5	30.47	880	950	5
Aluminium 6065 (A_6)	2.71	179	7	88.3	1	1.52	257	301	7
Aluminium 7075-T6 (A_7)	2.81	153	7	135	1	5.80	370	444	9
Nickel plated copper (cold drawn) (A_8)	8.64	190	9	145	1	6.53	383	511	5

Tungsten carbide is an extremely hard material possessing excellent wear resistance property, making it a strong candidate for nozzle material to reduce wearing of nozzles during 3D printing. TiAl6V4 (Ti 89%, Al 5.5%,V 4%), a titanium alloy, though a very poor conductor of heat, is also an excellent corrosion resistant material, comparatively having higher yield and ultimate tensile strength. Titanium nozzles are usually preferred for working over 400oC to print exotic filaments. Aluminium 6065 (Al 95%, Mg 1%, Si 0.6%) is a very good conductor of heat and has very low density. Thus, it would be an appropriate material when low extruder weight is required. Aluminium 7075-T6 (Al 90%, Cu 1.6%, Zn 5.5%, Mg 2.5%) possesses low density, better conductivity of heat and high strength-to-density ratio, which also makes it a suitable choice for nozzle material. Nickel is often plated on copper to enhance the corresponding corrosion resistance along with improved thermal conductivity. At high temperatures, brass and aluminium become very weak which constrains their applicability as 3D printer nozzle materials. Now this 3D printer nozzle selection problem is solved using eight newly developed MCDM methods. Entropy method is used to determine the weights using the Eqs. (2.1) – (2.4). The evaluated entropy weights are 0.0218, 0.1735, 0.0777, 0.2479, 0.2203, 0.0514, 0.0667, 0.0659, 0.075 respectively. The detailed ranking calculations and results of the MACONT and PARIS methods are presented to illustrate their computational procedures and outcomes. Summaries of the ranking steps for the remaining six newly developed MCDM methods are also provided. Complete calculation frameworks and final results for these methods are discussed in detail in the subsequent chapters.

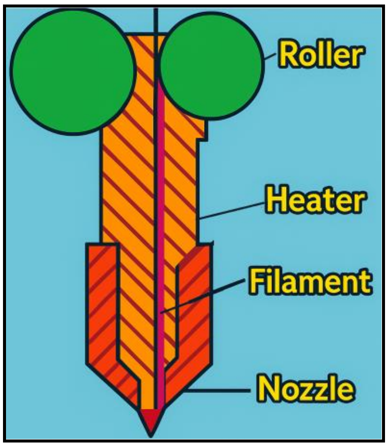


Figure 4.1 Schematic diagram of a 3D printer extruder

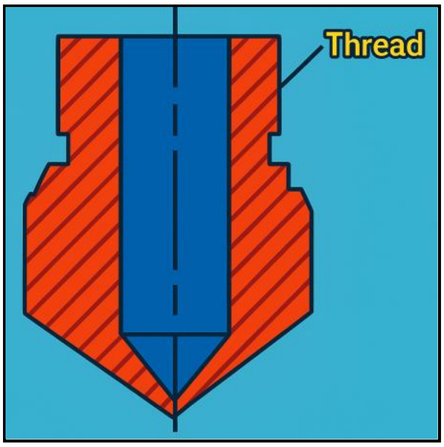


Figure 4.2 Sectional view of a 3D printer nozzle

MACONT method

The 3D printer nozzle material selection problem is now solved using MACONT method. In Table 4.1, Eq. (3.2), (3.3) and (3.4) are first applied to obtain the normalized values. These values are presented in Table 4.2, Table 4.3 and Table 4.4. To obtain the comprehensive decision matrix Table 4.5, Eq. (3.5) is applied. To calculate the subordinate comprehensive values, Eqs. (3.6) and (3.7) are used, considering the $\delta = 0.5$ and $\vartheta = 0.5$ respectively. The final comprehensive scores are calculated using Eq. (3.8). The ranking results are provided in Table 4.6. Based on descending values of final comprehensive score, the materials are ranked. It is revealed that tungsten carbide is the best nozzle material followed by hardened steel as they secure the first and second positions respectively.

Table 4.2 Normalized values through first normalization method

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	0.0780	0.1501	0.0192	0.0285	0.0417	0.1037	0.0632	0.0872	0.1591
A_2	0.0883	0.0568	0.0577	0.1145	0.1250	0.1297	0.2007	0.2049	0.1591
A_3	0.0848	0.0202	0.1731	0.1102	0.1250	0.1809	0.1650	0.1905	0.0682
A_4	0.0422	0.1331	0.1346	0.4398	0.3750	0.0122	0.1028	0.0698	0.0227
A_5	0.1496	0.0081	0.1731	0.1460	0.2083	0.0185	0.2180	0.1927	0.1136
A_6	0.2445	0.2166	0.1346	0.0386	0.0417	0.3712	0.0637	0.0611	0.1591
A_7	0.2358	0.1852	0.1346	0.0590	0.0417	0.0973	0.0917	0.0901	0.2045
A_8	0.0767	0.2299	0.1731	0.0634	0.0417	0.0864	0.0949	0.1037	0.1136

Table 4.3 Normalized values through second normalization method

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	0.3192	0.6526	0.1111	0.0647	0.1111	0.2794	0.2898	0.4257	0.7778
A_2	0.3613	0.2468	0.3333	0.2604	0.3333	0.3494	0.9205	1.0000	0.7778
A_3	0.3470	0.0879	1.0000	0.2505	0.3333	0.4872	0.7568	0.9297	0.3333
A_4	0.1726	0.5789	0.7778	1.0000	1.0000	0.0329	0.4716	0.3406	0.1111
A_5	0.6117	0.0353	1.0000	0.3320	0.5556	0.0499	1.0000	0.9406	0.5556
A_6	1.0000	0.9421	0.7778	0.0878	0.1111	1.0000	0.2920	0.2980	0.7778
A_7	0.9644	0.8053	0.7778	0.1342	0.1111	0.2621	0.4205	0.4396	1.0000
A_8	0.3137	1.0000	1.0000	0.1441	0.1111	0.2328	0.4352	0.5059	0.5556

Table 4.4 Normalized values through third normalization method

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	0.5550	0.6399	0.0000	0.0000	0.0000	0.9122	0.0000	0.1819	0.7500
A_2	0.6313	0.2193	0.2500	0.2093	0.2500	0.9366	0.8880	1.0000	0.7500
A_3	0.6074	0.0546	1.0000	0.1986	0.2500	0.9642	0.6576	0.8999	0.2500
A_4	0.0000	0.5636	0.7500	1.0000	1.0000	0.0000	0.2560	0.0606	0.0000
A_5	0.8676	0.0000	1.0000	0.2858	0.5000	0.3516	1.0000	0.9154	0.5000
A_6	1.0000	0.9400	0.7500	0.0247	0.0000	1.0000	0.0032	0.0000	0.7500
A_7	0.9923	0.7981	0.7500	0.0743	0.0000	0.9041	0.1840	0.2017	1.0000
A_8	0.5435	1.0000	1.0000	0.0849	0.0000	0.8878	0.2048	0.2962	0.5000

Table 4.5 Comprehensive decision matrix, where $\lambda=0.4$, $\mu=0.3$

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	0.2935	0.4478	0.0410	0.0308	0.0500	0.3990	0.1122	0.2172	0.5220
A_2	0.3331	0.1626	0.1981	0.1867	0.2250	0.4377	0.6228	0.6820	0.5220
A_3	0.3203	0.0508	0.6692	0.1788	0.2250	0.5077	0.4903	0.6251	0.2023
A_4	0.0687	0.3960	0.5122	0.7759	0.7500	0.0148	0.2594	0.1483	0.0424
A_5	0.5036	0.0138	0.6692	0.2437	0.4000	0.1279	0.6872	0.6339	0.3621
A_6	0.6978	0.6513	0.5122	0.0492	0.0500	0.7485	0.1140	0.1138	0.5220
A_7	0.6813	0.5551	0.5122	0.0862	0.0500	0.3888	0.2180	0.2284	0.6818
A_8	0.2878	0.6920	0.6692	0.0941	0.0500	0.3707	0.2300	0.2821	0.3621

Table 4.6 Ranking of the 3D printer nozzle material using MACONT method

Alternative	ρ_i	Q_i	$S_1(A_i)$	$S_2(A_i)$	$S(A_i)$	Rank
A_1	-0.1193	0.6983	-0.1649	-0.0150	-0.1988	8
A_2	-0.0119	0.3855	0.0252	-0.0077	-0.0470	6
A_3	-0.0298	0.4387	-0.0064	-0.0193	-0.1523	7
A_4	0.1919	2.1249	0.6930	0.0572	0.7892	1
A_5	0.0286	2.8164	0.4325	-0.0117	0.1255	2
A_6	-0.0228	0.7226	0.0461	0.0049	0.0610	4
A_7	-0.0227	0.7452	0.0493	-0.0033	-0.0011	5
A_8	-0.0139	0.2253	-0.0002	0.0085	0.0661	3

PARIS method

Now, the 3D printer nozzle material selection problem is solved using PARIS method with the same entropy weight as calculated earlier. In Table 4.1, Eqs. (3.10) to (3.16) are first applied to obtain the three different weighted normalized matrix, WAY_1, WAY_2 and WAY_3 respectively. These values are presented in Table 4.7, Table 4.8 and Table 4.9. To rank the alternatives, sum of the weighted matrix (π_i^{ω}) is calculated using Eq. (3.17). The results are presented in Table 4.10. Eq. (3.18) is applied to determine the reference ideal solution (z_j*). The distance from the reference ideal solution (π_i*) is calculated using Eq. (3.19). Table 4.11 displays the ranking results. Table 4.12 displays the results based on the value of R_i. Eq. (3.20) is used to compute the distance between the alternatives and the ideal solution (R_i). Based on ascending values of Ri, the materials are ranked. It can be revealed that tungsten carbide is the best nozzle material followed by titanium alloy (TiAl6V4).

Table 4.7 Weighted normalized values through vector normalization, WAY$_1$

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	0.0138	0.0617	0.0039	0.0141	0.0195	0.0464	0.0108	0.0148	0.0309
A_2	0.0148	0.0233	0.0117	0.0568	0.0584	0.0474	0.0344	0.0348	0.0309
A_3	0.0145	0.0083	0.0350	0.0546	0.0584	0.0485	0.0283	0.0324	0.0133
A_4	0.0071	0.0547	0.0272	0.2181	0.1752	0.0094	0.0176	0.0119	0.0044
A_5	0.0176	0.0033	0.0350	0.0724	0.0974	0.0237	0.0374	0.0327	0.0221
A_6	0.0192	0.0891	0.0272	0.0191	0.0195	0.0500	0.0109	0.0104	0.0309
A_7	0.0191	0.0761	0.0272	0.0293	0.0195	0.0461	0.0157	0.0153	0.0398
A_8	0.0137	0.0945	0.0350	0.0314	0.0195	0.0454	0.0163	0.0176	0.0221

Table 4.8 Weighted normalized values through linear normalization, WAY$_2$

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	0.0069	0.1132	0.0086	0.0160	0.0245	0.0144	0.0193	0.0281	0.0583
A_2	0.0079	0.0428	0.0259	0.0646	0.0734	0.0179	0.0614	0.0659	0.0583
A_3	0.0075	0.0152	0.0777	0.0621	0.0734	0.0250	0.0504	0.0613	0.0250
A_4	0.0038	0.1004	0.0605	0.2479	0.2203	0.0017	0.0314	0.0224	0.0083
A_5	0.0133	0.0061	0.0777	0.0823	0.1224	0.0026	0.0667	0.0620	0.0416
A_6	0.0218	0.1634	0.0605	0.0218	0.0245	0.0514	0.0195	0.0196	0.0583
A_7	0.0210	0.1397	0.0605	0.0333	0.0245	0.0135	0.0280	0.0290	0.0750
A_8	0.0068	0.1735	0.0777	0.0357	0.0245	0.0120	0.0290	0.0333	0.0416

Table 4.9 Weighted normalized values through max-min normalization, WAY$_3$

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	0.0121	0.1110	0.0000	0.0000	0.0000	0.0469	0.0000	0.0120	0.0562
A_2	0.0137	0.0380	0.0194	0.0519	0.0551	0.0481	0.0592	0.0659	0.0562
A_3	0.0132	0.0095	0.0777	0.0492	0.0551	0.0495	0.0438	0.0593	0.0187
A_4	0.0000	0.0978	0.0583	0.2479	0.2203	0.0000	0.0171	0.0040	0.0000
A_5	0.0189	0.0000	0.0777	0.0708	0.1102	0.0181	0.0667	0.0603	0.0375
A_6	0.0218	0.1631	0.0583	0.0061	0.0000	0.0514	0.0002	0.0000	0.0562
A_7	0.0216	0.1385	0.0583	0.0184	0.0000	0.0464	0.0123	0.0133	0.0750
A_8	0.0118	0.1735	0.0777	0.0210	0.0000	0.0456	0.0137	0.0195	0.0375

Table 4.10 Ranking based on π_i^{ω} values

Alternative	π_i^{ω} (WAY$_1$)	Rank	π_i^{ω} (WAY$_2$)	Rank	π_i^{ω} (WAY$_3$)	Rank
A_1	0.2160	8	0.2893	8	0.2382	8
A_2	0.3125	3	0.4181	6	0.4076	3
A_3	0.2933	5	0.3978	7	0.3761	6
A_4	0.5257	1	0.6967	1	0.6453	1
A_5	0.3416	2	0.4747	2	0.4601	2
A_6	0.2763	7	0.4407	3	0.3570	7
A_7	0.2881	6	0.4243	5	0.3837	5
A_8	0.2955	4	0.4342	4	0.4003	4

Table 4.11 Ranking based on π_i^* values

Alternative	π_i^* (WAY$_1$)	Rank	π_i^* (WAY$_2$)	Rank	π_i^* (WAY$_3$)	Rank
A$_1$	0.4353	8	0.6430	8	0.6887	8
A$_2$	0.3388	3	0.5142	6	0.5193	3
A$_3$	0.3581	5	0.5345	7	0.5508	6
A$_4$	0.1256	1	0.2356	1	0.2816	1
A$_5$	0.3098	2	0.4576	2	0.4668	2
A$_6$	0.3751	7	0.4917	3	0.5698	7
A$_7$	0.3633	6	0.5080	5	0.5432	5
A$_8$	0.3558	4	0.4981	4	0.5265	4

Table 4.12 Ranking based on R_i values using PARIS method

Alternative	R_i (WAY$_1$)	Rank	R_i (WAY$_2$)	Rank	R_i (WAY$_3$)	Rank
A$_1$	0.4380	8	0.5761	8	0.5757	8
A$_2$	0.3015	3	0.3940	6	0.3361	3
A$_3$	0.3288	5	0.4227	7	0.3806	6
A$_4$	0.0000	1	0.0000	1	0.0000	1
A$_5$	0.2604	2	0.3140	2	0.2619	2
A$_6$	0.3527	7	0.3621	3	0.4076	7
A$_7$	0.3361	6	0.3852	5	0.3699	5
A$_8$	0.3256	4	0.3713	4	0.3464	4

EAMR method

The initial stage in using the EAMR approach is to normalize the original decision matrix using Eq. (3.21). Using Eq. (3.22), the relevant weighted normalized matrix is then calculated from the normalized matrix while taking entropy weights into account. Now, employing Eqs. (3.23), (3.24) and (3.25), the related rank value and evaluation scores are evaluated and presented in Table 4.13. It can be unveiled that A$_4$ is the best alternative. It can also be observed that A$_5$ is the second best, whereas, A$_8$ is the worst alternative.

Table 4.13 Ranking results based on evaluation score, S_i using EAMR method

Alternative	G_i^+	G_i^-	$RV(G_i^+)$	$RV(G_i^-)$	S_i	Rank
A$_1$	0.3092	1.6864	0.1037	0.3574	0.2902	8
A$_2$	0.3737	0.4027	0.1253	0.0854	1.4685	3
A$_3$	0.2097	0.4762	0.0703	0.1009	0.6969	6
A$_4$	0.6829	0.0731	0.2290	0.0155	14.7781	1
A$_5$	0.4172	0.1550	0.1399	0.0328	4.2604	2
A$_6$	0.3402	0.8039	0.1141	0.1704	0.6697	7
A$_7$	0.3340	0.5908	0.1120	0.1252	0.8946	5
A$_8$	0.3149	0.5305	0.1056	0.1124	0.9393	4

CURLI method

The steps of the CURLI method are applied to solve this 3D printer nozzle selection problem. The process begins by scoring the alternatives for each criterion. This scoring is conducted through pairwise comparisons, where the criterion value of one alternative is compared with that of another. A score of 1 is assigned if the alternative performs better for a particular criterion, a score of 0 if it performs worse and no score is assigned when both alternatives have equal values for that criterion. These comparisons are used to construct a processing scoring matrix, which systematically captures the relative dominance of each alternative over the others. Table 4.14 presents this matrix, where each element reflects the comparative outcome for a specific criterion between a pair of alternatives. Once the matrix is developed, the rows and columns are strategically rearranged so that the upper triangle of the main diagonal predominantly contains negative or zero scores. This rearrangement helps in visually identifying the alternatives that are consistently outperformed by others. The final ranking is determined by analyzing this processed matrix. The alternative that appears at the top row of the rearranged square matrix and exhibits the highest number of negative scores is considered the most dominant, as it is least outperformed by others. Table 4.15 shows the resulting ranks of all alternatives based on this principle. It is evident from the results that A_4 secures first rank as it appears in the top row with most number of negative values.

Table 4.14 Processing scoring matrix after changing the positions of rows and columns

Alternative	P_4	P_5	P_2	P_8	P_7	P_3	P_6	P_1
A_4	0	-1	-4	-1	-1	-3	-3	-3
A_5	1	0	-4	-1	0	-5	-6	-1
A_2	4	4	0	-3	-1	-4	-5	-3
A_8	1	1	3	0	1	2	-6	-2
A_7	1	0	1	1	0	2	-5	0
A_3	3	5	4	-2	0	0	-2	-3
A_6	3	6	5	6	3	2	0	-1
A_1	3	1	3	2	6	3	1	0

Table 4.15 Rank of the alternative using CURLI method

Alternative	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
Rank	8	3	6	1	2	7	5	4

PEG method

The same problem is now solved using the PEG method. The normalized values are first computed using Eqs. (3.26) and (3.27). The criteria vectors are then arranged in ascending order using Eq. (3.28). The aggregate criteria vectors are calculated using Eq. (3.29) and subsequently arranged in descending order according to Eq. (3.30). The shifted vectors are then determined using Eqs. (3.31) and (3.32), followed by the calculation of the radial shift through Eqs. (3.33) and (3.34). The PEG scores are computed using the PEG function as per Eq. (3.35) and finally, the MSE values for each alternative are calculated using Eq. (3.36). The computation results are shown in Table 4.16. It can be noted that A_4 is the top ranked alternative. A_4 aligns well with the aggregated criteria under PEG, reinforcing its suitability as a preferred nozzle material alternative.

Table 4.16 Ranking results using PEG method

Alternative	x	y	x^*	y^*	MSE	Rank
A_1	0.6313	0.4011	0.7393	0.5765	1.0356	8
A_2	1.0000	0.0000	1.0000	0.2929	1.4452	4
A_3	0.5550	0.6877	0.6854	0.7792	1.4058	5
A_4	0.8676	0.3497	0.9064	0.5401	1.9769	1
A_5	0.0000	1.0000	0.2929	1.0000	1.7048	2
A_6	0.5435	0.7804	0.6772	0.8447	1.1131	7
A_7	0.6074	0.5066	0.7224	0.6511	1.2685	6
A_8	0.9923	0.1243	0.9946	0.3808	1.6272	3

OPTBIAS method

The OPTBIAS method is now applied to solve the same problem. The decision matrix is first normalized using the vector normalization approach as defined in Eq. (3.37) and the weighted normalized decision matrix is constructed using Eq. (3.38). The bi-positive ideal, bi-negative ideal and average solutions are then identified using Eqs. (3.39) to (3.42). Subsequently, the Euclidean distances of each alternative from the bi-positive ideal (*RP*), bi-negative ideal (*RN*) and average solution (*RA*) are computed using Eqs. (3.43), (3.44) and (3.45), respectively. The ratio of *RN* to *RP* for each alternative is calculated using Eq. (3.47). Finally, the performance scores (*PS*) of all alternatives are determined using Eq. (3.46). The results of these computations are presented in Table 4.17. It is observed that A_4 ranks first among the alternatives.

Table 4.17 Ranking results based on OPTBIAS method

Alternative	*RP*	*RN*	*RA*	*B*	*PS*	Rank
A_1	0.3094	0.1394	0.0679	0.4506	1.1663	8
A_2	0.2568	0.1705	0.0382	0.6637	1.2500	4
A_3	0.2702	0.1629	0.0488	0.6027	1.2255	7
A_4	0.3013	0.5367	0.1988	1.7815	1.8233	1
A_5	0.2756	0.2318	0.0684	0.8408	1.3278	2
A_6	0.3150	0.1950	0.0719	0.6191	1.2337	5
A_7	0.2984	0.1806	0.0597	0.6054	1.2273	6
A_8	0.3070	0.2072	0.0670	0.6749	1.2565	3

PROBID method

Applying PROBID method, the decision matrix is now vector normalized and the weighted normalized decision matrix is developed using Eqs. (3.48) and (3.49). The ideal (Z_k) and average ($\bar{Z}$) solutions are obtained based on Eqs. (3.50)-(3.52). The Euclidean distances ($E_{i(k)}$) (most PIS, second PIS..., eighth PIS) and the average solutions ($E_{i(avg)}$) are computed based on Eqs. (3.53) and (3.54). Table 4.18 provides the positive ideal ($E_{i(pos\text{-}ideal)}$), negative ideal ($E_{i(neg\text{-}ideal)}$), positive-ideal or negative-ideal ratio (RA_i) and performance score (PS_i) of each of the alternatives, which are obtained using Eqs. (3.55)-(3.58). It is clearly evident that A_4 occupies the top position in the ranking list with the maximum performance score, followed by A_5.

Table 4.18 Ranking results using PROBID method

Alternative	$E_{pos\text{-}deal}$	$E_{neg\text{-}ideal}$	*RA*	*PS*	Rank
A_1	0.3572	0.1292	2.7638	0.1837	8
A_2	0.2852	0.1558	1.8304	0.2680	5
A_3	0.3055	0.1509	2.0242	0.2449	7
A_4	0.2845	0.5370	0.5297	0.9796	1
A_5	0.2858	0.2223	1.2859	0.4453	2
A_6	0.3417	0.1785	1.9146	0.2862	4
A_7	0.3248	0.1592	2.0398	0.2535	6
A_8	0.3238	0.1872	1.7296	0.3175	3

DNMA method

Now, employing DNMA method, the decision matrix is normalized using both linear and vector normalization approaches, based on Eqs. (3.59) and (3.60), respectively. In the next step, using Eqs. (3.61), (3.62) and (3.63) the adjusted weight coefficients are estimated. Based on this weight adjusted coefficients and normalized values of the decision matrix and applying Eqs. (3.64) - (3.66), the corresponding utility values are computed using three different aggregation operators, i.e. CCM, UCM and ICM, as shown in Table 4.19. In Table 4.19, based on the computed utility values, the alternatives are subsequently ranked in descending, ascending and descending orders for CCM, UCM and ICM aggregators, respectively. Finally, the comprehensive utility values for each of the alternative are calculated using Eq. (3.67), considering values of different tuning parameters as $\varphi = 0.5$, $\overline{\omega}_1 = 0.6$, $\overline{\omega}_2 = 0.1$ and $\overline{\omega}_3 = 0.3$. Eight nozzle materials are subsequently ranked in decreasing order of their S_i values. Table 4.19 shows that A_4 is the best alternative with maximum comprehensive utility score, followed by A_5.

Table 4.19 Ranking results using DNMA method

Alternative	CCM		UCM		ICM		Utility value (S_i)	Rank
	$u_1(a_i)$	Rank	$u_2(a_i)$	Rank	$u_3(a_i)$	Rank		
A_1	0.2925	8	0.1729	8	0.6256	8	0.3243	8
A_2	0.4814	3	0.1367	2	0.7131	2	0.7193	3
A_3	0.4553	6	0.1526	3	0.6962	4	0.5716	6
A_4	0.5328	1	0.0921	1	0.7229	1	0.8613	1
A_5	0.5173	2	0.1615	4	0.7098	3	0.7417	2
A_6	0.4341	7	0.1686	7	0.6778	7	0.4748	7
A_7	0.4675	5	0.1658	5	0.6921	5	0.5767	5
A_8	0.4683	4	0.1658	5	0.6894	6	0.5940	4

Comparative analyses of MCDM methods

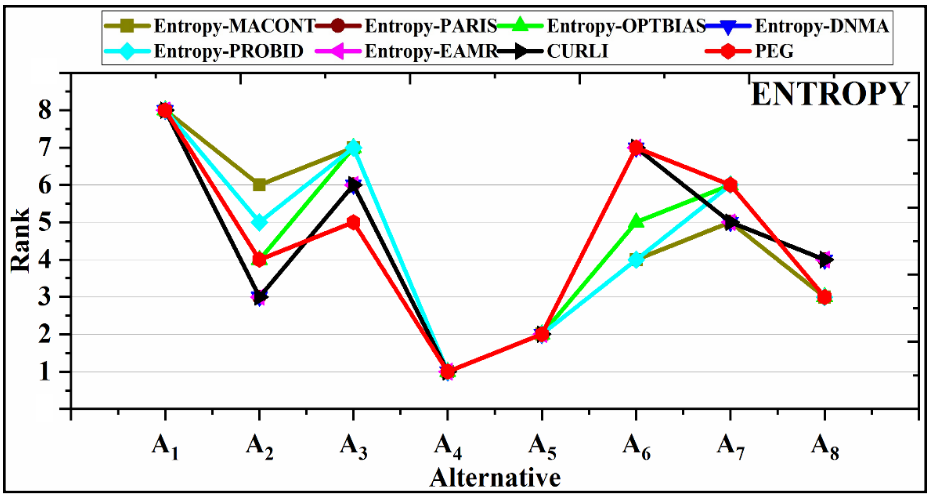
A detailed comparative analysis is carried out in this section. Parameters such as rank comparison under different criteria weights, Spearman correlation coefficient (R_s), weighted Spearman rank correlation coefficient (R_w), coefficient of ranking similarity (*WS*) and the number of operations required are discussed to assess the performance of various MCDM methods under different conditions.

Table 4.20 Set of criteria weights

Weighting methods	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Entropy	0.0218	0.1735	0.0777	0.2479	0.2203	0.0514	0.0667	0.0659	0.075
CRITIC	0.1195	0.1199	0.1361	0.0967	0.1008	0.1183	0.1036	0.1121	0.0931
MEREC	0.0783	0.2096	0.1463	0.0977	0.0659	0.1662	0.0485	0.0519	0.1355
PCA	0.1346	0.2873	0.0213	0.1653	0.2146	0.1549	0.2637	0.2387	0.159
SPC	0.05	0.1505	0.0584	0.18	0.1388	0.299	0.0408	0.0402	0.0422
LOPCOW	0.1672	0.1171	0.1574	0.0253	0.0444	0.1839	0.0744	0.0701	0.1601
CILOS	0.0954	0.1124	0.2352	0.0818	0.0875	0.0697	0.0907	0.127	0.1003
IDOCRIW	0.0198	0.1858	0.1742	0.1932	0.1837	0.0341	0.0577	0.0798	0.0717

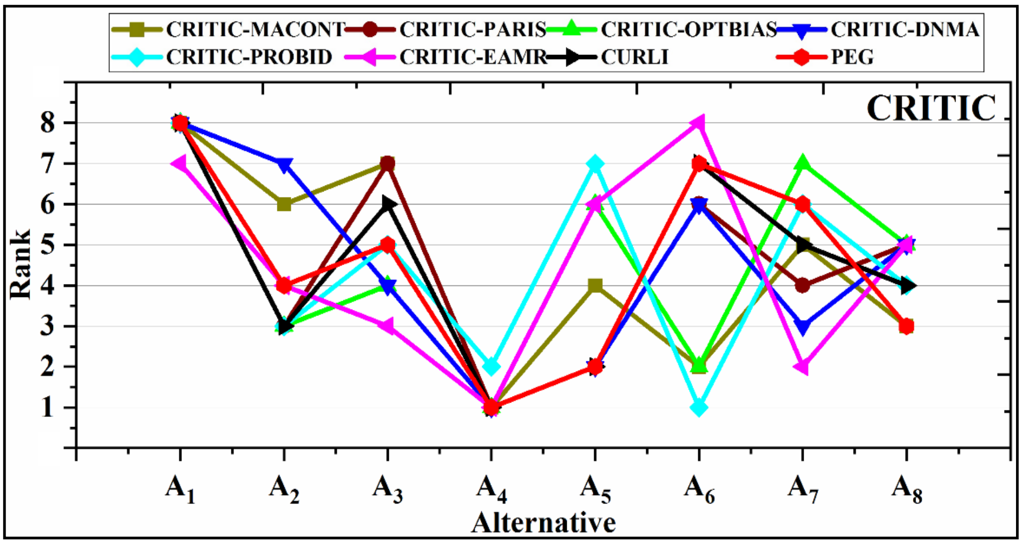
a) Based on rank comparison

This section presents the ranking results of applying each MCDM method using various criteria weight sets from Table 4.20. Figure 4.3 shows the rankings of eight recently developed MCDM methods. Alternative A_4 ranks highest in most cases, followed by A_6 and A_5 in a few, while A_1 consistently ranks lowest. With the entropy method, A_4 ranks first and A_1 last across all methods, showing complete agreement in top and bottom positions. Under CRITIC, A_4 leads in all but PROBID (where A_6 ranks first), and A_1 ranks last except in EAMR. MEREC and PCA also place A_4 at the top, though MEREC displays notable ranking variations, reflecting inconsistency. SPC shows considerable fluctuation in rankings, indicating instability. Under LOPCOW, all methods except DNMA rank A_4 highest, though other alternatives vary. CILOS shows A_4 at the top in most methods except OPTBIAS and PROBID, while IDOCRIW places A_4 highest in all but EAMR, with some variation in lower ranks. Based on the rank comparison, A_4 consistently outperforms others across multiple weightings, while A_1 ranks lowest. Entropy, IDOCRIW, and CRITIC demonstrate strong and consistent performance. Among MCDM methods, MACONT ranks top alternative most effectively, followed by PARIS and DNMA.

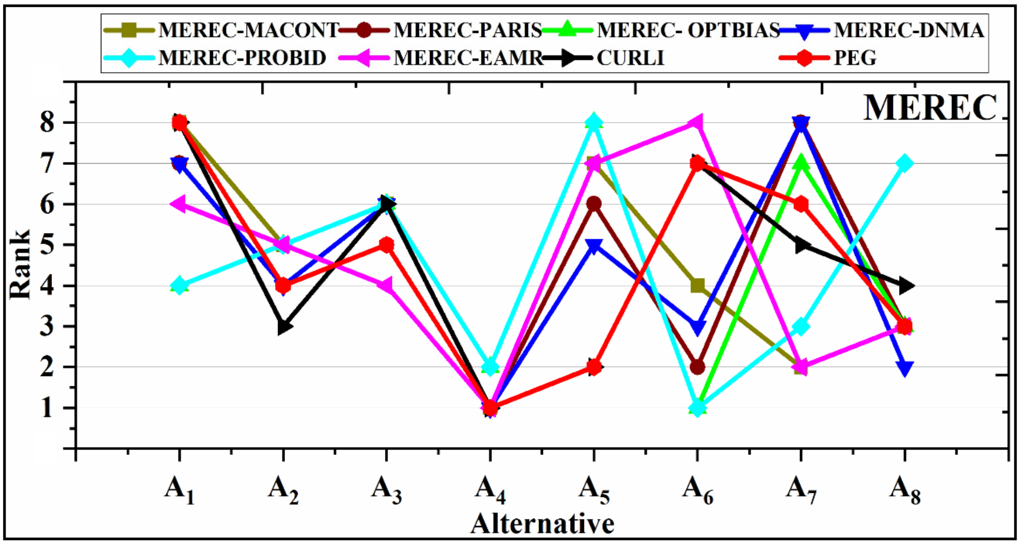


(a)

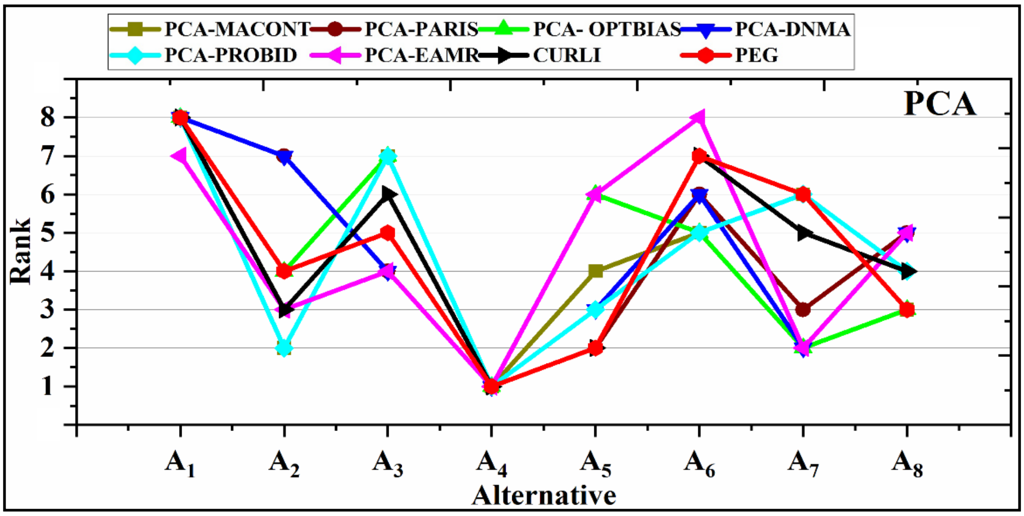
Figure 4.3 Weight wise ranking results of 3D printing nozzle material selection



(b)

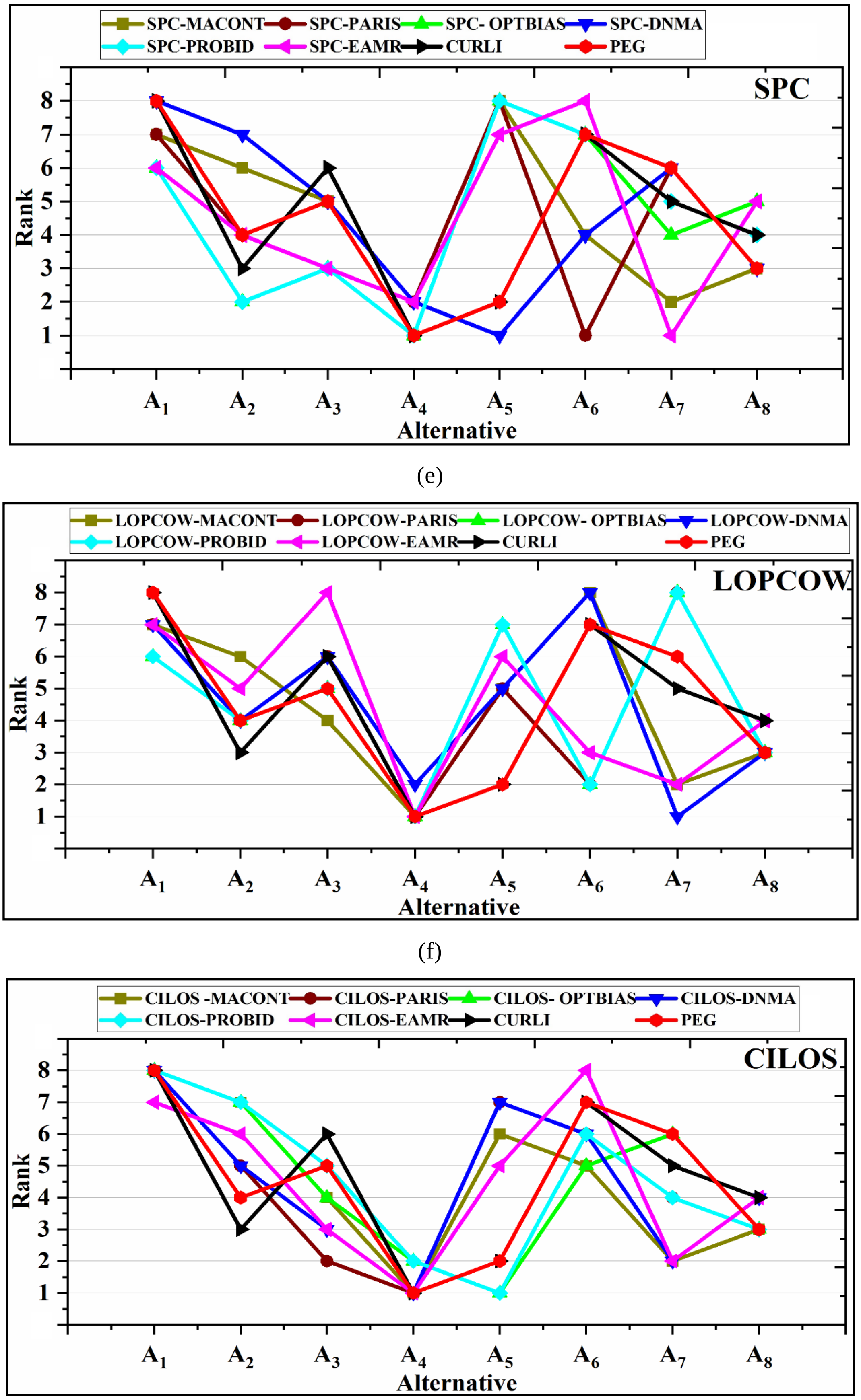


(c)



(d)

Figure 4.3 Continued

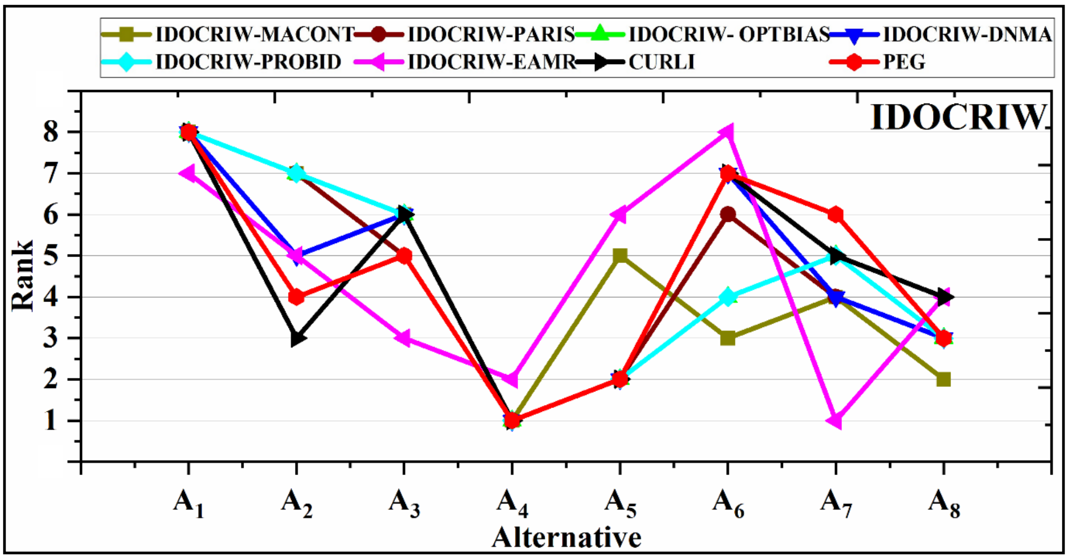


(e)

(f)

(g)

Figure 4.3 Continued



(h)

Figure 4.3 Continued

b) Based on Spearman correlation coefficients

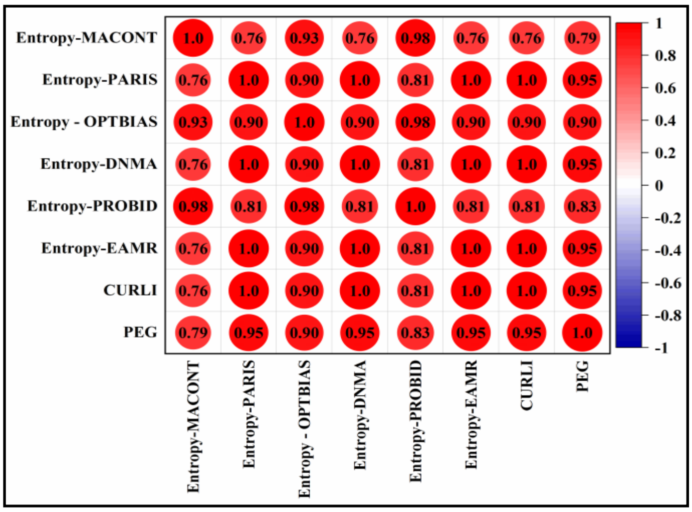
The ranking performance of different MCDM methods was previously analyzed using line charts, offering a visual interpretation of variations across multiple decision problems. While these graphical insights provide an overview of ranking trends, a more rigorous statistical approach is necessary to quantify the agreement between rankings generated by different methods. To achieve this, Spearman's correlation coefficient is utilized to measure the degree of similarity between rankings, providing a more structured evaluation. A high correlation indicates strong alignment in ranking patterns, reinforcing the reliability of MCDM methods, whereas a low correlation suggests inconsistencies that require further investigation. Given the application of nine different weighting conditions, assessing the extent of agreement between rankings is essential to determine the consistency of each method. By integrating Spearman's correlation analysis, a more objective validation of ranking stability is achieved, complementing the graphical observations derived from line charts. This approach strengthens the overall evaluation of MCDM methods, ensuring a comprehensive understanding of their ranking behaviour. The Spearman's correlation coefficient (R_s) is expressed by the Eq. (4.1).

$$R_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{4.1}$$

Figure 4.4 shows the R_s results between the different MCDM methods obtained using the Eq. (4.1). Value 1 indicates perfect correlation between methods, while zero indicates no relationship and negative value indicates an opposite or non-significant relationship. Mostly the values closer to 1 indicate the best possible results between the methods. This study reveals several insights about the performance of different MCDM methods when combined with various weighting methods. Entropy-based MCDM methods yield the highest correlation values, significantly improving results. With CRITIC weighting, PROBID and OPTBIAS show a 0.93 correlation, with PEG and CURLI maintaining

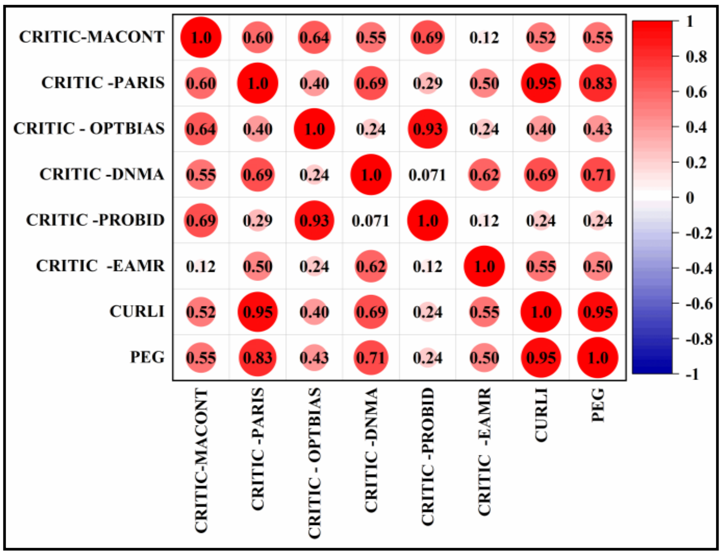
0.95. MEREC weighting shows similar results, with DNMA and PARIS at 0.95 and PEG and CURLI again at 0.95. PCA weighting results in a 0.98 correlation for MACONT-PROBID and DNMA-PARIS, with PEG and CURLI at 0.95. SPC weighting sees PROBID and OPTBIAS at 0.98. Under LOPCOW weighting, PROBID and OPTBIAS achieve a perfect 1 correlation, with PROBID-PARIS and OPTBIAS-PARIS at 0.93. CILOS weighting shows PARIS-DNMA and OPTBIAS-PROBID both at 0.93. IDOCRIW weighting sees OPTBIAS and PROBID at 1, with PARIS-OPTBIAS, PARIS-DNMA and PARIS-PROBID at 0.93. Except for EAMR, most methods show high correlation values under IDOCRIW, highlighting the importance of appropriate weighting methods to achieve consistent and reliable rankings in decision making problems. This study reveals that DNMA and PARIS consistently have the highest correlation values under various conditions, particularly with entropy, IDOCRIW and MEREC weightings, indicating their reliability in decision making. PEG and CURLI also perform well in no-weight scenarios.

The correlation analysis clearly identifies DNMA as one of the most consistent and dependable MCDM methods, as it achieves high Rs values across several objective weighting techniques, including entropy, MEREC, PCA and IDOCRIW. Notably, DNMA records a correlation of 0.95 with PARIS under MEREC, 0.98 under PCA and 0.93 with PARIS under both CILOS and IDOCRIW, reflecting its strong agreement with other high-performing methods. These results underscore ability of DNMA to produce stable and reliable rankings across diverse decision making scenarios and weighting strategies, particularly those that rely on objective, data-driven approaches with minimal subjective influence. The PARIS method performs exceptionally well, showing a correlation as high as 0.98 with DNMA (under PCA) and maintaining robust correlations with methods such as PROBID and OPTBIAS under entropy, MEREC and IDOCRIW. The consistently high correlation values associated with PARIS indicate its strong compatibility with other effective MCDM techniques and its capability to handle quantitative input effectively.

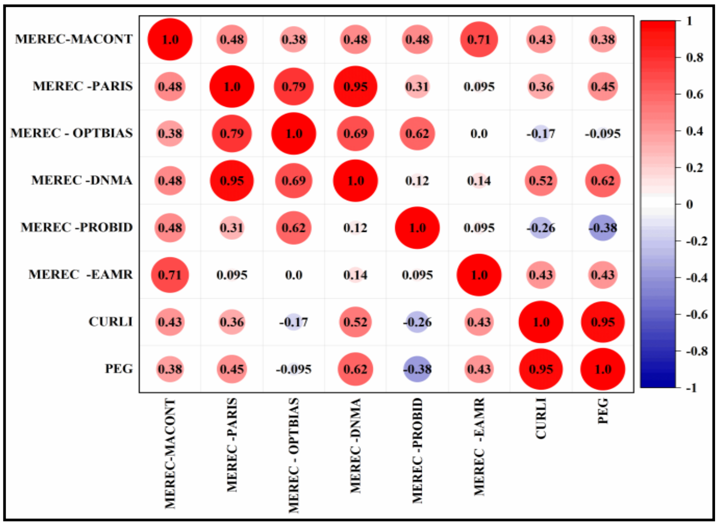


(a)

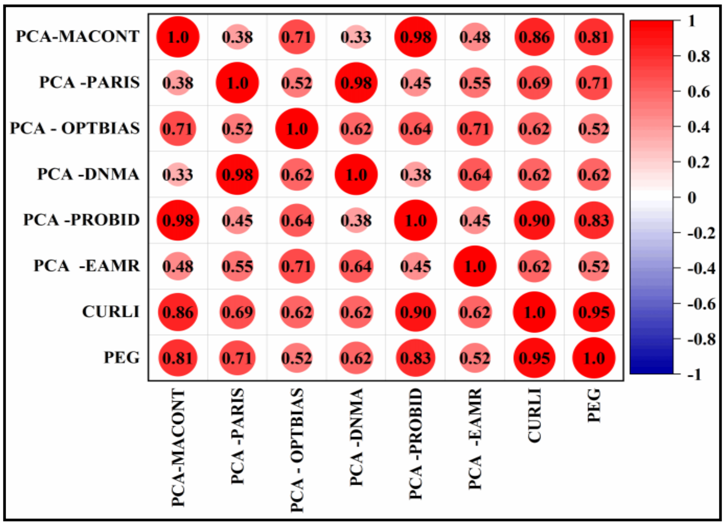
Figure 4.4 Spearman correlation coefficient results of 3D Printing nozzle selection



(b)

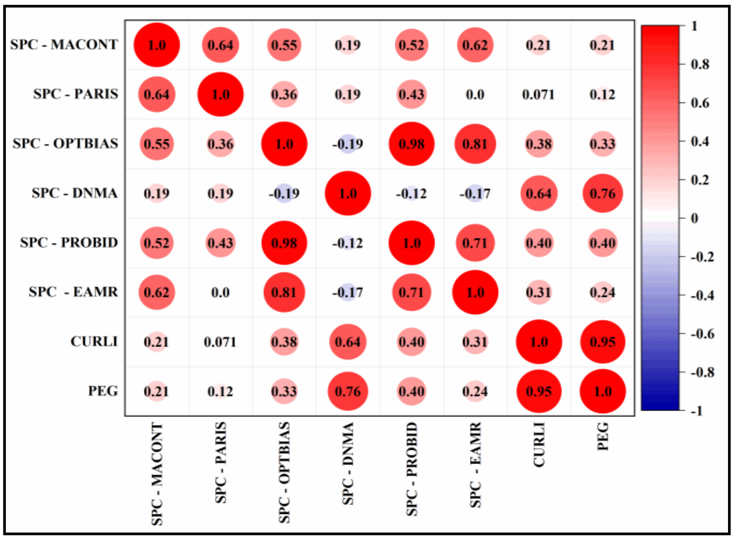


(c)

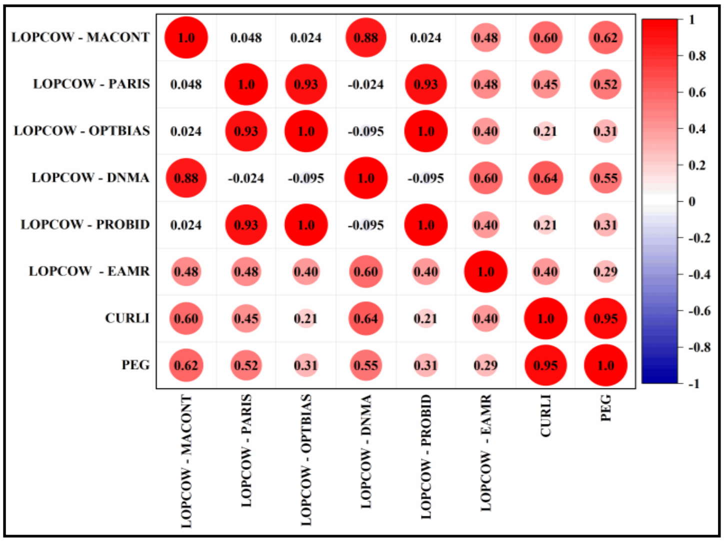


(d)

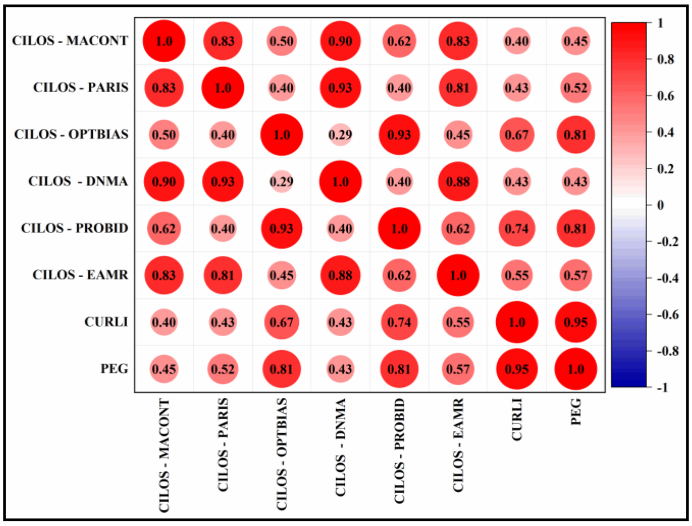
Figure 4.4 Continued



(e)

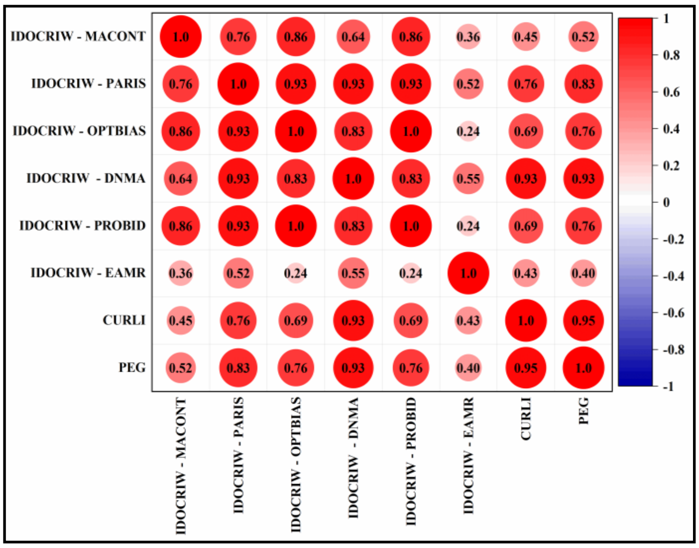


(f)



(g)

Figure 4.4 Continued



(h)

Figure 4.4 Continued

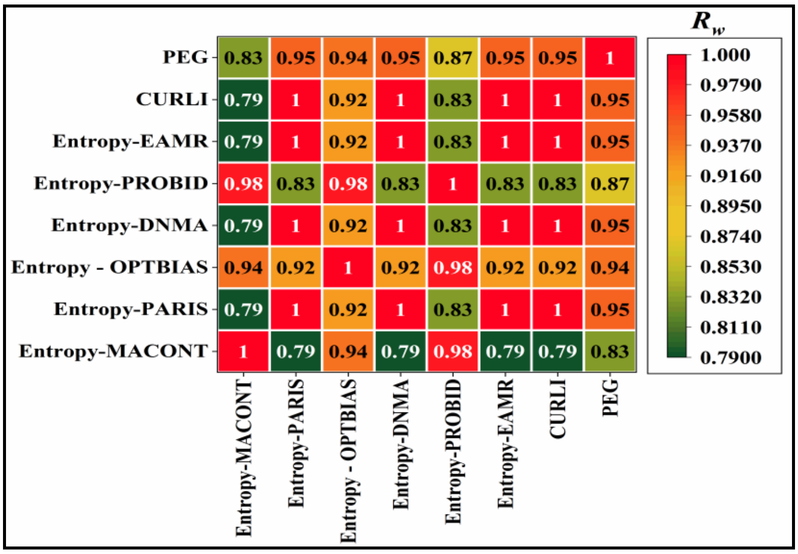
c) Based on weighted Spearman (R_w) rank co-relation coefficient

Spearman correlation treats all the rankings equally, which sometime poses a deep challenge. Further, it is more sensitive to larger differences between ranks as it squares the differences, resulting in disproportionate score of correlation. Additionally, it does not exhibit symmetry in treatment of two or more ranking vectors. To overcome these challenges, R_w is computed as it provides larger significance to higher ranked alternatives. R_w as mentioned in Eq. (4.2) is defined for two generic vectors, $x = x_i$ and $y = y_i$ where i=1,2,…,m and both vectors have a size of m referring to number of alternatives.

$$R_w = 1 - \frac{6\sum_{1}^{m}(x_i - y_i)^2\left((m - x_i + 1) + (m - y_i + 1)\right)}{m^4 + m^3 - m^2 - m} \tag{4.2}$$

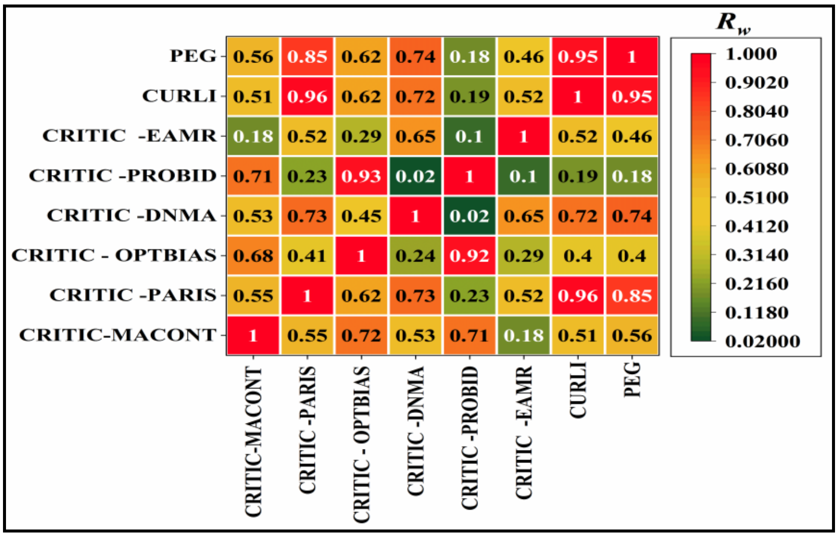
Additionally, it is more sensitive to higher ranked alternatives, resulting better observations where top ranked alternatives are important. Further, it is symmetric to both the ranking vectors. The proposed weighted measure is more suitable than traditional rank correlation coefficients for applications where higher ranks are more important. It gives more importance to higher ranks while still considering the entire ranking. This makes it a versatile measure of similarity between two rankings. Although it may not capture specific details of individual problems, it offers a broad assessment of overall agreement between rankings and serves as a useful complement to problem-specific measures. Figure 4.5 presents an overall result of R_w as computed using Eq. (4.2), where values above 0.9 can be significantly treated as very high representing that a very good correlation among higher ranked alternatives. Several MCDM methods show strong correlations with various weighting techniques. Under entropy combined conditions, the R_w value is 1 in most cases, with DNMA exhibiting higher R_w values above 0.79 with all other MCDM methods and overall values are 0.79 and above. CRITIC weighting sees PEG-CURLI at 0.95, PARIS-CURLI at 0.96 and PROBID-OPTBIAS at 0.93, with the rest not being as significant. MEREC weighting results in DNMA-PARIS and PEG-CURLI both at

0.95. PCA weighting shows high correlations for PROBID-MACONT and DNMA-PARIS at 0.97. SPC weighting sees PROBID-OPTBIAS at 0.98, while the rest perform poorly. LOPCOW weighting results in OPTBIAS-PROBID at 1 and PARIS-OPTBIAS at 0.98, PARIS-PROBID at 0.95 and DNMA-MACONT at 0.88. Under CILOS weighting, DNMA-MACONT, DNMA-PARIS, DNMA-EAMR, all above 0.9, PEG-CURLI are at 0.95 and PROBID-OPTBIAS at 0.94. Finally, IDOCRIW weighting shows DNMA-PARIS, DNMA-OPTBIAS, DNMA-PROBID, DNMA-CURLI and DNMA-PEG, all performing extremely well with very high R_w values. This analysis highlights DNMA as a highly reliable MCDM method, consistently showing strong correlations across various objective weighting techniques. Under entropy, it achieves above 0.79 in all cases, often reaching 1. With MEREC and PCA, DNMA records 0.95 and 0.97 with PARIS respectively and under CILOS and IDOCRIW, it maintains values above 0.9 with several top methods such as MACONT, EAMR, PEG and OPTBIAS.



	Entropy-MACONT	Entropy-PARIS	Entropy - OPTBIAS	Entropy-DNMA	Entropy-PROBID	Entropy-EAMR	CURLI	PEG
PEG	0.83	0.95	0.94	0.95	0.87	0.95	0.95	1
CURLI	0.79	1	0.92	1	0.83	1	1	0.95
Entropy-EAMR	0.79	1	0.92	1	0.83	1	1	0.95
Entropy-PROBID	0.98	0.83	0.98	0.83	1	0.83	0.83	0.87
Entropy-DNMA	0.79	1	0.92	1	0.83	1	1	0.95
Entropy - OPTBIAS	0.94	0.92	1	0.92	0.98	0.92	0.92	0.94
Entropy-PARIS	0.79	1	0.92	1	0.83	1	1	0.95
Entropy-MACONT	1	0.79	0.94	0.79	0.98	0.79	0.79	0.83

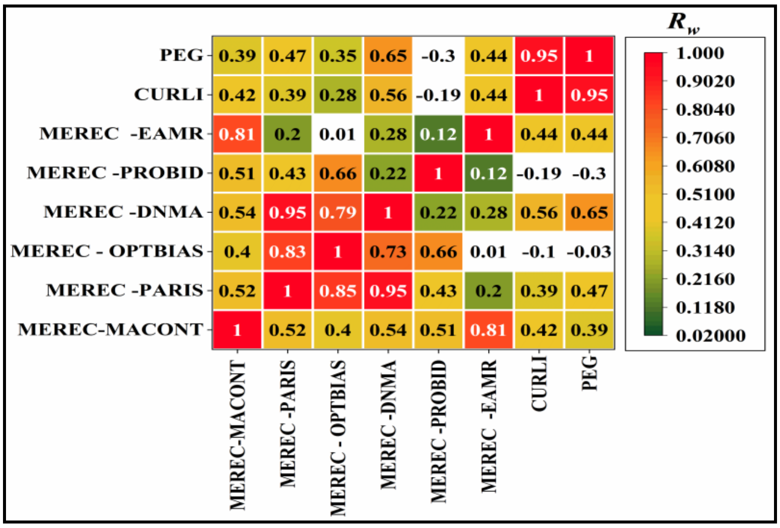
(a)



	CRITIC-MACONT	CRITIC -PARIS	CRITIC - OPTBIAS	CRITIC -DNMA	CRITIC -PROBID	CRITIC -EAMR	CURLI	PEG
PEG	0.56	0.85	0.62	0.74	0.18	0.46	0.95	1
CURLI	0.51	0.96	0.62	0.72	0.19	0.52	1	0.95
CRITIC -EAMR	0.18	0.52	0.29	0.65	0.1	1	0.52	0.46
CRITIC -PROBID	0.71	0.23	0.93	0.02	1	0.1	0.19	0.18
CRITIC -DNMA	0.53	0.73	0.45	1	0.02	0.65	0.72	0.74
CRITIC - OPTBIAS	0.68	0.41	1	0.24	0.92	0.29	0.4	0.4
CRITIC -PARIS	0.55	1	0.62	0.73	0.23	0.52	0.96	0.85
CRITIC-MACONT	1	0.55	0.72	0.53	0.71	0.18	0.51	0.56

(b)

Figure 4.5 Weighted Spearman correlation coefficient (R_w)



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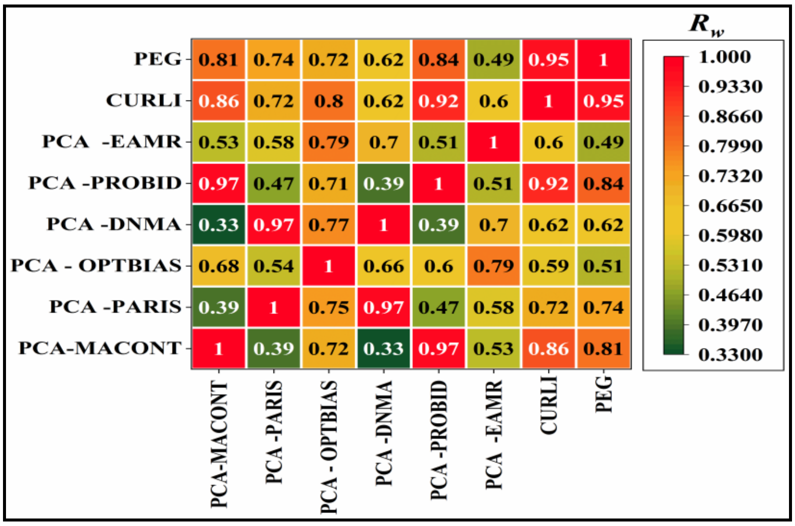

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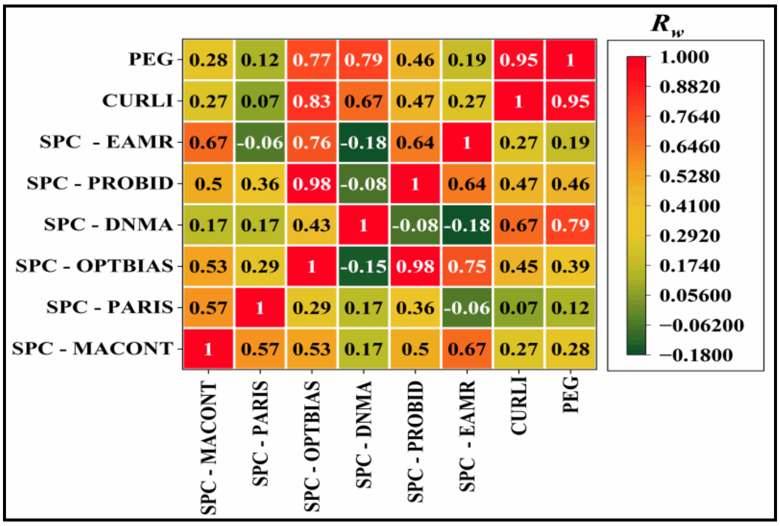

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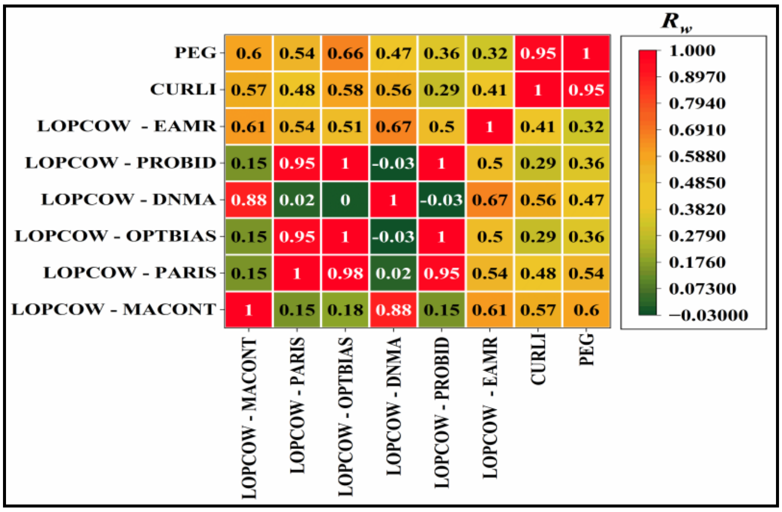
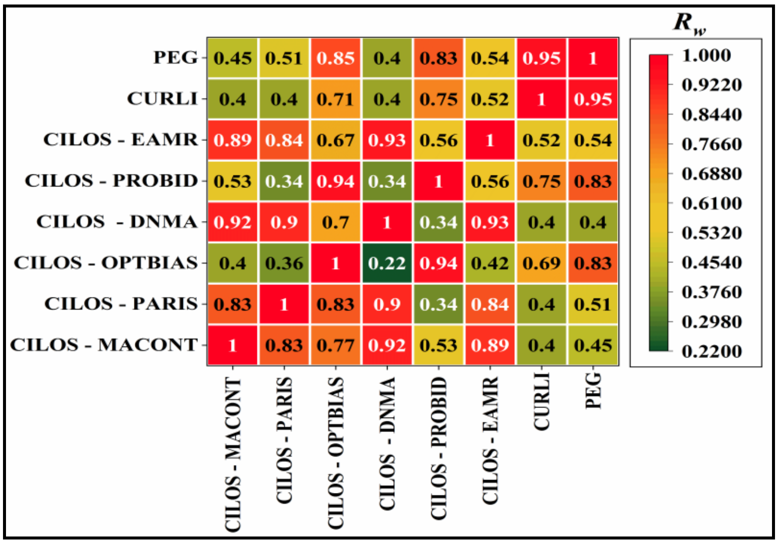
Figure 4.5 Continued



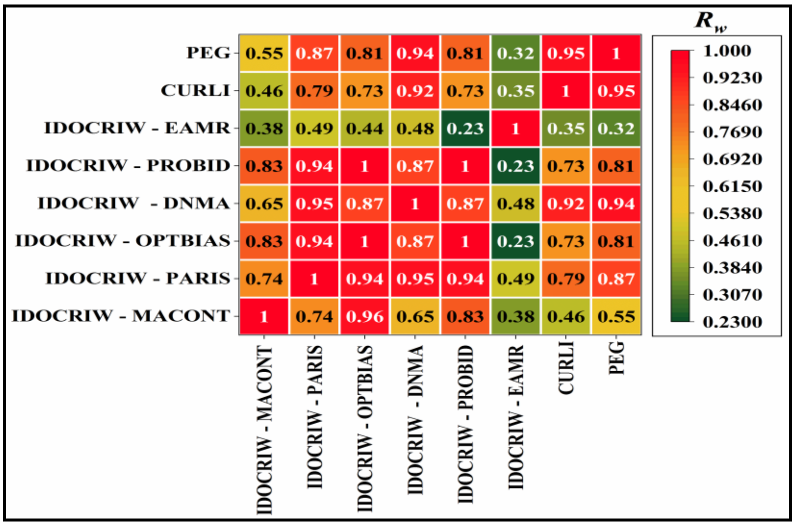
	LOPCOW - MACONT	LOPCOW - PARIS	LOPCOW - OPTBIAS	LOPCOW - DNMA	LOPCOW - PROBID	LOPCOW - EAMR	CURLI	PEG
PEG	0.6	0.54	0.66	0.47	0.36	0.32	0.95	1
CURLI	0.57	0.48	0.58	0.56	0.29	0.41	1	0.95
LOPCOW - EAMR	0.61	0.54	0.51	0.67	0.5	1	0.41	0.32
LOPCOW - PROBID	0.15	0.95	1	-0.03	1	0.5	0.29	0.36
LOPCOW - DNMA	0.88	0.02	0	1	-0.03	0.67	0.56	0.47
LOPCOW - OPTBIAS	0.15	0.95	1	-0.03	1	0.5	0.29	0.36
LOPCOW - PARIS	0.15	1	0.98	0.02	0.95	0.54	0.48	0.54
LOPCOW - MACONT	1	0.15	0.18	0.88	0.15	0.61	0.57	0.6

(f)



	CILOS - MACONT	CILOS - PARIS	CILOS - OPTBIAS	CILOS - DNMA	CILOS - PROBID	CILOS - EAMR	CURLI	PEG
PEG	0.45	0.51	0.85	0.4	0.83	0.54	0.95	1
CURLI	0.4	0.4	0.71	0.4	0.75	0.52	1	0.95
CILOS - EAMR	0.89	0.84	0.67	0.93	0.56	1	0.52	0.54
CILOS - PROBID	0.53	0.34	0.94	0.34	1	0.56	0.75	0.83
CILOS - DNMA	0.92	0.9	0.7	1	0.34	0.93	0.4	0.4
CILOS - OPTBIAS	0.4	0.36	1	0.22	0.94	0.42	0.69	0.83
CILOS - PARIS	0.83	1	0.83	0.9	0.34	0.84	0.4	0.51
CILOS - MACONT	1	0.83	0.77	0.92	0.53	0.89	0.4	0.45

(g)



	IDOCRIW - MACONT	IDOCRIW - PARIS	IDOCRIW - OPTBIAS	IDOCRIW - DNMA	IDOCRIW - PROBID	IDOCRIW - EAMR	CURLI	PEG
PEG	0.55	0.87	0.81	0.94	0.81	0.32	0.95	1
CURLI	0.46	0.79	0.73	0.92	0.73	0.35	1	0.95
IDOCRIW - EAMR	0.38	0.49	0.44	0.48	0.23	1	0.35	0.32
IDOCRIW - PROBID	0.83	0.94	1	0.87	1	0.23	0.73	0.81
IDOCRIW - DNMA	0.65	0.95	0.87	1	0.87	0.48	0.92	0.94
IDOCRIW - OPTBIAS	0.83	0.94	1	0.87	1	0.23	0.73	0.81
IDOCRIW - PARIS	0.74	1	0.94	0.95	0.94	0.49	0.79	0.87
IDOCRIW - MACONT	1	0.74	0.96	0.65	0.83	0.38	0.46	0.55

(h)

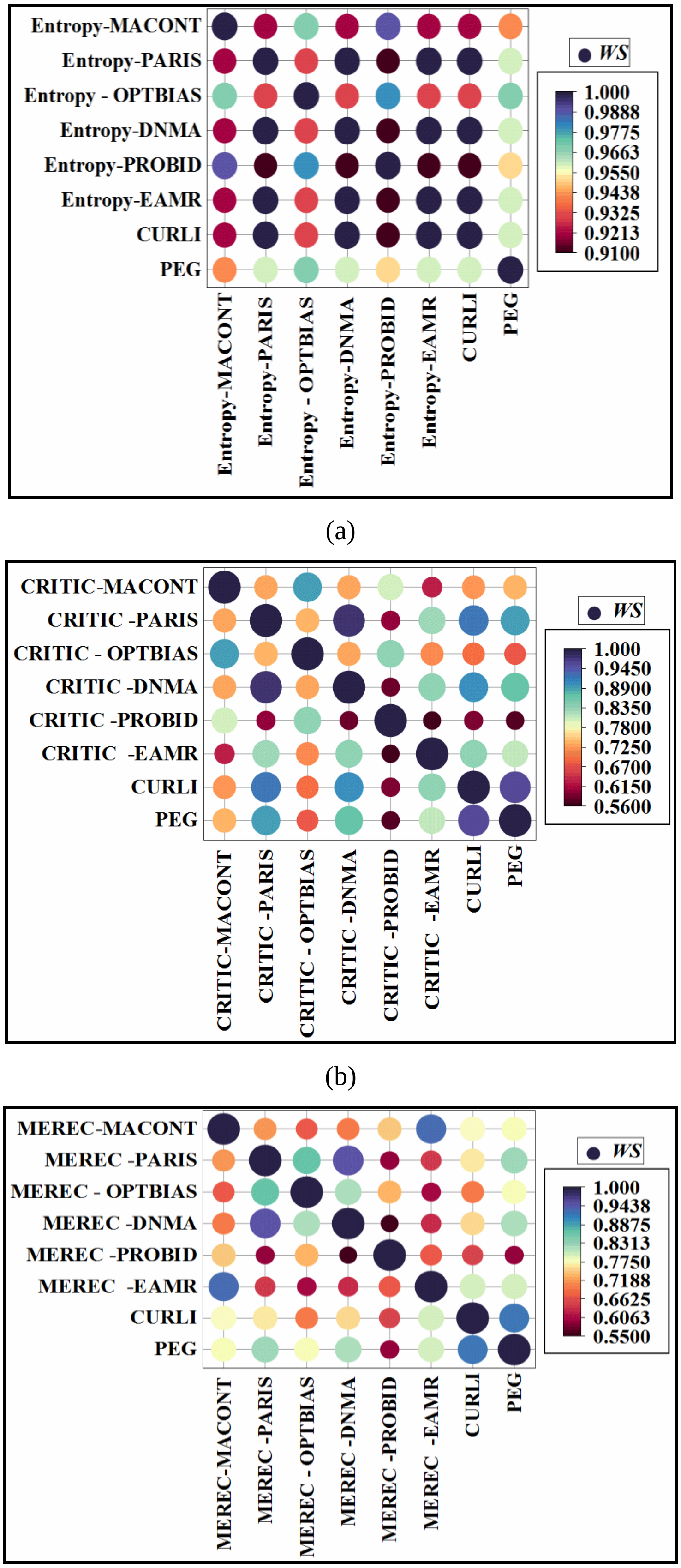
Figure 4.5 Continued

d) Based on coefficient of ranking similarity

To further analyse the ranking results, the WS values are computed using Eq. (4.3).

$$WS = 1 - \sum_{i=1}^{m} 2^{-x_i} \frac{|x_i - y_i|}{max(|x_i - 1|, |x_i - m|)} \tag{4.3}$$

WS values prioritize the positions in the rankings, giving more importance to higher-ranked alternatives than lower ones. They depend on the differences in rankings for each position, making them very sensitive to changes in ranks. Unlike Spearman and weighted Spearman correlations, which can be negative, WS values are always positive. The WS coefficient measures how similar two rankings are from best to worst, focusing more on differences at the top of the list than at the bottom. For example, if the top-ranked alternatives in two lists are swapped, the score reflects that more strongly than if the swap happens with lower-ranked items. The WS measure considers the position of each item and their distances in the rankings, with results falling within a specific range for easy understanding. A higher WS score means the rankings are very similar, while a lower score indicates significant differences. Figure 4.6 shows the result of WS values of all the rankings obtained using Eq. (4.3). Values above 0.95 are significantly high and indicate higher degree of similarity among top ranked alternatives. Under entropy-based conditions, the WS values consistently exceed 0.91 across all cases, indicating a strong ranking similarity among the top-ranked alternatives. The CRITIC weighting method highlights PARIS-DNMA, PEG-CURLI and OPTBIAS-MACONT with values exceeding 0.9, further emphasizing their high similarity in rankings. Similarly, under the MEREC, PCA and SPC weighting methods, the ranking similarity values surpass 0.85, reflecting a notable agreement between these methods. The LOPCOW weighting method shows exceptionally high similarity, with PARIS-OPTBIAS and OPTBIAS-PROBID both achieving values above 0.95. In the case of CILOS weighting, there is significant similarity among the top-ranked alternatives, with DNMA-MACONT and DNMA-EAMR reaching values above 0.95. Finally, the IDOCRIW weighting method demonstrates very high-ranking similarity across most MCDM methods, with the exception of EAMR, which stands out as an outlier. The WS analysis clearly shows that DNMA delivers highly consistent and similar rankings compared to other top-performing methods across various weighting techniques. Under entropy, MEREC, PCA and SPC, DNMA maintains WS values well above 0.85, reflecting strong agreement in its top-ranked alternatives. Notably, under CILOS weighting, DNMA shows very high similarity with methods such as MACONT and EAMR, both exceeding 0.95, which indicates a strong alignment in their ranking structures. Even under the rigorous IDOCRIW weighting, DNMA continues to perform exceptionally well, showing high similarity with most other methods. This consistent performance across diverse weighting techniques reinforces stability and adaptability of DNMA in different decision making environments. It emerges as a robust method that maintains its ranking integrity even under changing criteria weights. The strong WS alignment with multiple methods confirms reliability in preserving top ranked alternatives. As a result, DNMA proves to be not only mathematically sound but also practically dependable for complex problems.

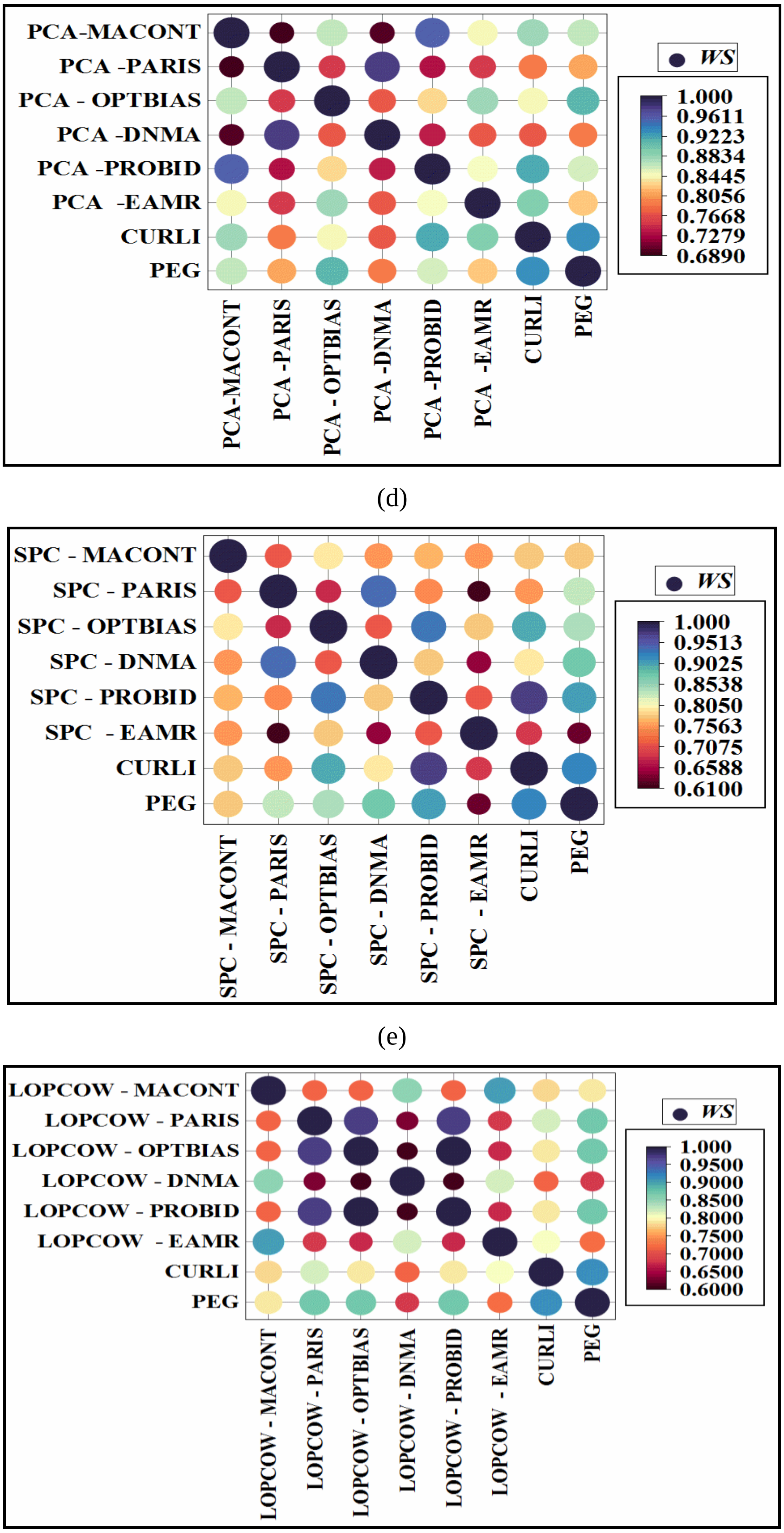


(a)

(b)

(c)

Figure 4.6 Coefficient of rank similarity (*WS*) results



(d)

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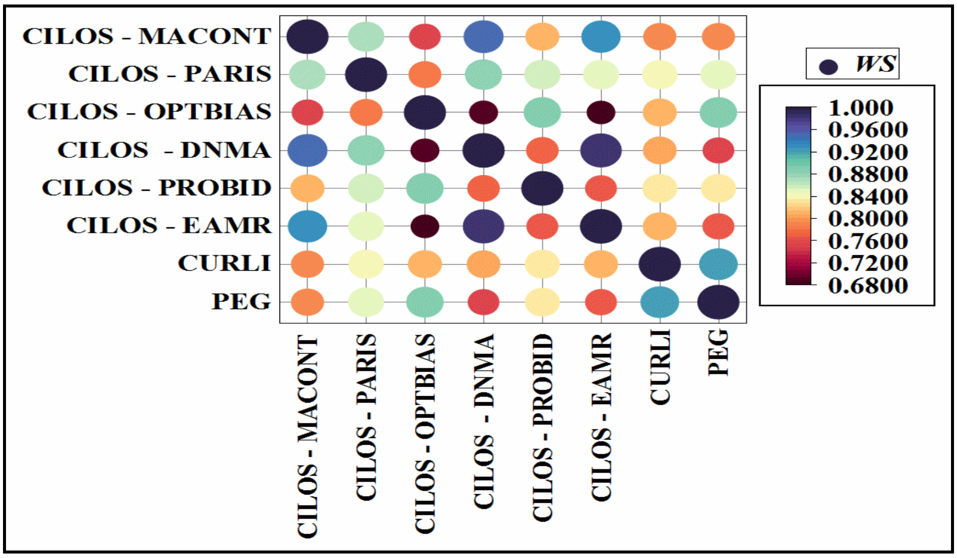
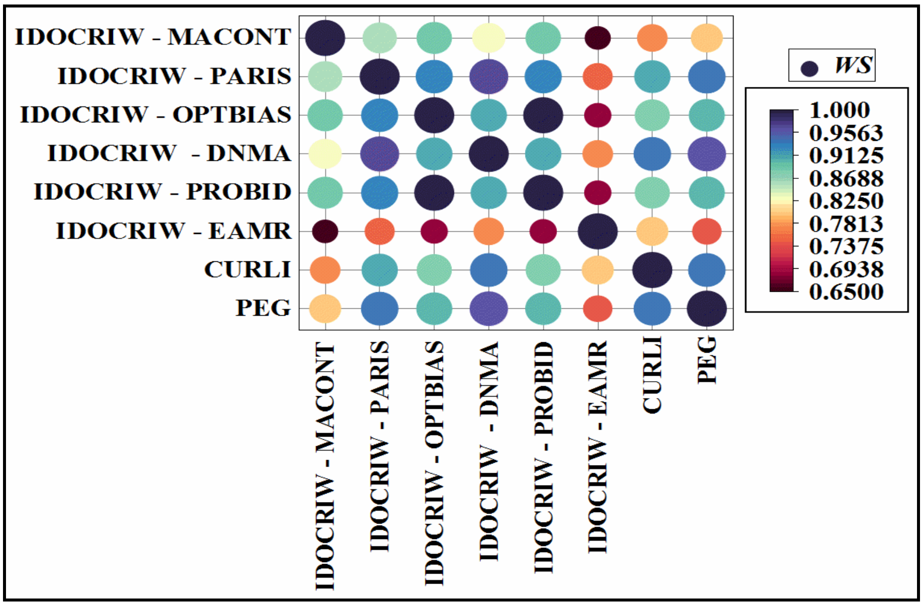
Figure 4.6 Continued



(g)



(h)

Figure 4.6 Continued

e) Based on number of operations

In order to assess the complexity of various MCDM methods, the number of mathematical operations implicated in their computations are identified, which can be compared to measuring time complexity based on the number of calculations performed [75]. Given that there are *P* alternatives for each decision making problems and *C* criteria for evaluation, the Tables 4.21 and 4.22 present in detail the number of operations required by each method. Figure 4.7 show a comparative analysis between the considered MCDM methods with reference to the total number of mathematical operations required. Figure unveils that to solve this decision making problem, EAMR requires 184 operations, followed by OPTBIAS with 288 and on the other hand DNMA with 401, MACONT with 409 and CURLI, which needs 704 operations to get the rankings.

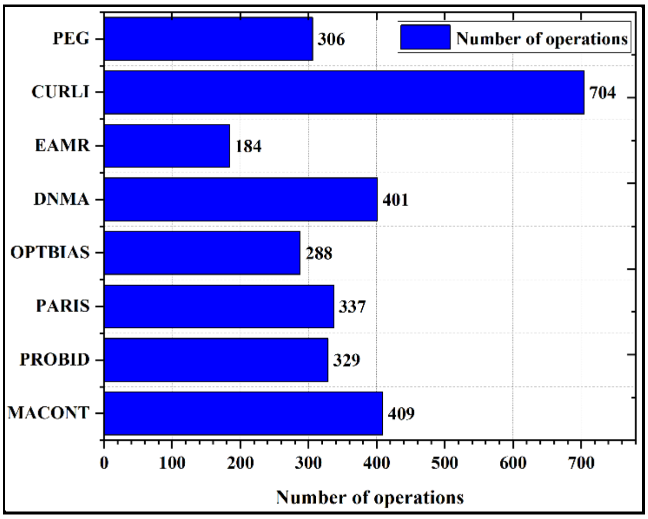


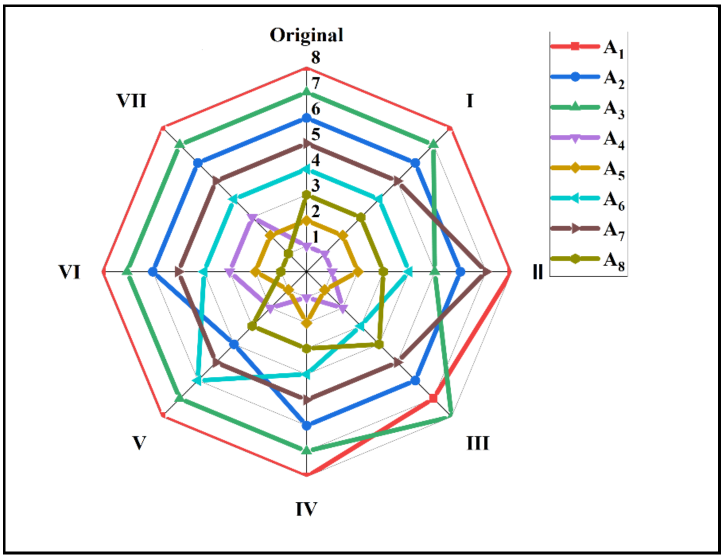
Figure 4.7 Number of operations

Sensitivity analyses

Sensitivity analysis studies are conducted in this section to evaluate the reliability and stability of rankings generated by the eight MCDM methods. The analysis examines the effects of varying criterion weights, including cases where weights are gradually removed based on least weighted criterion, cases where all criteria have equal weights and cases where predefined weights from different weighting methods are applied. Each MCDM method is tested under these different weighting conditions.

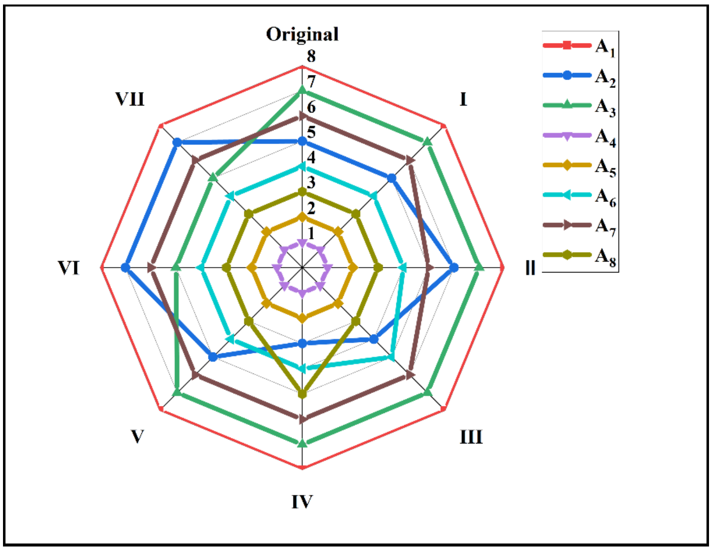
Sensitivity analysis based on gradual removal of criteria

Figure 4.8 presents the sensitivity analysis results for all alternatives, illustrating how rankings change under different weighting scenarios. The analysis begins with the original entropy weights, followed by the gradual removal of the least significant criterion weights, represented by condition I, II, III, IV, V, VI and VII. At each condition, a new set of weights is generated for the remaining criteria. This process continues until only the last two criterion weights remain, which is represented by condition VII. Based on each set of entropy weights, the performance of different MCDM methods is computed and plotted in Figure 4.8. The MACONT method demonstrates moderate ranking stability, with A_4 maintaining the top position in most cases but occasionally dropping to rank 2 or 3 under conditions IV, VI and VII. A_5 and A_8 show rank shifts, with A_8 improving to rank 1 under VI and VII, while A_3 fluctuates in Scenario II. In the PROBID method, ranking stability is high, with A_4 consistently at rank 1 except in VI and VII, where it drops to rank 3. A_1 remains at rank 8 and A_6 shows improvements under VI and VII, reflecting some sensitivity to weight changes. The DNMA method exhibits the highest stability, with A_4 consistently ranked first across all scenarios, A_5 maintaining rank 2 and A_1 staying at rank 8, indicating minimal ranking fluctuations. The OPTBIAS method displays moderate sensitivity, with A_4 holding rank 1 in most cases but dropping to rank 3 in II and rank 2 in IV and VII. A_5 and A_8 shift rankings, particularly in Scenario II, where A_8 moves to rank 1. A_2 and A_3 show rank reversals and A_1 remains stable at rank 8. The PARIS method demonstrates a mix of stability and sensitivity, with A_4 staying at rank 1 in all cases, but A_2 fluctuating significantly from rank 3 to 7 and A_3 shifting between rank 5 and 7, indicating responsiveness to weight variations. EAMR exhibits moderate stability, with A_4 holding rank 1 except in IV and VI, where it drops to rank 2. A_5 and A_8 frequently swap positions and A_1 remains at rank 8, showing stability at the bottom, while A_3 and A_2 undergo minor ranking changes. Overall, DNMA emerges as the most stable method, maintaining ranking consistency across all weighting conditions, while OPTBIAS and MACONT exhibit more sensitivity to weight changes, particularly for mid-ranked alternatives. A_4 consistently ranks as the top alternative across all methods, confirming its robustness. If ranking stability is the priority, DNMA is the most reliable method.



MACONT

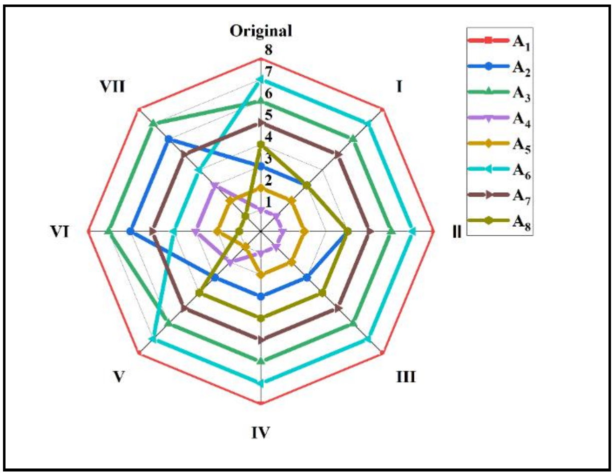
(a)



PARIS

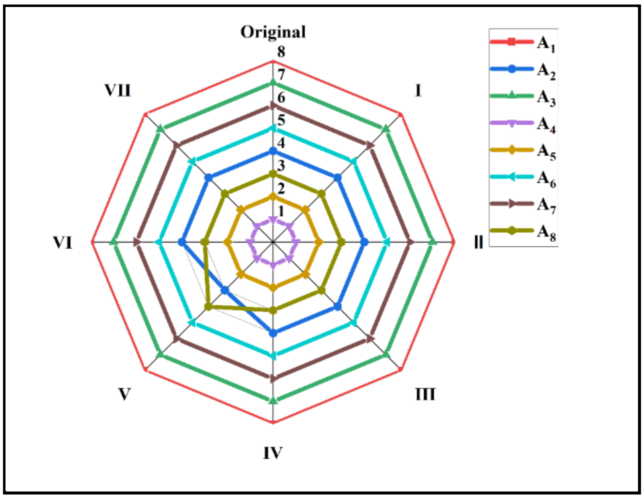
(b)

Figure 4.8 Sensitivity analyses results by gradual removal of criterion weight



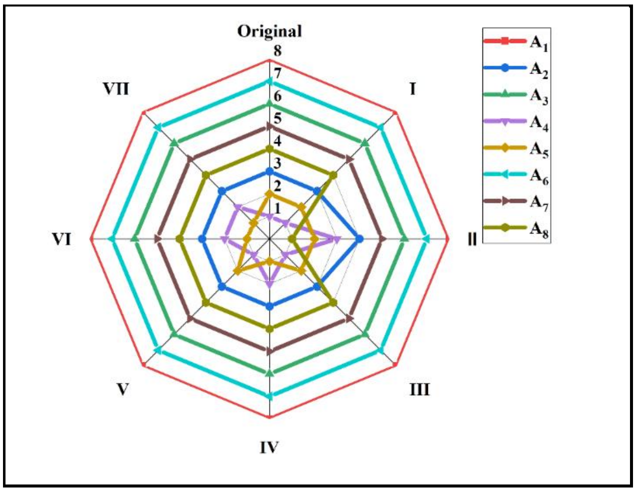
PROBID

(c)



DNMA

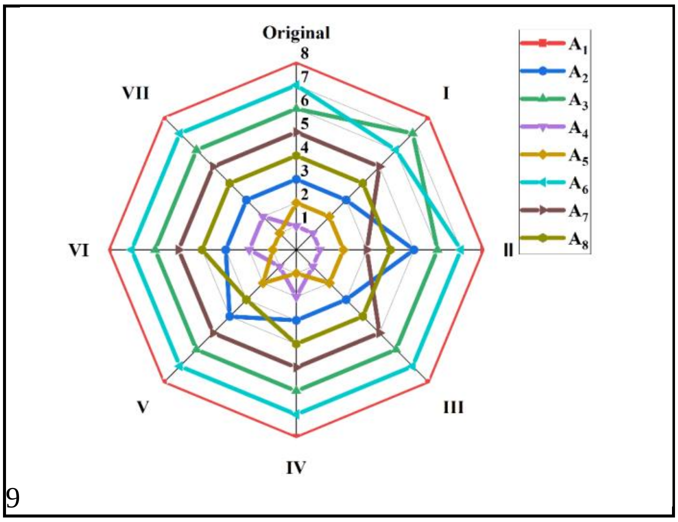
(d)



OPTBIAS

(e)

Figure 4.8 Continued



EAMR

(f)

Figure 4.8 Continued

Sensitivity analysis based on equal weighting conditions

This sensitivity analysis evaluates the performance of different MCDM methods specifically under equal weighting conditions. This study also includes CURLI and PEG methods. The uniqueness of this study is to provide fair chance to analyze the CURLI and PEG method along with other MCDM methods. To nullify the effect of weight and analyze the sensitivity performance of all these methods, this study is performed. Figure 4.9 indicates that A_4 is the most stable and consistently ranked first across all methods, confirming its robustness as the best alternative. A_1 remains consistently ranked last (eighth place) in all scenarios, highlighting its poor performance regardless of weight variations. A_5 and A_6 exhibit high sensitivity, with A_5 fluctuating between rank one in PARIS and rank six in OPTBIAS, while A_6 ranges from rank one in MACONT to rank eight in EAMR, making them unreliable choices due to their dependence on weight variations. A_2 and A_3 show moderate sensitivity, shifting rankings between two and seven depending on the method. A_8 remains relatively stable, ranking between four and seven, except for a slight improvement in PEG with rank three, indicating moderate resistance to weight changes. PEG and CURLI, which do not rely on predefined weights, produce ranking results that align closely with weighted MCDM methods, reinforcing their effectiveness in decision making without weight dependency. The analysis confirms that if ranking stability is a priority, A_4 remains the best alternative across all methods, while PEG and CURLI offer reliable results independent of weighting conditions.

Sensitivity analysis based on all weighting conditions

Figure 4.10 shows the results under all weighting conditions, including equal weight conditions. The MACONT method demonstrates strong and consistent performance, with A_4 frequently ranking first or near the top across multiple weighting schemes, such as entropy, CRITIC, SPC and CILOS. A_4 maintains a solid middle-tier performance under equal weight, ranking third. This method performance remains quite stable under most weighting conditions, particularly in complex methods such as CRITIC and SPC, which consistently place A_4 in top spots. While there is some variability in its ranking under different schemes, A_4 generally performs well, highlighting the robustness of the MACONT method. The PROBID method shows stable yet slightly fluctuating results across different weighting conditions. A_4 performs consistently well, particularly under equal weight and entropy, where it ranks first. CRITIC and MEREC show a slight drop to second, indicating that PROBID may be sensitive to some weighting schemes. Nevertheless, the performance of A_4 remains strong, ranking first or second in most other conditions, such as PCA, SPC, LOPCOW, CILOS and IDOCRIW. For the PARIS method, A_4 generally ranks in the top 2 across all weighting conditions. It holds first place in several methods such as entropy, CRITIC, MEREC, PCA and LOPCOW, while slightly dropping to second in SPC. This indicates that PARIS is a stable method, with A_4 being consistently high-performing, especially under equal weight, entropy and CRITIC. The OPTBIAS method exhibits strong consistency, with A_4 frequently securing the top rank, particularly in equal weight, entropy, CRITIC, PCA and CILOS. Minor fluctuations in methods such as MEREC and LOPCOW do not significantly affect its overall strong performance. OPTBIAS proves to be a reliable method with A_4 consistently being one of the highest performers. DNMA shows excellent stability with A_4 ranking first across most weighting schemes, including equal weight, entropy, CRITIC and PCA. While there is a small drop in SPC, A_4 rebounds to first place in methods such as LOPCOW, CILOS and IDOCRIW, reinforcing the reliability of DNMA. The EAMR method displays variability, with A_4 ranking well in equal weight, CRITIC and entropy but showing some volatility in methods such as SPC and LOPCOW, where A_4 drops to lower ranks. Overall, the performance of A_4 across these methods shows a general trend of consistency with minor fluctuations in certain methods. Methods such as MACONT, PROBID, PARIS, OPTBIAS, DNMA and EAMR demonstrate strong, stable results, with A_4 frequently ranking first or near the top in most conditions. However, methods such as EAMR show more volatility, particularly in complex weight schemes. Despite these fluctuations, A_4 generally performs as a high-ranking alternative across all MCDM methods, making it a reliable and robust alternative in decision making processes.

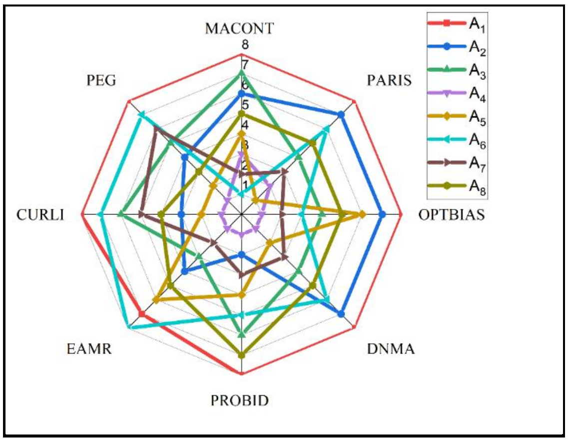
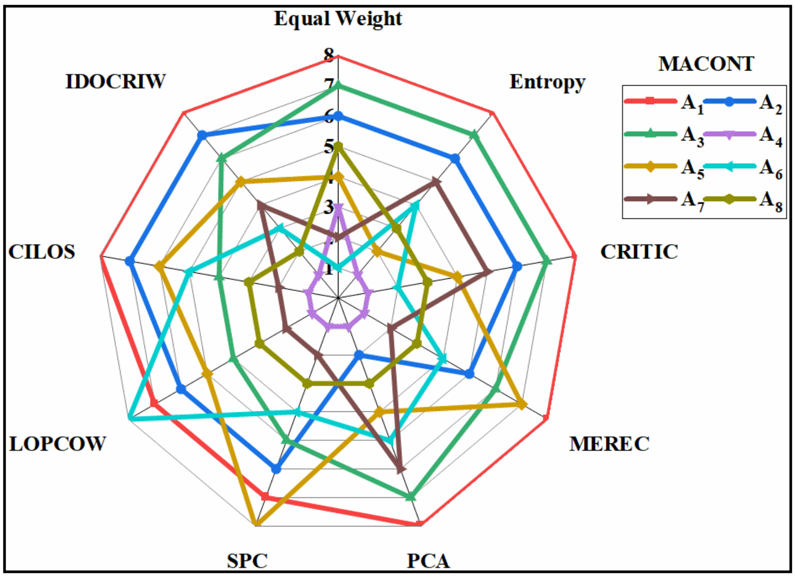
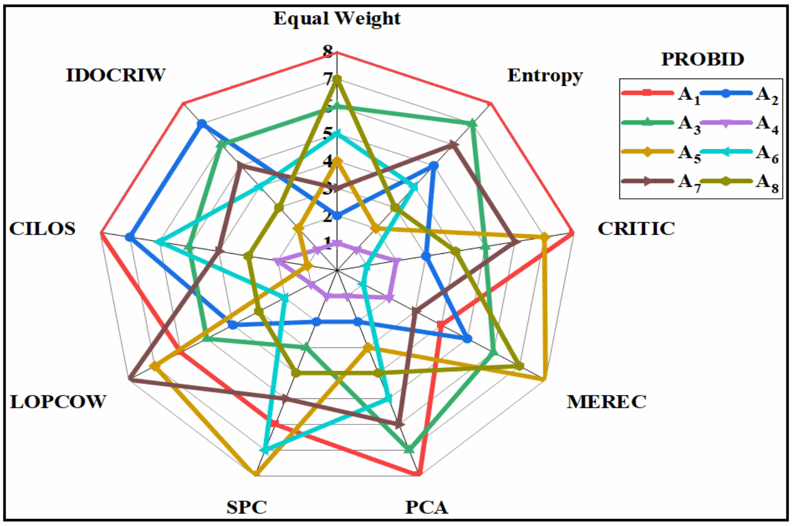


Figure 4.9 Sensitivity analyses results under equal weight condition



(a)



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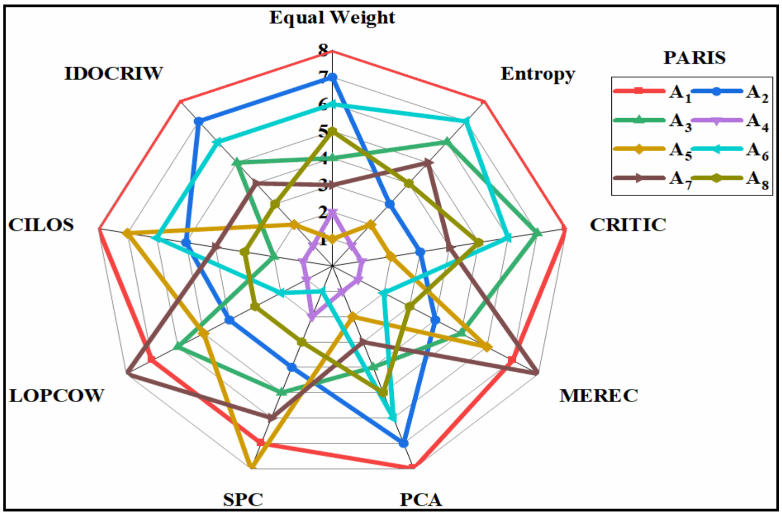
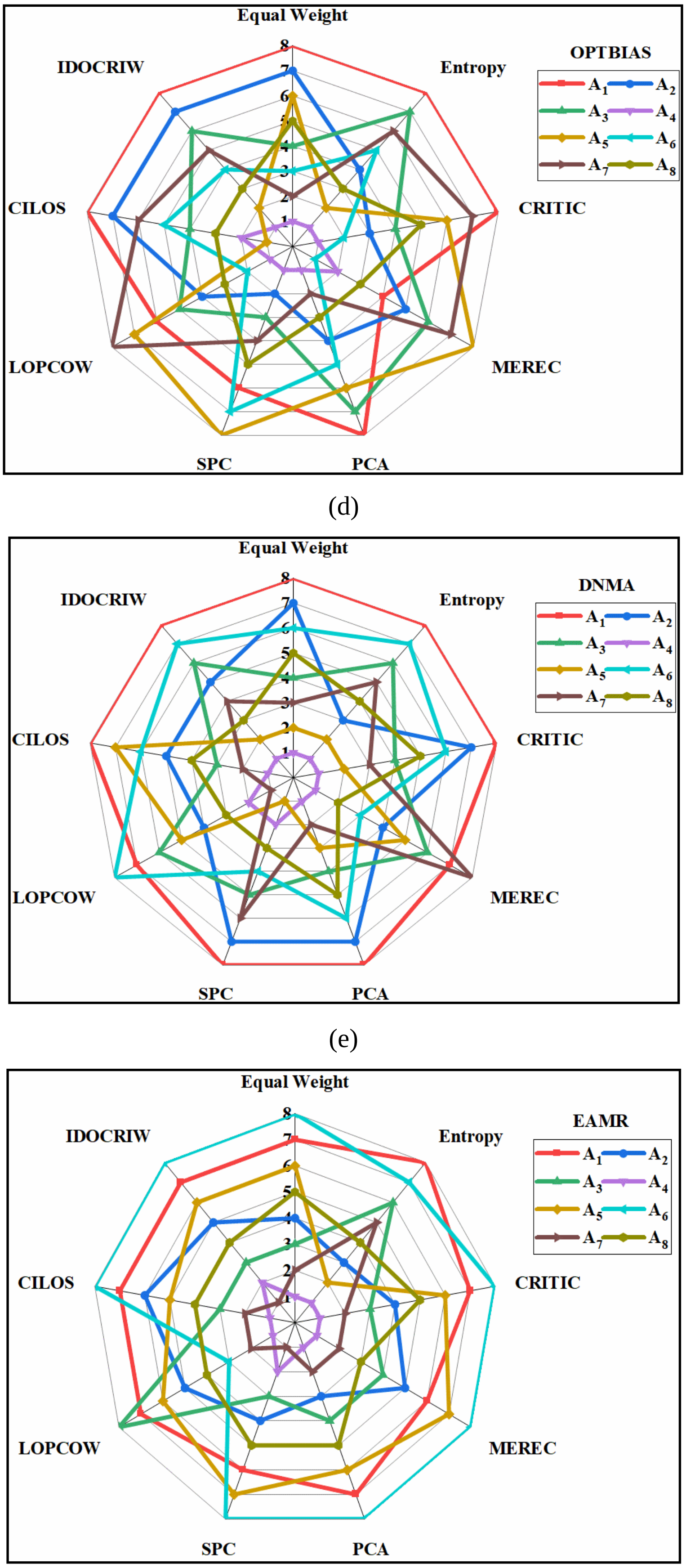


(c)

Figure 4.10 Sensitivity analyses results considering the criteria weight



(d)

(e)

(f)

Figure 4.10 Continued

Table 4.21 Number of computation steps for MACONT, PROBID, PARIS and OPTBIAS

MACONT		PROBID		PARIS		OPTBIAS	
Step	Computation	Step	Computation	Step	Computation	Step	Computation
Apply three normalization techniques	3× (P × C)	Normalize the decision matrix	P × C	Apply three normalization techniques	3× (P × C)	Normalize the decision matrix	P × C
Integrate values using λ and μ	P × C	Compute weighted normalized decision matrix	P × C	Calculate weighted matrix and sum, π_I^w	(P × C) + P	Compute weighted normalized matrix	P × C
Compute average and distance from reference	C + (P × C)	Identify positive ideal solutions	P × C	Determine reference ideal solution	C	Arranging ideal solutions	P × C
Calculate of ρi , Qi , S_1, S_2	4P	Compute average values	C	Compute distance from reference ideal solution, π_I^*	P	Compute Bi positive, Bi negative and average solution	2P+2P+P
Compute comprehensive score	P	Calculate Euclidean distances	P × P	Compute R_i and related distances, such as, (π_I^w- $\pi_I^{w,max}$), (π_I^*- $\pi_I^{*,min}$), R_i	3P	Compute Euclidean distances, ratio, performance score and positive and negative ideal solutions	4P
No further steps required		Compute average solution	P	No further steps required		No further steps required	

Table 4.21 Continued

Step	Computation	Step	Computation	Step	Computation	Step	Computation
-		Calculate positive and negative ideal, S_i, positive and negative ideal ratio (R_i) and performance score P_i	4P	-		-	
Total computations required	5× (P × C) + 5P +C	No further steps required	3× (P × C) + P^2 + 5P + C	-	4× (P × C) + 5P+ C	-	3× (P × C) + 9P

Table 4.22 Number of computation steps for DNMA, EAMR, CURLI and PEG

DNMA		EAMR		CURLI		PEG	
Step	Computation	Step	Computation	Step	Computation	Step	Computation
Normalize the decision matrix using two normalization technique	2× (P × C)	Normalize the decision matrix	P × C	Construct square matrix for each criterion	C (P × P)	Determination of criteria vectors	P × C
Adjustment of the weight values of criteria	C	Weighted normalized decision matrix	P × C	Compute scoring matrix	P × P	Arrangement of criteria vectors	P × C
To compute CCM	(P × C) + P	To compute normalized points for benefit and non-benefit criteria	2P	Restructuring the scoring matrix	P × P	Determination of aggregate vectors	P × C
To compute UCM	(P × C) + P	Rank of value	2P	No further steps required		Arrangement of aggregate vectors and Calculation of shifted vectors	P × C + 1
To compute ICM	(P × C) + P	Calculation of evaluation score	P	-		Calculation of PEG functions	C
To compute comprehensive utility value	P	No further steps required		-		Calculation of mean square error	P
Total computations required	5× (P × C) + 4P + C	-	2× (P × C) + 5 P	-	2× (P × P) + C (P × P)	No further steps required	4 × (P × C) + P+ C+ 1

5. PISTON MATERIAL SELECTION

A piston is an essential reciprocating component of engines, pumps and cylinders. Its sole purpose is to transmit force from fluid inside the cylinder to the crankshaft via connecting rod, while in case of a pump, its role is just reversed. In few cases, piston also acts as a valve inside the cylinder. The piston is the mobile end and cylinder head is the stationary end inside a combustion chamber. Inside the chamber, due to the forces of the expanding combustion gases, the piston reciprocates and transmits the forces to the crankshaft via connecting rod [82]. Thus, the piston head is subjected to thermal stresses, mechanical load and pressure fluctuations during normal working of the engine. Ability to operate in different working conditions, safety against piston seizure, effortless running, less weight, higher strength, less oil consumption and minimum pollutant emission are the major requirements which largely affect the piston material selection process. Moreover, the material that seems to be good in any particular instance may not be suitable in another case. From the past experience, aluminium silicon alloys are found to be the most preferred piston material under the operational requirements of various internal combustion engine designs. Steel pistons are also used in few cases with the provision of appropriate cooling measures. The piston skirt is used to guide the piston inside the cylinder. The mass of piston, piston rings, wristpin and circlips together forms the reciprocating mass, which compels to achieve its lowest possible value by choosing a suitable piston material. Another influencing factor for reliable and safe working of the piston and cylinder is the operational temperature due to hot combustion gases. Acute thermal stresses severely affect the durability of the piston material. Moreover, the piston temperature significantly affects the engine speed, mean pressure, ignition angle and volume injected.

Many new developments on design of pistons have been observed over the years, e.g. pistons made of composites with local reinforcing elements being used for low profile applications. Lightweight piston designs with symmetrical or asymmetrical oval shapes are preferred for gasoline engines. These newer designs based on weight and flexibility criteria reveal that the regulating piston design is becoming an important issue. Extreme operating conditions, such as pistons for racing cars always post a challenge to the designers. Low compression height, optimized weight and fast cooling are the decisive cri teria where high engine power and speed are the common requirements. Piston in two cycle engine is exposed to severe thermal stresses and mechanical loadings due to ignition in every rotation of the crankshaft and it has also to act as a valve inside the cylinder during its upward and downward strokes. Typically, gravity die-casting, centrifugal casting, continuous casting, machining, and forging are used in the production of pistons. Because there are several tangible options available and contradictory criteria are involved, it has become more difficult for the designers to identify the most suited piston material.

5.1 Review of MCDM in material selection for mechanical components

Purohit and Ramachandran [83] applied fuzzy TOPSIS in engine flywheels material selection and identified maragiring 350 steel as the optimal choice. Anojkumar et al. [84] integrated fuzzy AHP with TOPSIS and VIKOR methods for singling out the best material for pipes to reduce corrosive wear in sugar industries. Liao [85] presented two new material selection techniques based on fuzzy sets and validated their performance. Kumar and Singal [59] presented the applications of AHP, TOPSIS and modified TOPSIS methods to assess the optimal material for penstock. It was concluded that mild steel would be the best material for penstock. Kumar and Ray [86] adopted MOOSRA technique for material selection of a mechanical component and observed that PROMETHEE II and OCRA method also performed satisfactorily while solving the same problem. Maity and Chakraborty [69] employed PROMETHEE II method for solving a tool steel material selection problem. Oqla et al. [71] applied AHP method to evaluate composites for interior parts in an automobile while simultaneously considering several evaluation criteria. Khandekar and Chakraborty [72] presented axiomatic design principles in problems having both the qualitative and quantitative material properties. Bhattacharyya and Chakraborty [73] explored the feasibility and applicability of Q-analysis technique as an MCDM tool in solving material selection problems. Xue et al. [74] proposed fuzzy-MABAC method for solving material selection problems with incomplete weight information. Das et al. [87] applied Suh's design axioms, multi-attribute utility theory and AHP technique for a spur gear material selection problem while simultaneously considering several geometric variables in Hazelrigg's decision based design framework. Yazdani et al. [88] utilized grey-COPRAS method to two material selection problems and studied the effect of normalization procedures on the ranking results. Hafezalkotob and Hafezalkotob [89] developed a risk-based FAD approach for selection of industrial gas turbine blade material using the principles of Suh and Shannon entropies supported by information theory. Patel and Prajapati [90] adopted MOORA method to select the apposite blanking die material for an engineering application. Zindani et al. [76] applied TODIM method to identify the best suited materials for engine flywheel and metallic gear. Moradian et al. [91] applied MOORA, TOPSIS and VIKOR to select material for a brake booster valve body. Hybridizing TOPSIS with PSI methods, Yadav et al. [77] proposed their applications in marine field. Dev et al. [64] employed VIKOR to rank the considered alternative materials to be used in manufacturing of automotive piston components.

From the above literature survey, it can be observed that applications of various MCDM techniques, such as AHP, TOPSIS, VIKOR, MOORA, PROMETHEE, COPRAS etc. have dominated the past researches in the domain of material selection for different mechanical components. Very limited effort has been put forward for selection of appropriate piston material. In this direction, some research works, such as design of motor engine components, specifically piston, rings and cylinder liner for enhancing fuel efficiency and emission reduction [92]; design guidelines related to main frictional pairs in a water hydraulic piston pump and its material selection [93]; development of a software prototype for manufacturing of a piston [94]; investigation of thermal analyses on uncoated and coated diesel engine pistons using ANSYS [95] etc. have been carried out.

5.2 Case study

The selection of the best piston material for an internal combustion engine is the subject of this case study. The operating performance of a piston greatly depends on its constituent material along with its physical properties. Hence, to have enhanced operating performance of a piston, it is always crucial to select the most appropriate material which would provide high strength to resist gas pressure, less weight, minimum noise, less wear, ability to dispense heat and excellent resistance to distortion under heavy loading and high temperature. In spite of the availability of numerous MCDM techniques, some new methods are explored to deal with different types of criteria. Therefore, the associated decision matrix, which consists of eight assessment criteria and eight candidate alternatives, is established in Table 5.1 in order to solve the accompanying piston material selection problem and demonstrate the applicability of these approaches in the new domain of material selection. Figure 5.1 depicts the critical criteria based on which alternatives are screened. In this table, values of different physical properties of the considered piston material alternatives are accumulated from the Matweb website [81]. Table 5.2 provides the criteria weights, which were calculated using the CILOS approach. With the exception of machinability, every criterion value is stated in absolute units. A 9-point scale is included for machinability.

Density is the degree of compactness of a particular material. Piston, piston rings, wristpin and circlips together form the reciprocating mass inside the cylinder. One of the most important design criteria should be to decrease the piston material mass in order to reduce fuel consumption. Moreover, reduced mass would minimize the inertia forces associated with it, thus arising the need to have the lowest possible reciprocating mass while finding out a suitable piston material. Hardness measures the ability of a material to resist wear and tear. Hard materials do not get scratched easily, are easy to polish, able to resist distortion and more durable. It is an important evaluation criterion as the piston has a relative motion inside the cylinder. The yield strength of a piston material is the stress at which it starts to deform plastically. This property can fractionally change the dimension of the piston inside the cylinder, directly affecting the engine performance. It is thus desirable to have a piston material with high yield strength. Modulus of elasticity for a piston material is the measure of stiffness or resistance to deform elastically. Specific heat capacity is the amount of heat energy required to raise the temperature of a piston material per unit of mass. It is a physical extensive property which depends on mass. Stability of a piston inside the cylinder increases with increase in heat capacity. Machinability is the ease with which a piston material can be machined as compared to 160 Brinell B1112 steel. Materials with machinability ratings less than 100% are difficult to machine, while those having more than 100% rating are easier to machine. Machinability rating can be evaluated while weighing and combining various factors, such as normal cutting speed, surface finish, type of the cutting tool material etc. Fatigue strength of a piston material can be defined as the maximum stress that it can withstand for a given number of cycles without breakage or failure. Thermal fatigue and mechanical fatigue play predominant roles leading to fatigue failure of the piston material. While selecting a piston material for a given application, its cost is also considered as one of the most important criteria. Except density and material cost, all others are beneficial.

Softness and susceptibility to wear restrain the applicability of pure aluminium in pistons. Thus, the need of aluminium alloys arises where different elements are combined together at definite proportions to inherit the required properties of low weight, low wear, high heat strength and high thermal conductivity. Aluminum 2618-T61 (Al 93.7%, Cu 2.30%, Mg 1.6%, Fe 1.2%, Ni 1%) is an age-hardenable alloy containing magnesium and copper and is mainly used for manufacturing of aircraft engines. The composition of this alloy also contains a notable amount of iron and nickel. Iron is added to improve yield strength at high temperature without much impact on the electrical properties. Nickel is used to increase mechanical strength at elevated temperatures and reduce thermal expansion. This alloy has an excellent machinability rating as compared to other candidate piston materials. Aluminum 4032-T6 (Al 87.2%, Si 13.5%, Cu 1.5%, Mg 1.5%, Ni 1.5%) contains silicon as the main constituent. To achieve standard mechanical properties and tempered form according to the end requirements, it is solution-heat treated and artificially aged. It is lighter and possesses good specific heat capacity, thus making it one of the widely preferred materials in manufacturing of pistons. Aluminum A360.0-F die casting alloy (Al 90.6%, Si 9%, Fe 1.3%, Cu 0.6%) offers high corrosion resistance, superior yield strength at elevated temperatures and good ductility, but it is difficult to cast. It has low density and excellent specific heat capacity. Aluminum 6061-T6 (Al 98.6%, Mg 1.2%, Si 0.8%) exhibits an exceptional joining characteristic, showing relatively high yield strength, excellent machinability and high resistance to corrosion. It has wide applications in aircraft fittings, marine fittings and hardware, electrical fittings, couplings, connectors, brake pistons and hydraulic pistons. Grey cast iron has satisfactory hardness and modulus of elasticity and it finds wide applications in casting of diesel engines, liners, engine cylinders and pistons. AISI 8660 steel (Fe 97.6%, Mg 1%, C 0.65%, Cr 0.60%) has high yield strength and its higher modulus of elasticity makes it a suitable candidate for piston material. AISI 4140 steel (Fe 97.7%, Cr 1.1%, Mg 1%) is a medium carbon steel material with good fatigue and impact resistance properties. High hardness, good modulus of elasticity and low cost make it a good choice as the piston material. Ductile iron grade 65-45-12 (Fe 94.17%, C 3.8%, Si 2.8%) has several favourable properties as compared to other candidate materials. It finds applications in manufacturing of components subjected to shock and fatigue loads.

Now, to determine the best possible alternative, the various newly developed MCDM methods are applied to this piston selection problem. CILOS weight is used to evaluate the rankings. EAMR, CURLI and PEG method calculations are presented in detail. Remaining MCDM method results are provided subsequently.

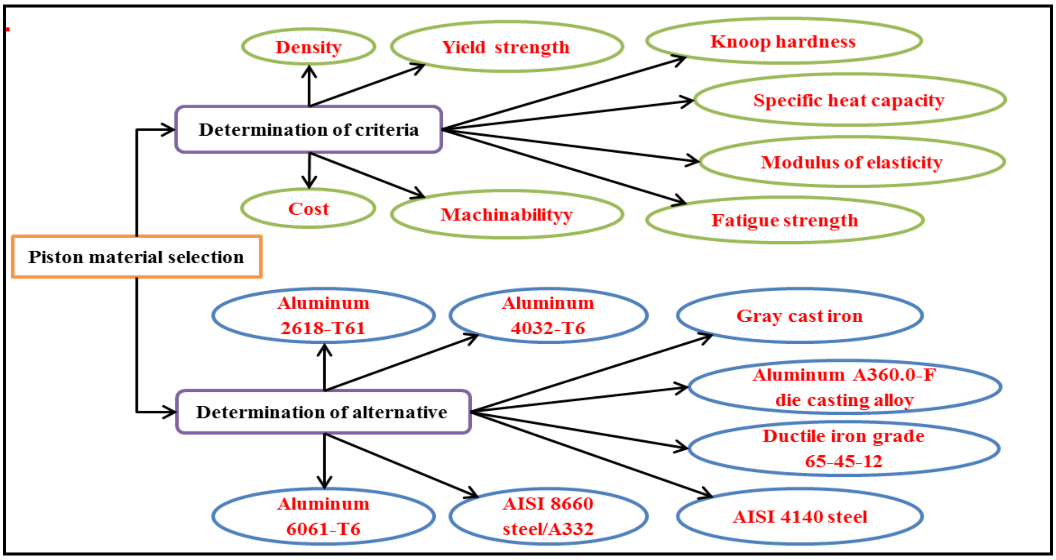


Figure 5.1 Piston material selection problem

Table 5.1 Decision matrix

Alternative	Criteria							
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	2.76	144	372	74.5	0.875	2.072	9	90
A_2	2.68	150	317	78.6	0.85	2.128	7	110
A_3	2.68	97	165	71	0.963	1.064	5	150
A_4	2.7	120	276	68.9	0.896	1.904	9	95
A_5	7.15	271	310	200	0.49	1.428	3	119
A_6	7.85	220	1551	205	0.475	0.854	5	335
A_7	7.85	369	1050	205	0.561	0.532	5	590
A_8	7.15	195	310	168	0.49	1.54	5	193

C_1: Density in g/cc, C_2: Knoop hardness in HK, C_3: Yield strength in MPa, C_4: Modulus of elasticity in GPa ,C_5: Specific heat capacity in J/g-°C, C_6: Material cost in USD/kg, C_7: Machinability, C_8: Fatigue strength in MPa; A_1: Aluminum 2618-T61, A_2: Aluminum 4032-T6, A_3: Aluminum A360.0-F die casting alloy, A_4: Aluminum 6061-T6, A_5: Grey cast iron, A_6: AISI 8660 steel, A_7: AISI 4140 steel, A_8: Ductile iron grade 65-45-12.

EAMR method

CILOS method is initially applied to obtain the criteria weights using Eqs. (2.5) - (2.8). Table 5.2 presents the computed CILOS weights. Later, the EAMR method is applied to determine the ranking. In the beginning, normalized and weighted normalized values are computed by Eqs. (3.21) and (3.22) as shown in Table 5.3 and Table 5.4 respectively. Then Eqs. (3.23), (3.24) and (3.25) are applied to evaluate G_i^+, G_i^- and the evaluation score. The evaluated values are presented in Table 5.5. The results indicate that A_3 performs best using EAMR method for this piston material selection problem.

Table 5.2 Criteria weight using CILOS

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
Weight	0.1310	0.1100	0.0982	0.1352	0.1853	0.1088	0.1407	0.0908

Table 5.3 Normalized matrix

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.3516	0.3902	0.2398	0.3634	0.9086	0.9737	1.0000	0.1525
A_2	0.3414	0.4065	0.2044	0.3834	0.8827	1.0000	0.7778	0.1864
A_3	0.3414	0.2629	0.1064	0.3463	1.0000	0.5000	0.5556	0.2542
A_4	0.3439	0.3252	0.1779	0.3361	0.9304	0.8947	1.0000	0.1610
A_5	0.9108	0.7344	0.1999	0.9756	0.5088	0.6711	0.3333	0.2017
A_6	1.0000	0.5962	1.0000	1.0000	0.4933	0.4013	0.5556	0.5678
A_7	1.0000	1.0000	0.6770	1.0000	0.5826	0.2500	0.5556	1.0000
A_8	0.9108	0.5285	0.1999	0.8195	0.5088	0.7237	0.5556	0.3271

Table 5.4 Weighted normalized matrix

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.0461	0.0429	0.0236	0.0491	0.1683	0.1059	0.1407	0.0139
A_2	0.0447	0.0447	0.0201	0.0519	0.1635	0.1088	0.1094	0.0169
A_3	0.0447	0.0289	0.0104	0.0468	0.1853	0.0544	0.0781	0.0231
A_4	0.0451	0.0358	0.0175	0.0455	0.1724	0.0973	0.1407	0.0146
A_5	0.1193	0.0808	0.0196	0.1319	0.0943	0.0730	0.0469	0.0183
A_6	0.1310	0.0656	0.0982	0.1352	0.0914	0.0437	0.0781	0.0516
A_7	0.1310	0.1100	0.0665	0.1352	0.1079	0.0272	0.0781	0.0908
A_8	0.1193	0.0581	0.0196	0.1108	0.0943	0.0787	0.0781	0.0297

Table 5.5 Ranking results based on EAMR method

Alternative	G_i^+	G_i^-	$RV(G_i^+)$	$RV(G_i^-)$	S_i	Rank
A_1	0.4385	0.1520	0.1240	0.1196	1.0366	5
A_2	0.4065	0.1535	0.1150	0.1208	0.9515	6
A_3	0.3727	0.0991	0.1054	0.0780	1.3510	1
A_4	0.4264	0.1424	0.1206	0.1121	1.0759	3
A_5	0.3918	0.1924	0.1108	0.1514	0.7320	7
A_6	0.5201	0.1747	0.1471	0.1375	1.0699	4
A_7	0.5886	0.1582	0.1665	0.1245	1.3368	2
A_8	0.3907	0.1981	0.1105	0.1559	0.7088	8

CURLI method

While applying CURLI method, a scoring matrix is developed for each of the eight criterion (C_1 to C_8). The scoring result for criterion C_1 is shown in Table 5.6. Similarly, scoring matrices are calculated for other criteria. The processing scoring matrix is obtained by summing the eight scoring matrices, as indicated in Table 5.7. Table 5.8 displays the results of changing the row and column positions in Table 5.7 so that all cells above the main diagonal are either negative in value or 0. Final ranks are displayed in Table 5.9. A_7 secures the top position followed by A_6.

PEG method

The PEG method is applied to this problem. Table 5.10 displays the normalized values obtained using Eqs. (3.26) and (3.27). Further, the detailed calculated values of aggregate criteria vectors, shifted vectors and MSE are subsequently computed and presented in Table 5.11. Table 5.11

shows that A_7 is the best alternative when all of the alternatives are arranged according to their MSE values, with A_6 coming in second. A_3 is ranked as the worst alternative, on the other hand.

Table 5.6 Scoring matrix of criterion C_1

Alternative	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8
A_1	0	1	1	1	-1	-1	-1	-1
A_2	-1	0	0	-1	-1	-1	-1	-1
A_3	-1	0	0	-1	-1	-1	-1	-1
A_4	-1	1	1	0	-1	-1	-1	-1
A_5	1	1	1	1	0	-1	-1	0
A_6	1	1	1	1	1	0	0	1
A_7	1	1	1	1	1	0	0	1
A_8	1	1	1	1	0	-1	-1	0

Table 5.7 Processing scoring matrix

Alternative	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8
A_1	0	0	0	1	0	2	2	0
A_2	0	0	-1	-2	00	2	2	0
A_3	0	1	0	-2	-2	3	3	1
A_4	-1	2	2	0	2	2	2	2
A_5	0	0	2	-2	0	2	6	-1
A_6	-2	-2	-3	-2	-2	0	3	-3
A_7	-2	-2	-3	-2	-6	-3	0	-5
A_8	0	0	-1	-2	1	3	5	0

Table 5.8 Processing scoring matrix after changing the positions of rows and columns

Alternative	P_7	P_6	P_2	P_3	P_8	P_5	P_4	P_1
A_7	0	-3	-2	-3	-5	-6	-2	-2
A_6	3	0	-2	-3	-3	-2	-2	-2
A_2	2	2	0	-1	0	0	-2	0
A_3	3	3	1	0	1	-2	-2	0
A_8	5	3	0	-1	0	1	-2	0
A_5	6	2	0	2	-1	0	-2	0
A_4	2	2	2	2	2	2	0	-1
A_1	2	2	0	0	0	0	1	0

Table 5.9 Ranking result using CURLI method

Alternative	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
Rank	8	3	4	7	6	2	1	5

Table 5.10 Normalized matrix

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.9845	0.1728	0.1494	0.0411	0.8197	0.0351	1	0
A_2	1	0.1949	0.1097	0.0713	0.7684	0	0.6667	0.0400
A_3	1	0	0	0.0154	1	0.6667	0.3333	0.1200
A_4	0.9961	0.0846	0.0801	0	0.8627	0.1404	1	0.0100
A_5	0.1354	0.6397	0.1046	0.9633	0.0307	0.4386	0	0.0580

A_6	0	0.4522	1	1	0	0.7982	0.3333	0.4900
A_7	0	1	0.6385	1	0.1762	1	0.3333	1
A_8	0.1354	0.3603	0.1046	0.7281	0.0307	0.3684	0.3333	0.2060

Table 5.11 Ranking results using PEG method

Alternative	x	y	x^*	y^*	MSE	Rank
A_1	0	0.8750	0.2929	0.9116	0.5847	5
A_2	0	0.6786	0.2929	0.7728	0.4777	7
A_3	0.1354	0.4905	0.3886	0.6397	0.2042	8
A_4	0.1354	0.3573	0.3886	0.5455	0.5081	6
A_5	0.9845	0.1633	0.9891	0.4084	0.9526	3
A_6	0.9961	0.1079	0.9973	0.3692	1.7580	2
A_7	1	0.0737	1	0.3450	2.0636	1
A_8	1	0	1	0.2929	0.8421	4

MACONT method

MACONT method is now applied to this problem. In Table 5.1, Eqs. (3.2), (3.3) and (3.4) are first applied to obtain the normalized values. To obtain comprehensive decision matrix values Eq. (3.5) is applied. To calculate the subordinate comprehensive values, Eqs. (3.6) and (3.7) are used, considering the $\delta = 0.5$ and $\vartheta = 0.5$ respectively. Finally, the comprehensive scores are evaluated using Eq. (3.8). Table 5.12 reveals that A_7 is the best piston material followed by A_6 as they secure the first and second positions respectively. These top alternatives show strong overall performance, confirming their suitability. The method ensures consistent and balanced evaluation.

Table 5.12 Ranking results of the piston material using MACONT method

Alternative	ρ_i	Q_i	$S_1(A_i)$	$S_2(A_i)$	$S(A_i)$	Rank
A_1	0.0137	0.7213	0.2148	0.0031	0.2154	4
A_2	-0.0127	0.8547	0.1701	0.0021	0.1572	6
A_3	-0.0041	0.6726	0.1510	0.0071	0.3224	3
A_4	0.0106	0.7522	0.2133	0.0016	0.1616	5
A_5	-0.0797	0.3448	-0.1488	-0.0013	-0.1208	7
A_6	0.0374	1.1393	0.3852	0.0040	0.3319	2
A_7	0.1188	0.7450	0.5270	0.0046	0.4232	1
A_8	-0.0840	0.1214	-0.2155	-0.0101	-0.4572	8

PARIS method

Now, the piston material selection problem is solved using the PARIS method with the same CILOS weight as calculated earlier. In Table 5.1, Eqs. (3.10) to (3.16) are first applied to obtain the three different weighted normalized matrixes. To rank the alternatives, the sum of the weighted matrix (π_i^{ω}) is calculated using Eq. (3.17). Eq. (3.18) is applied to determine the reference ideal solution (z_j*). Eq. (3.19) is used to determine the distance from the reference ideal solution (π_i^*). Table 5.13 displays the outcomes of ranking the alternatives based on the value of R_i. Eq. (3.20) is used to compute the distance between the alternatives and the ideal solution (R_i). Based on the ascending values of R_i, A_7 followed by A_1 secure the first and second positions respectively.

Table 5.13 Ranking based on PARIS method

Alternative	*Ri* (WAY$_1$)	Rank	*Ri* (WAY$_2$)	Rank	*Ri* (WAY$_3$)	Rank
A$_1$	0.1927	3	0.1535	2	0.1733	2
A$_2$	0.2466	6	0.2604	5	0.2467	6
A$_3$	0.2379	5	0.2692	6	0.1957	5
A$_4$	0.2289	4	0.2839	7	0.1736	3
A$_5$	0.2754	7	0.2434	4	0.4239	7
A$_6$	0.1372	2	0.115	1	0.1777	4
A$_7$	0.0787	1	0.1625	3	0	1
A$_8$	0.2787	8	0.3331	8	0.4378	8

OPTBIAS method

Now, employing the procedural steps of OPTBIAS method, the decision matrix is normalized using vector normalization approach. Then bi-positive ideal, bi-negative ideal and average solutions are computed using Eqs. (3.43) - (3.45). Table 5.14 exhibits the corresponding values of the Euclidean distances of the alternatives from the positive ideal solution, negative ideal solution and average solutions. This table also provides values of *B* and *PS* obtained using Eqs. (3.46) and (3.47). It is evident from the table that A$_7$, with the highest performance score, is at the top of the ranking list, followed by A$_6$.

Table 5.14 Ranking results based on OPTBIAS method

Alternative	*RP*	*RN*	*RA*	*B*	*PS*	Rank
A$_1$	0.1786	0.1583	0.0465	0.8861	1.3465	3
A$_2$	0.1725	0.1392	0.0399	0.8071	1.3112	6
A$_3$	0.1686	0.1395	0.0474	0.8277	1.3207	5
A$_4$	0.1813	0.1576	0.0489	0.8693	1.3392	4
A$_5$	0.1839	0.1327	0.0458	0.7217	1.2748	7
A$_6$	0.1657	0.2040	0.0663	1.2318	1.5118	2
A$_7$	0.1643	0.2308	0.0741	1.4046	1.6018	1
A$_8$	0.1705	0.1129	0.0311	0.6623	1.2490	8

PROBID method

Employing PROBID method, the normalized and the weighted normalized decision matrix is developed using Eqs. (3.48) and (3.49). The ideal (Z_k) and average ($\bar{Z}$) solutions are obtained based on Eqs. (3.50) - (3.52). The Euclidean distances ($E_{i(k)}$) (most PIS, second PIS, ..., eighth PIS) and the average solutions ($E_{i(avg)}$) are computed based on Eqs. (3.53) and (3.54). Table 5.15 provides the positive ideal ($E_{i(pos\text{-}ideal)}$), negative ideal ($E_{i(neg\text{-}ideal)}$), positive-ideal or negative-ideal ratio (RA_i) and performance score (PS_i) of each of the alternatives, obtained using Eqs. (3.55)-(3.58). It can be clearly noticed from the table that A$_7$ occupies the top position in the ranking list with maximum performance score, followed by A$_6$.

Table 5.15 Ranking results using PROBID method

Alternative	$E_{pos-ideal}$	$E_{neg-ideal}$	RA	PS	Rank
A_1	0.1733	0.1362	1.2721	0.4277	3
A_2	0.2003	0.1128	1.7759	0.2896	6
A_3	0.1951	0.1113	1.7526	0.2921	5
A_4	0.1589	0.1134	1.4018	0.3683	4
A_5	0.2009	0.1057	1.9	0.2643	7
A_6	0.1392	0.208	0.6695	0.7568	2
A_7	0.127	0.2326	0.5459	0.8446	1
A_8	0.1948	0.0868	2.2441	0.2056	8

DNMA method

Employing DNMA method, the decision matrix is normalized using both linear and vector normalization approaches, based on Eqs. (3.59) and (3.60), respectively. In the next step, using Eqs. (3.61), (3.62) and (3.63) the adjusted weight are estimated. Based on this weight adjusted coefficients and normalized values of the decision matrix and applying Eqs. (3.64) - (3.66). In the same table, based on the computed utility values, the alternative piston materials are subsequently ranked in descending, ascending and descending orders for CCM, UCM and ICM aggregators, respectively. Finally, the comprehensive utility values for each of the alternatives are calculated using Eq. (3.67), considering values of different tuning parameters as φ = 0.5, $\overline{\omega}_1$= 0.6, $\overline{\omega}_2$= 0.1 and $\overline{\omega}_3$= 0.3. Eight pistons are subsequently ranked in decreasing order of their S_i values. It can be clearly noticed from Table 5.16 that A_7 emerges out as the best alternative with maximum comprehensive utility score, followed by A_6.

Table 5.16 Ranking results using DNMA method

Alternative	CCM $u_1(a_i)$	Rank	UCM $u_2(a_i)$	Rank	ICM $u_3(a_i)$	Rank	Utility value (S_i)	Rank
A_1	0.4212	3	0.1353	4	0.7393	3	0.5923	3
A_2	0.3774	6	0.1311	1	0.7295	6	0.4307	6
A_3	0.4123	5	0.139	5	0.7357	4	0.4925	5
A_4	0.4183	4	0.1411	8	0.7341	5	0.4972	4
A_5	0.3003	7	0.1329	2	0.7252	8	0.34	7
A_6	0.4993	2	0.1404	6	0.8317	2	0.6902	2
A_7	0.6211	1	0.1404	6	0.8742	1	0.8119	1
A_8	0.2856	8	0.1329	2	0.7277	7	0.3176	8

Comparative analyses of MCDM methods

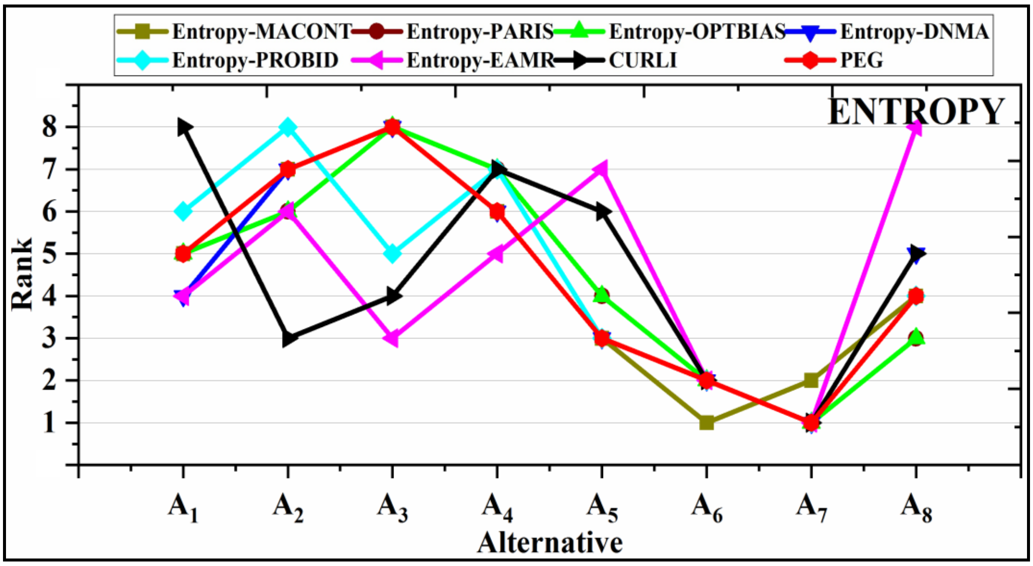
A detailed comparative analysis is performed in this section. For this, different criteria weights are determined and presented in Table 5.17.

a) Based on rank comparison

Figure 5.2 displays the ranking results using the weight set provided in Table 5.17, where it clearly shows that alternative A_7 is the top ranked alternative in most of the cases followed by A_6, A_2 and A_3 in very few cases. Using the entropy weighting method, A_7 achieves the top rank across all methods except MACONT. With the CRITIC weighting method, A_7 emerges as the top-ranked alternative in all methods except MACONT and EAMR. Under MEREC and PCA, A_7 is identified as the top-ranked alternative, although MACONT shows different rankings, indicating inconsistencies. Similarly, the SPC, CILOS and IDOCRIW weighting methods identify A_7 as the best, except for MACONT in SPC and IDOCRIW and EAMR in CILOS, which differ. In the case of LOPCOW, all methods rank A_7 as the top alternative, showing general agreement. DNMA and PARIS secured consistent ranking of A_7 as the top alternative across all the weighting methods. Unlike other methods, these methods demonstrate minimal ranking fluctuations, offering reliability and stability in decision making.

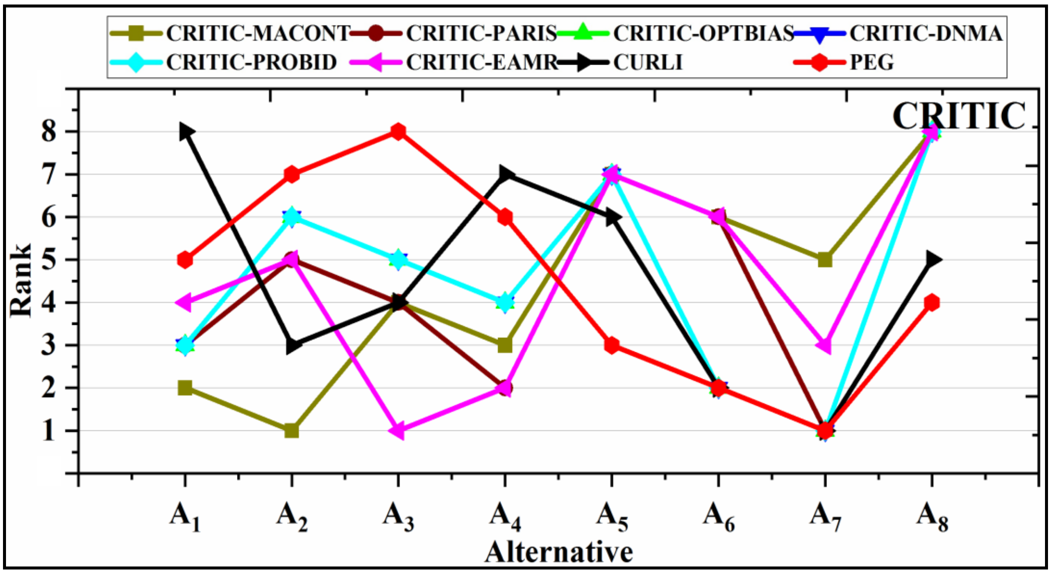
Table 5.17 Set of criteria weights

Weighting methods	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
Entropy	0.0287	0.1	0.3362	0.1255	0.0474	0.0202	0.0636	0.2784
CRITIC	0.1995	0.0911	0.0904	0.145	0.1657	0.0972	0.1274	0.0836
MEREC	0.1312	0.128	0.1881	0.1132	0.0787	0.0961	0.1409	0.124
PCA	0.282	0.281	0.3105	0.2816	0.2538	0.237	0.1157	0.2993
SPC	0.1071	0.0866	0.2801	0.1015	0.0541	0.0749	0.0582	0.2375
LOPCOW	0.1215	0.1362	0.0735	0.125	0.1621	0.1705	0.1511	0.0602
CILOS	0.131	0.11	0.0982	0.1352	0.1853	0.1088	0.1407	0.0908
IDOCRIW	0.0342	0.1	0.3003	0.1543	0.0799	0.02	0.0814	0.2299



(a)

Figure 5.2 Weight wise ranking results



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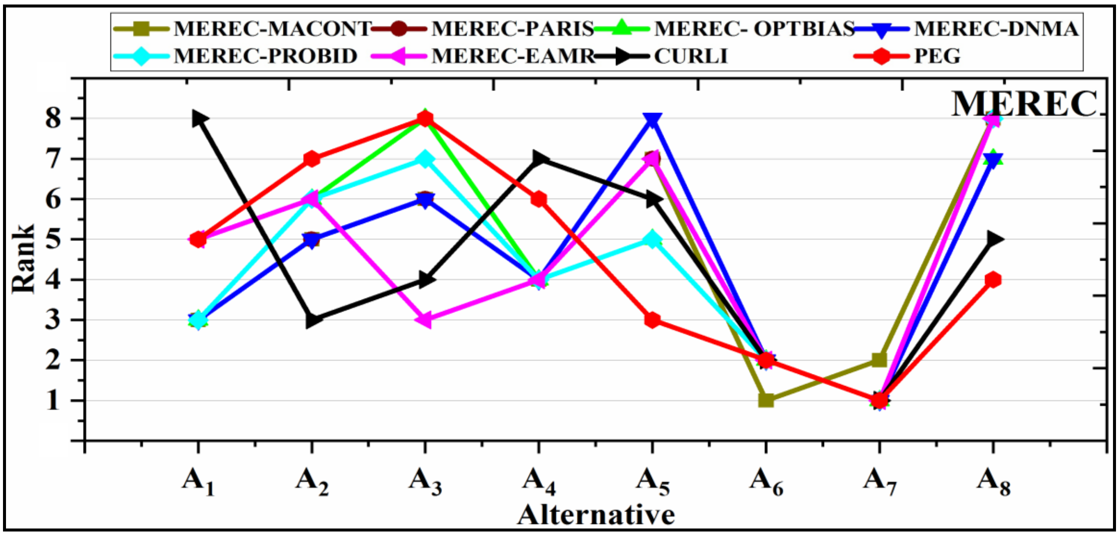

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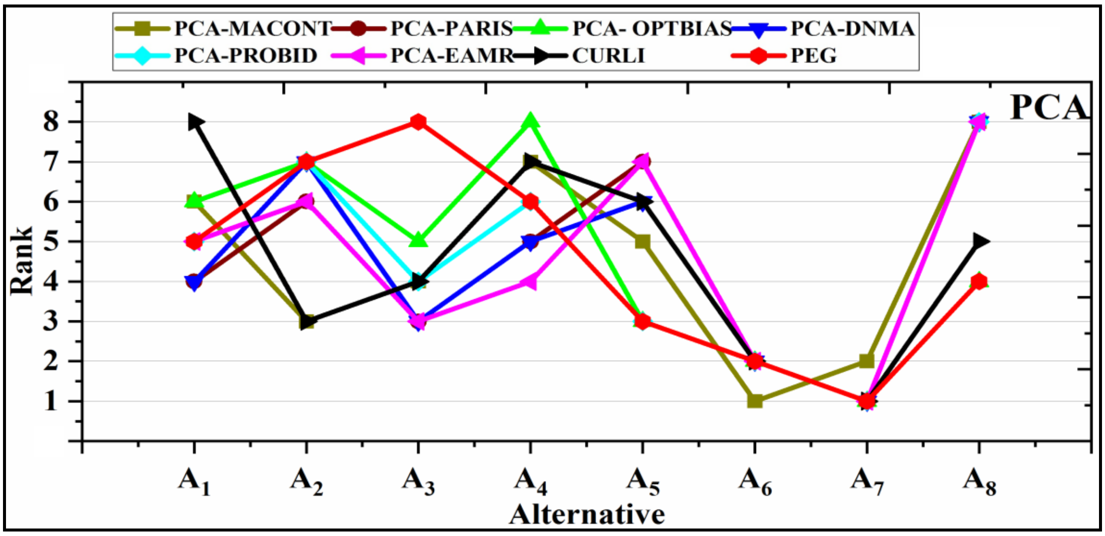

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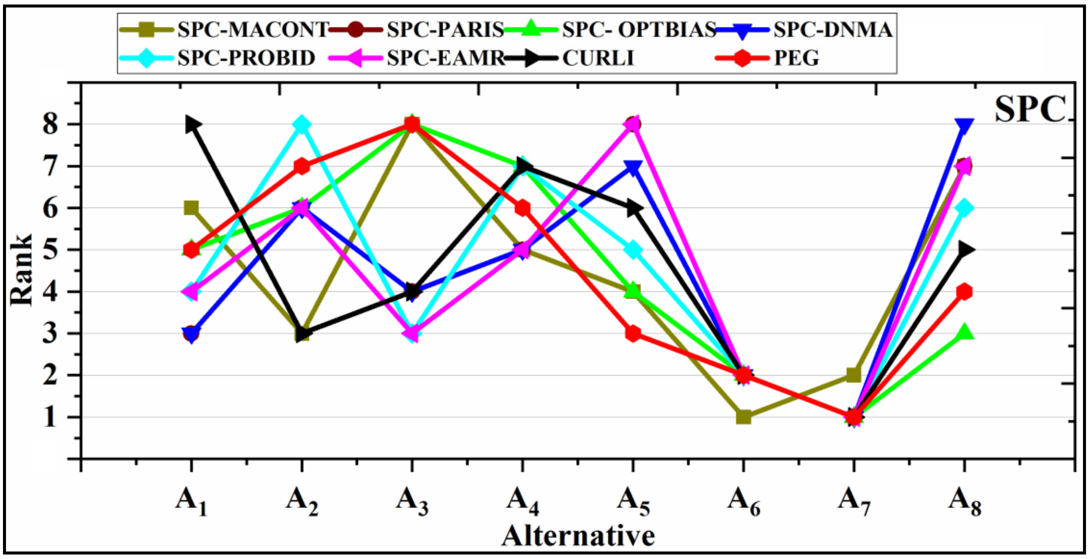
Figure 5.2 Continued



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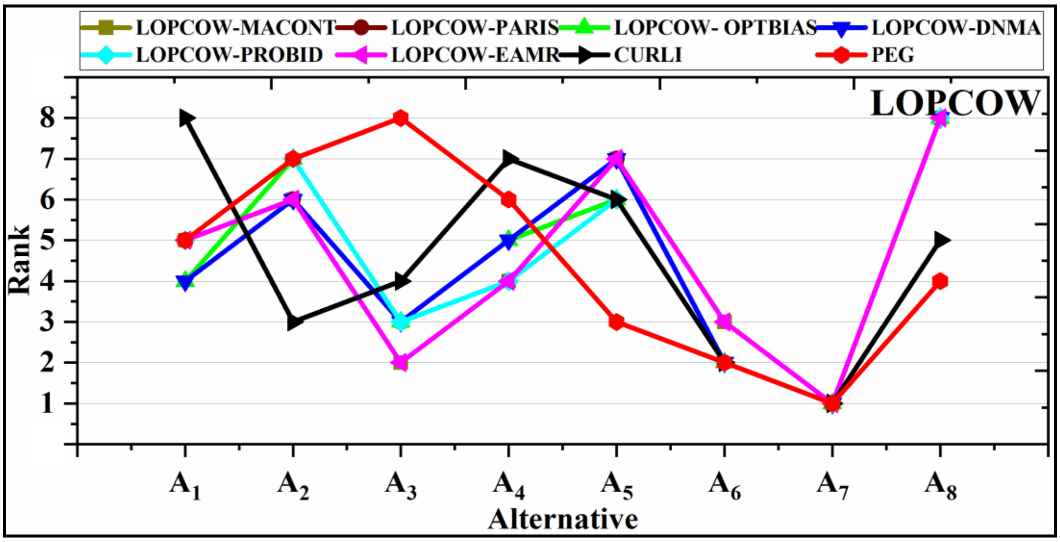

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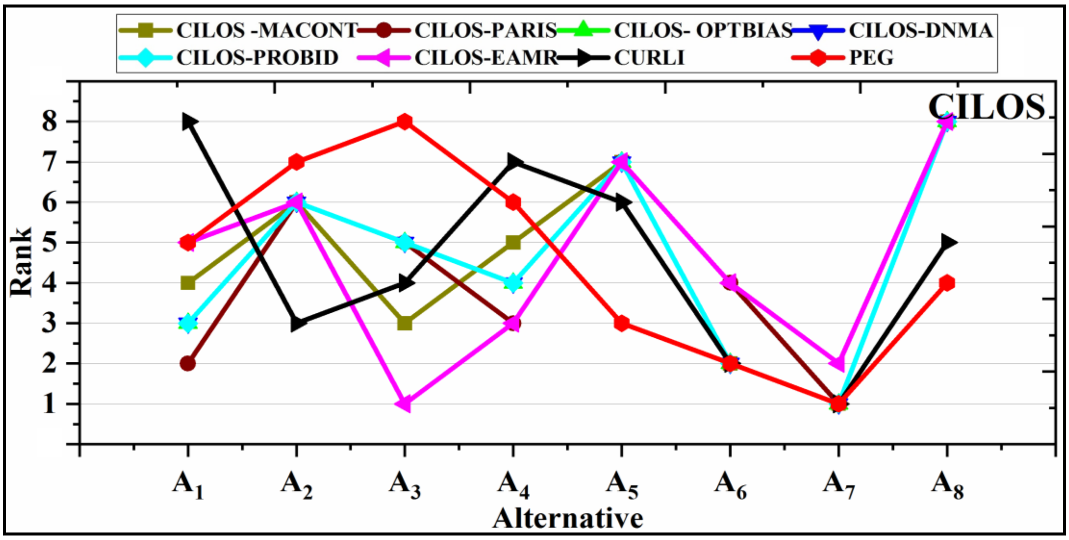

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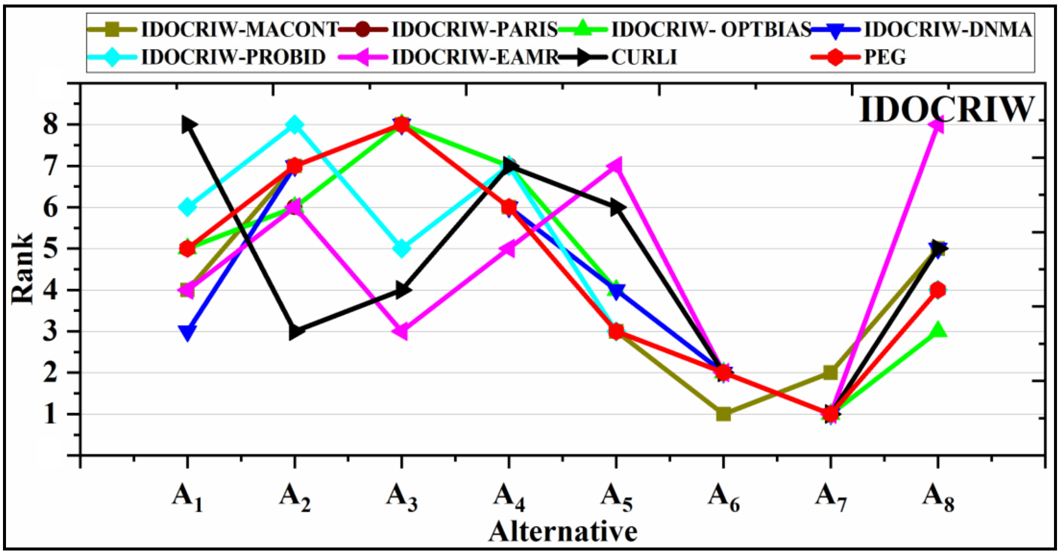
Figure 5.2 Continued



(h)

Figure 5.2 Continued

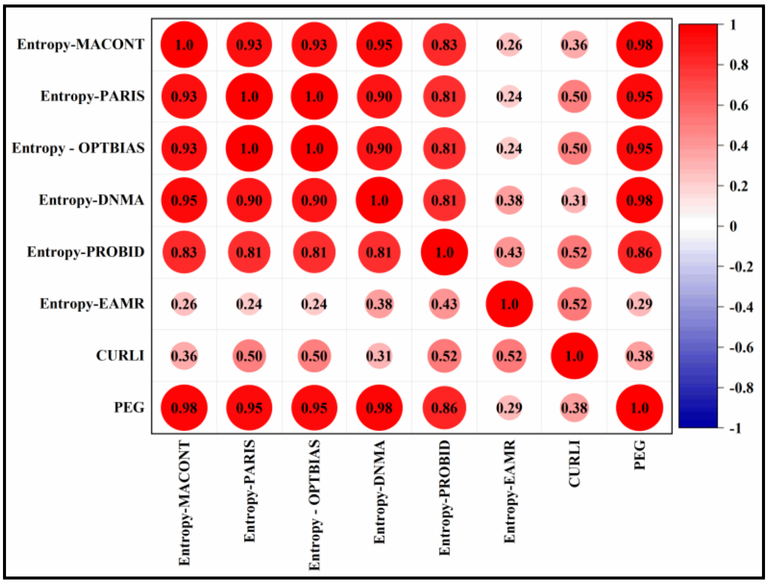
b) Based on Spearman co-relation coefficients

Figure 5.3 shows the Spearman correlation coefficient results where entropy-based methods, specifically, PARIS-OPTBIAS exhibits perfect correlation at 1, DNMA-PEG at 0.98 and DNMA-MACONT at 0.95, along with strong correlations among other methods except for EAMR and CURLI. Under CRITIC weighting, DNMA-OPTBIAS, DNMA-PROBID and PROBID-OPTBIAS achieve a perfect correlation of 1, while MACONT, CURLI and PEG perform poorly. MEREC weighting results show DNMA-PARIS and OPTBIAS-PROBID with a 0.98 correlation, DNMA-MACONT with 0.95 correlation and again CURLI and PEG performing poorly. PCA weighting maintains high correlations for DNMA-PARIS and EAMR-PARIS at 0.98, with PEG and CURLI performing poorly. SPC weighting also sees DNMA-PARIS and EAMR-PARIS at 0.98. Under LOPCOW weighting, all methods show very high correlations, except PEG and CURLI. CILOS weighting results in OPTBIAS-DNMA and OPTBIAS-PROBID both at 1, with PEG and CURLI underperforming. Finally, IDOCRIW weighting sees OPTBIAS-PARIS and PEG-PARIS at 0.98, with high correlations among most methods except EAMR and CURLI. This study concludes that DNMA and PARIS consistently show the highest correlation under specific weighted conditions, particularly excelling with entropy, MEREC, PCA and SPC weightings. These results affirm the computational compatibility of DNMA and PARIS across various weighting schemes, with CURLI and PEG consistently showing weak alignment.

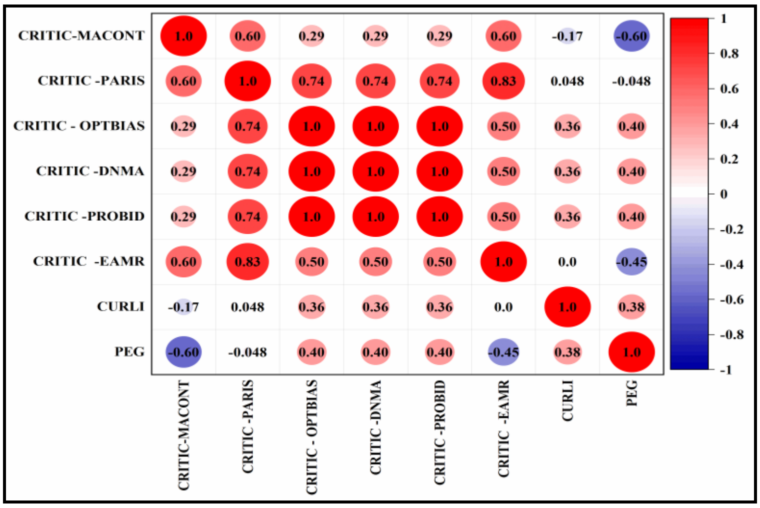
c) Based on weighted Spearman rank co-relation coefficient

To overcome the challenges that Spearman correlation possesses as discussed earlier, R_w is computed as it provides larger significance to higher ranked alternatives. Figure 5.4 presents an overall result of R_w correlation coefficient, where under entropy combined conditions, the R_w value is 1 in OPTBIAS-PARIS, with most cases being above 0.9, while CURLI-EAMR struggle. CRITIC weighting sees OPTBIAS-PROBID and OPTBIAS-DNMA at 1, with the rest not being as significant.

MEREC weighting results in PROBID-OPTBIAS and DNMA-PARIS both at 0.99, with EAMR, CURLI and PEG performing poorly. PCA weighting shows high correlations for DNMA-PARIS at 0.99 and EAMR-PARIS at 0.98. SPC weighting sees DNMA-PARIS at 0.99, while many of the methods perform poorly. LOPCOW weighting results in OPTBIAS-DNMA and PROBID-PARIS both at 0.99, with all other methods, except CURLI and PEG, performing very well. Under CILOS weighting, except for EAMR, CURLI and PEG, all other methods perform very well. Finally, IDOCRIW weighting shows that all methods perform well except for EAMR and CURLI. The R_w results clearly highlight DNMA as it achieves perfect or near-perfect R_w scores with OPTBIAS under CRITIC and 0.99 with PARIS under MEREC, PCA and SPC, indicating strong consistency in top-ranked alternatives. DNMA also performs well under LOPCOW, CILOS and IDOCRIW, reinforcing its reliability. Similarly, PARIS consistently ranks among the best, especially with DNMA, showing 0.99 correlations under multiple conditions, confirming its stable and dependable performance.

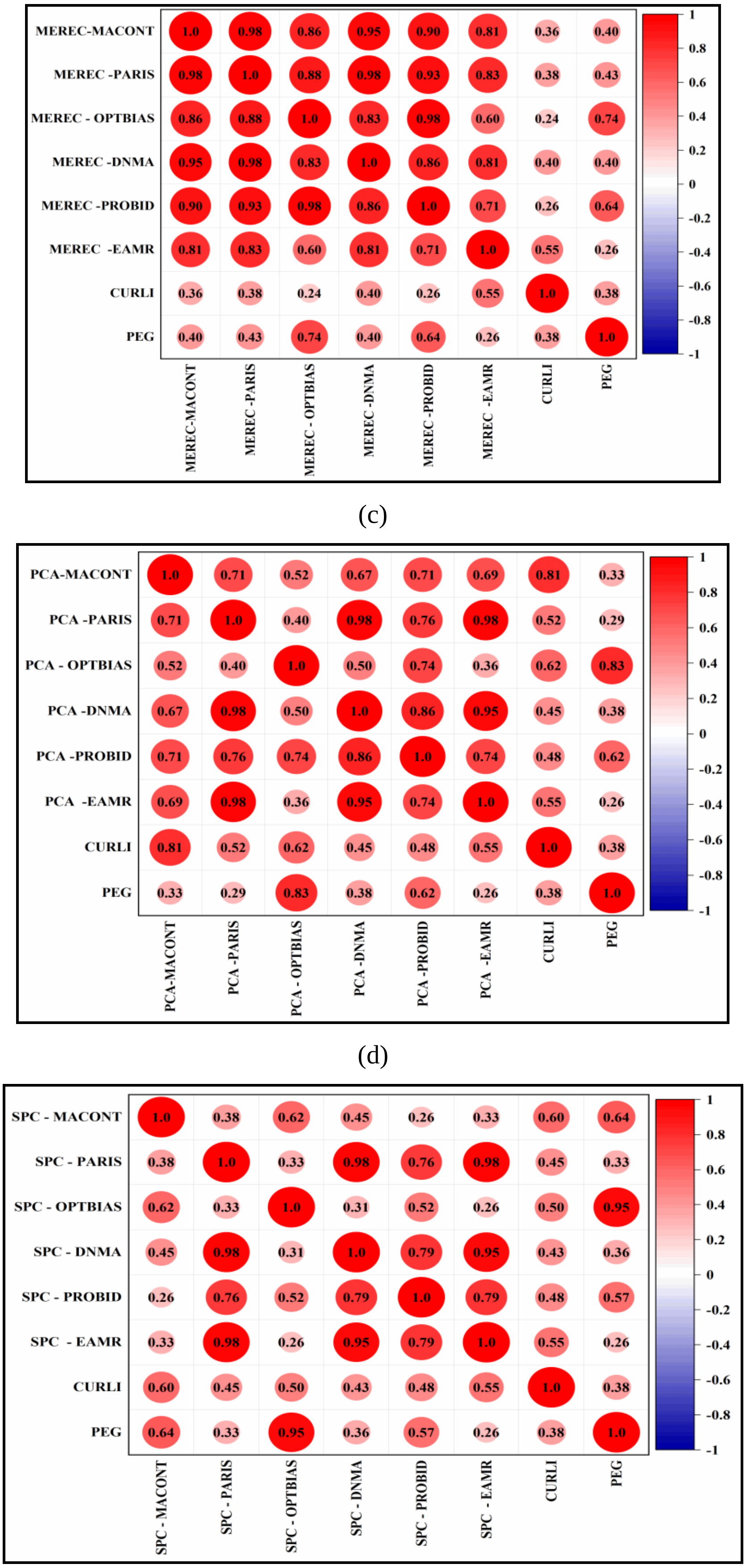


(a)



(b)

Figure 5.3 Spearman correlation ranking result

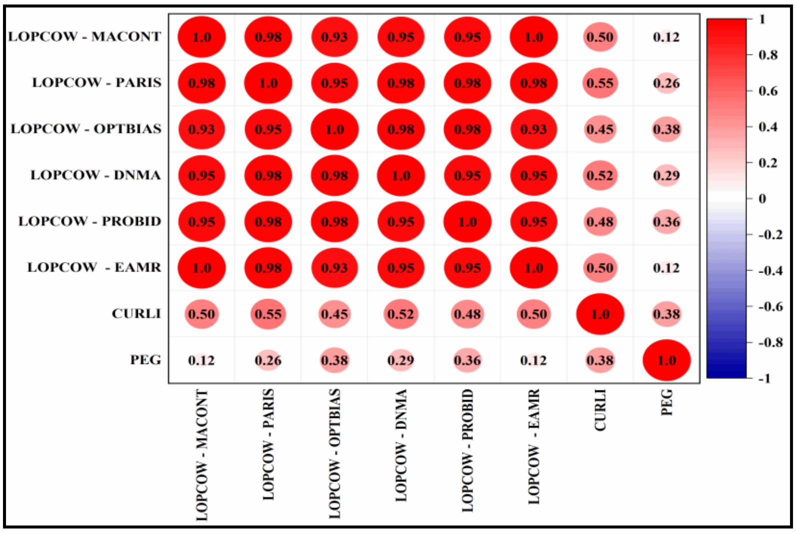


(c)

(d)

(e)

Figure 5.3 Continued



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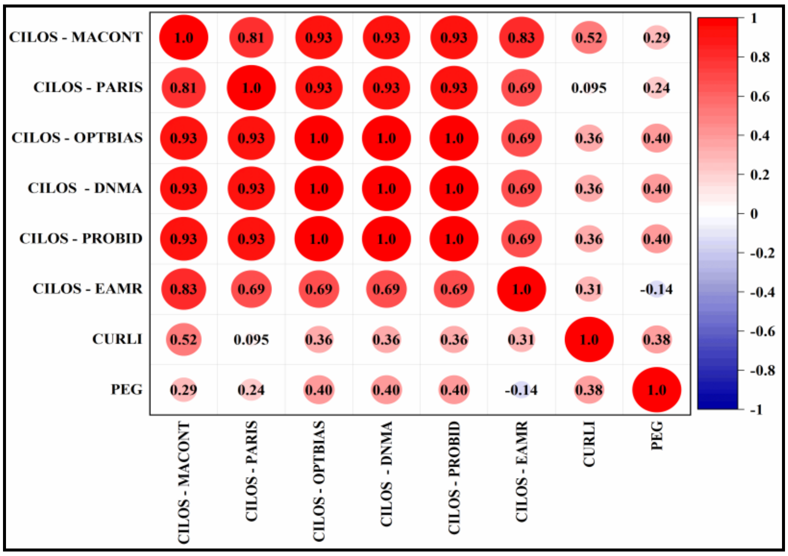

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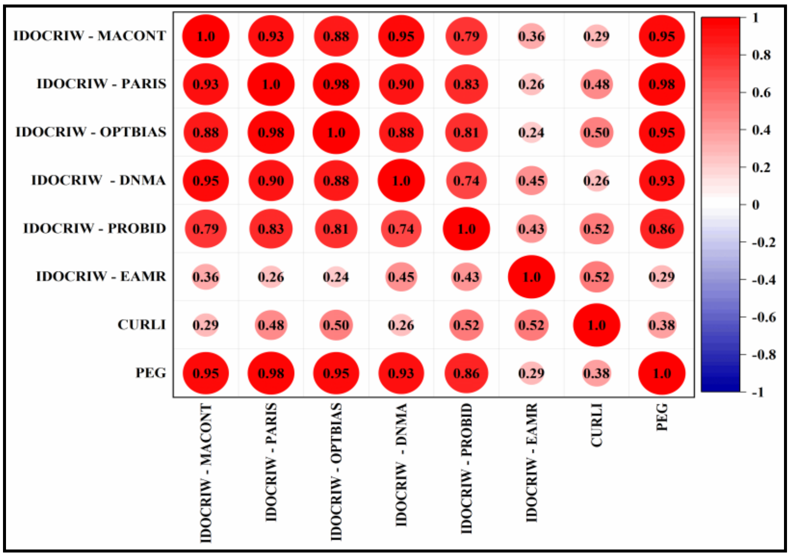

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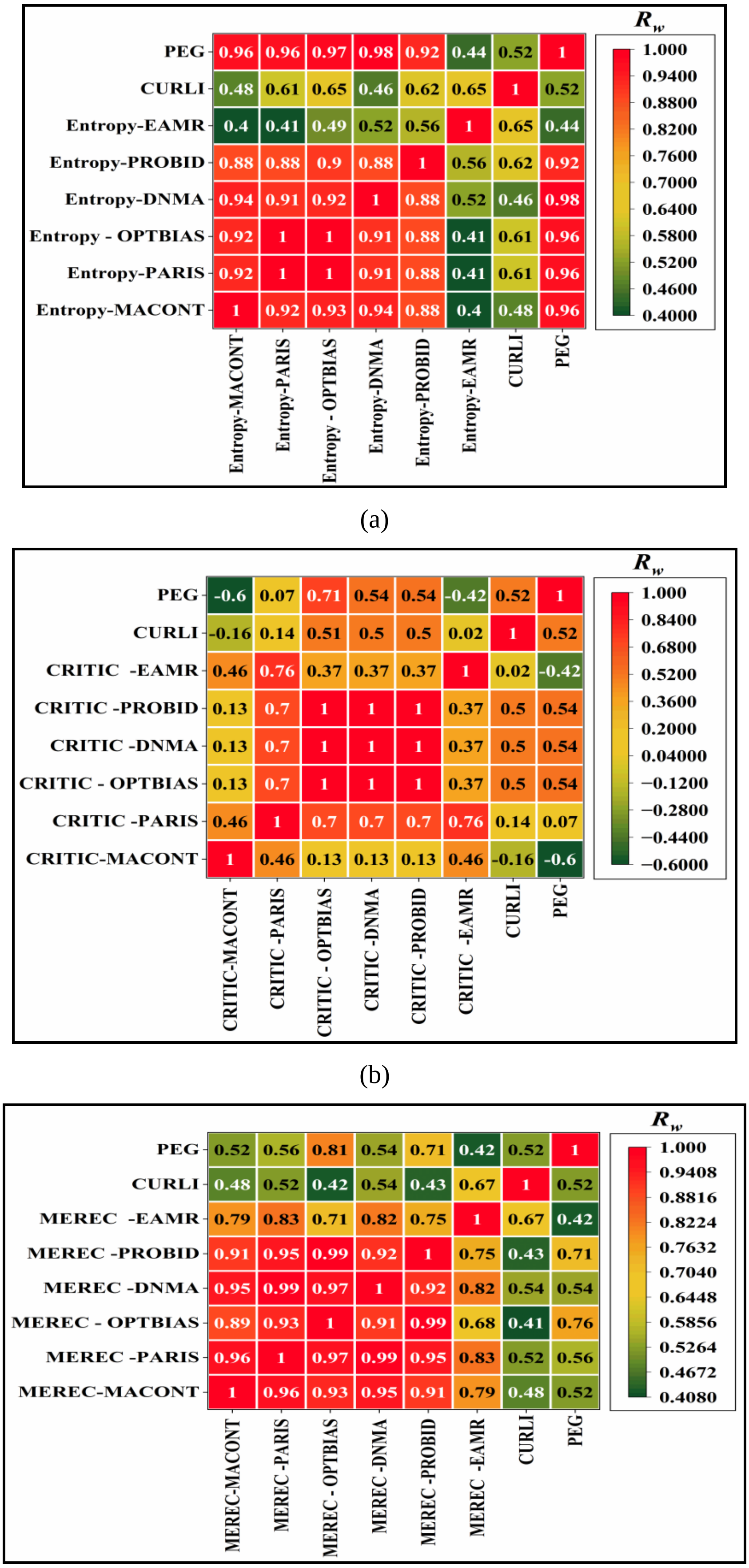
Figure 5.3 Continued



	Entropy-MACONT	Entropy-PARIS	Entropy - OPTBIAS	Entropy-DNMA	Entropy-PROBID	Entropy-EAMR	CURLI	PEG
PEG	0.96	0.96	0.97	0.98	0.92	0.44	0.52	1
CURLI	0.48	0.61	0.65	0.46	0.62	0.65	1	0.52
Entropy-EAMR	0.4	0.41	0.49	0.52	0.56	1	0.65	0.44
Entropy-PROBID	0.88	0.88	0.9	0.88	1	0.56	0.62	0.92
Entropy-DNMA	0.94	0.91	0.92	1	0.88	0.52	0.46	0.98
Entropy - OPTBIAS	0.92	1	1	0.91	0.88	0.41	0.61	0.96
Entropy-PARIS	0.92	1	1	0.91	0.88	0.41	0.61	0.96
Entropy-MACONT	1	0.92	0.93	0.94	0.88	0.4	0.48	0.96

(a)

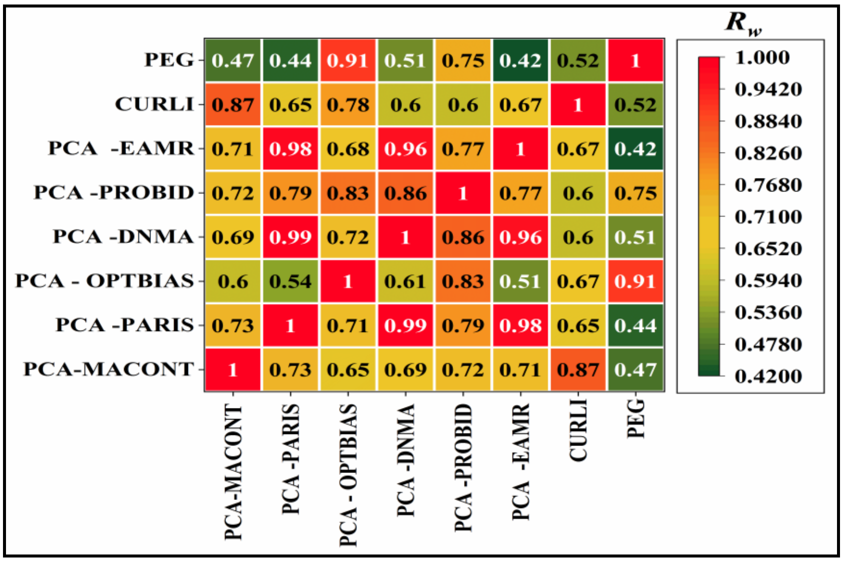
	CRITIC-MACONT	CRITIC -PARIS	CRITIC - OPTBIAS	CRITIC -DNMA	CRITIC -PROBID	CRITIC -EAMR	CURLI	PEG
PEG	-0.6	0.07	0.71	0.54	0.54	-0.42	0.52	1
CURLI	-0.16	0.14	0.51	0.5	0.5	0.02	1	0.52
CRITIC -EAMR	0.46	0.76	0.37	0.37	0.37	1	0.02	-0.42
CRITIC -PROBID	0.13	0.7	1	1	1	0.37	0.5	0.54
CRITIC -DNMA	0.13	0.7	1	1	1	0.37	0.5	0.54
CRITIC - OPTBIAS	0.13	0.7	1	1	1	0.37	0.5	0.54
CRITIC -PARIS	0.46	1	0.7	0.7	0.7	0.76	0.14	0.07
CRITIC-MACONT	1	0.46	0.13	0.13	0.13	0.46	-0.16	-0.6

(b)

	MEREC-MACONT	MEREC-PARIS	MEREC - OPTBIAS	MEREC -DNMA	MEREC -PROBID	MEREC -EAMR	CURLI	PEG
PEG	0.52	0.56	0.81	0.54	0.71	0.42	0.52	1
CURLI	0.48	0.52	0.42	0.54	0.43	0.67	1	0.52
MEREC -EAMR	0.79	0.83	0.71	0.82	0.75	1	0.67	0.42
MEREC -PROBID	0.91	0.95	0.99	0.92	1	0.75	0.43	0.71
MEREC -DNMA	0.95	0.99	0.97	1	0.92	0.82	0.54	0.54
MEREC - OPTBIAS	0.89	0.93	1	0.91	0.99	0.68	0.41	0.76
MEREC -PARIS	0.96	1	0.97	0.99	0.95	0.83	0.52	0.56
MEREC-MACONT	1	0.96	0.93	0.95	0.91	0.79	0.48	0.52

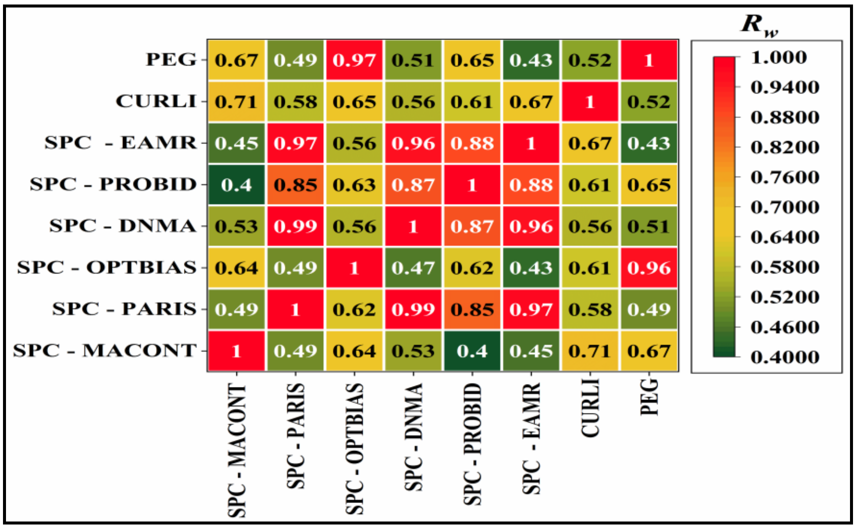
(c)

Figure 5.4 Weighted Spearman correlation coefficient (R_w)



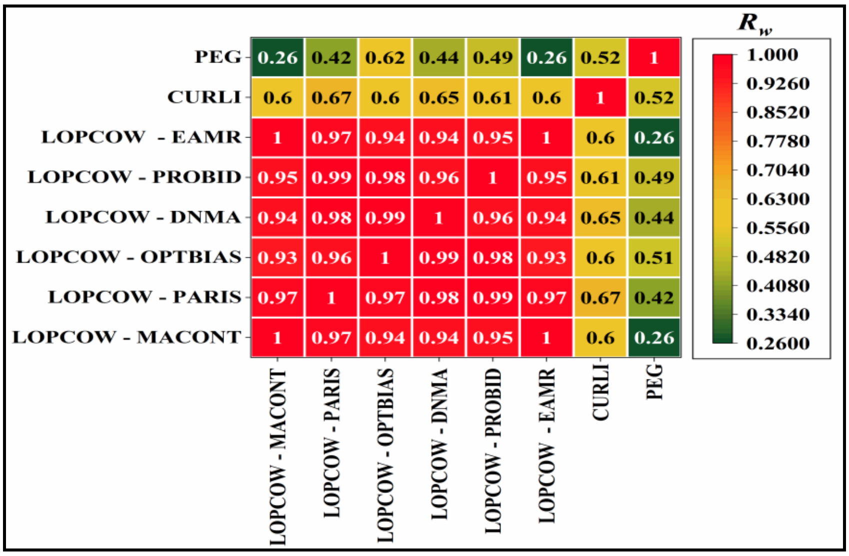
	PCA-MACONT	PCA -PARIS	PCA - OPTBIAS	PCA -DNMA	PCA -PROBID	PCA -EAMR	CURLI	PEG
PEG	0.47	0.44	0.91	0.51	0.75	0.42	0.52	1
CURLI	0.87	0.65	0.78	0.6	0.6	0.67	1	0.52
PCA -EAMR	0.71	0.98	0.68	0.96	0.77	1	0.67	0.42
PCA -PROBID	0.72	0.79	0.83	0.86	1	0.77	0.6	0.75
PCA -DNMA	0.69	0.99	0.72	1	0.86	0.96	0.6	0.51
PCA - OPTBIAS	0.6	0.54	1	0.61	0.83	0.51	0.67	0.91
PCA -PARIS	0.73	1	0.71	0.99	0.79	0.98	0.65	0.44
PCA-MACONT	1	0.73	0.65	0.69	0.72	0.71	0.87	0.47

(d)



	SPC - MACONT	SPC - PARIS	SPC - OPTBIAS	SPC - DNMA	SPC - PROBID	SPC - EAMR	CURLI	PEG
PEG	0.67	0.49	0.97	0.51	0.65	0.43	0.52	1
CURLI	0.71	0.58	0.65	0.56	0.61	0.67	1	0.52
SPC - EAMR	0.45	0.97	0.56	0.96	0.88	1	0.67	0.43
SPC - PROBID	0.4	0.85	0.63	0.87	1	0.88	0.61	0.65
SPC - DNMA	0.53	0.99	0.56	1	0.87	0.96	0.56	0.51
SPC - OPTBIAS	0.64	0.49	1	0.47	0.62	0.43	0.61	0.96
SPC - PARIS	0.49	1	0.62	0.99	0.85	0.97	0.58	0.49
SPC - MACONT	1	0.49	0.64	0.53	0.4	0.45	0.71	0.67

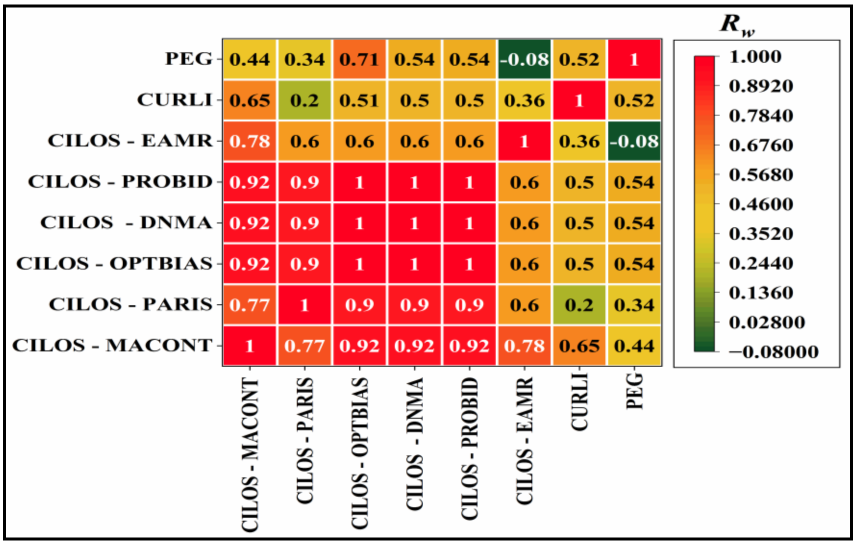
(e)



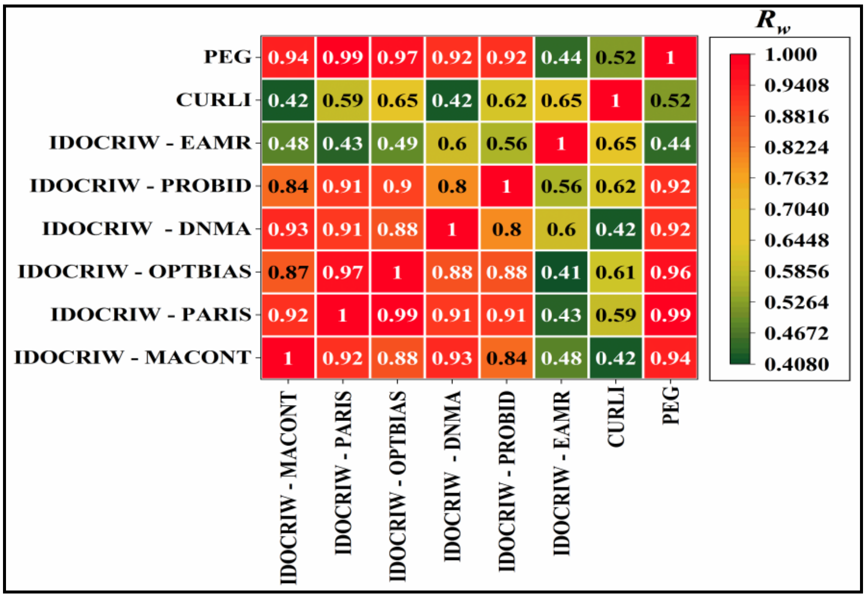
	LOPCOW - MACONT	LOPCOW - PARIS	LOPCOW - OPTBIAS	LOPCOW - DNMA	LOPCOW - PROBID	LOPCOW - EAMR	CURLI	PEG
PEG	0.26	0.42	0.62	0.44	0.49	0.26	0.52	1
CURLI	0.6	0.67	0.6	0.65	0.61	0.6	1	0.52
LOPCOW - EAMR	1	0.97	0.94	0.94	0.95	1	0.6	0.26
LOPCOW - PROBID	0.95	0.99	0.98	0.96	1	0.95	0.61	0.49
LOPCOW - DNMA	0.94	0.98	0.99	1	0.96	0.94	0.65	0.44
LOPCOW - OPTBIAS	0.93	0.96	1	0.99	0.98	0.93	0.6	0.51
LOPCOW - PARIS	0.97	1	0.97	0.98	0.99	0.97	0.67	0.42
LOPCOW - MACONT	1	0.97	0.94	0.94	0.95	1	0.6	0.26

(f)

Figure 5.4 Continued



(g)

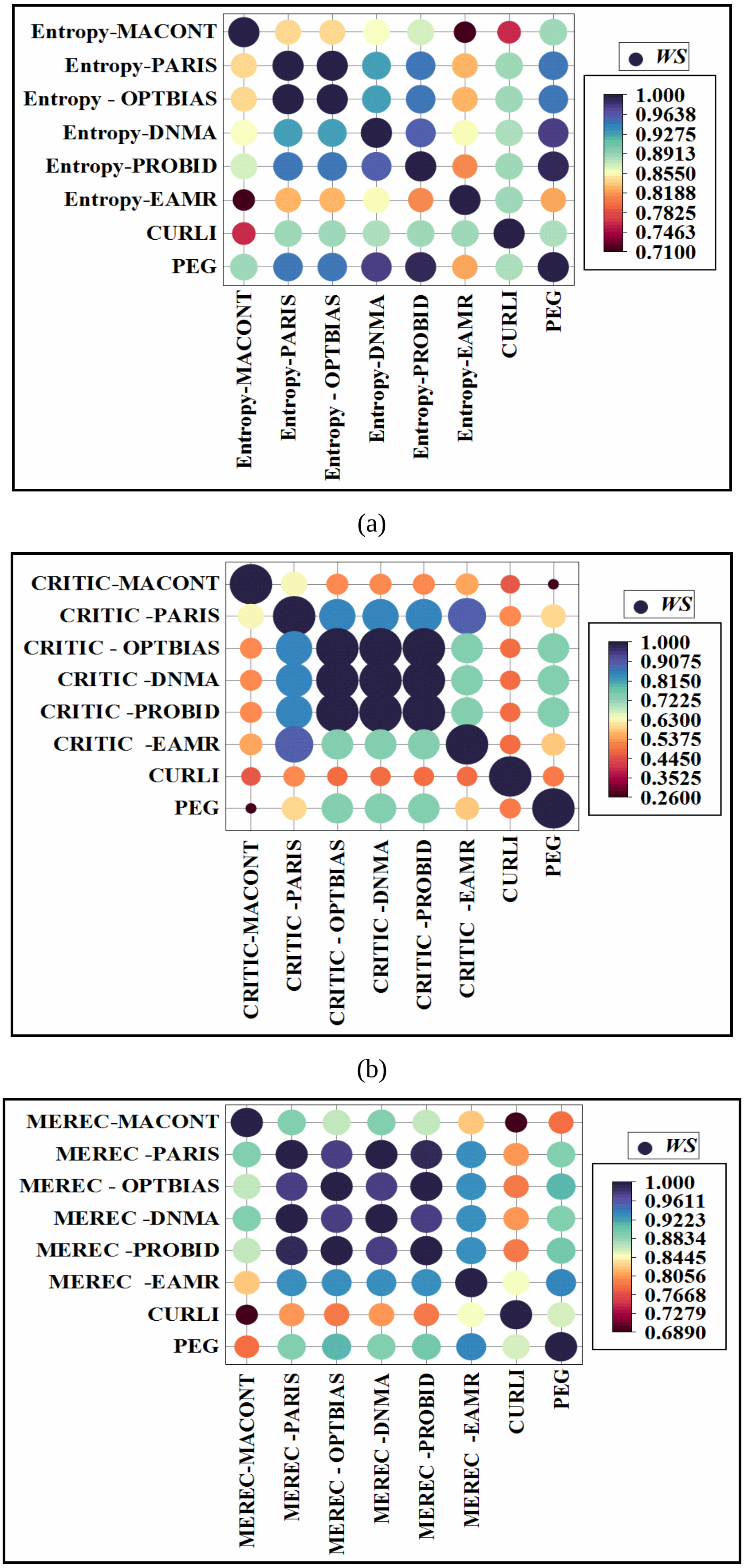


(h)

Figure 5.4 Continued

d) Based on coefficient of ranking similarity (*WS*)

To analyze the ranking positions results, *WS* values are computed. It gives more priority to higher ranked alternatives than the lower ranks. It depends on difference in rankings for each position, thus very sensitive to changes in ranks. Figure 5.5 shows the result of *WS* values of all the rankings. Under entropy-based conditions, the *WS* value is a perfect 1 between PARIS-OPTBIAS. The CRITIC weighting method highlights DNMA-OPTBIAS and DNMA-PROBID, both achieving a perfect 1. Similarly, under the MEREC, PCA and SPC weighting methods, the ranking similarity values surpass 0.85, reflecting a notable agreement between these methods. The LOPCOW weighting method shows exceptionally high similarity, with DNMA-OPTBIAS at 1 and OPTBIAS-PROBID at 0.96. For the CILOS weighting, DNMA-OPTBAIS achieve a perfect 1. Finally, the IDOCRIW weighting method demonstrates very high ranking similarity across most MCDM methods, particularly with DNMA.

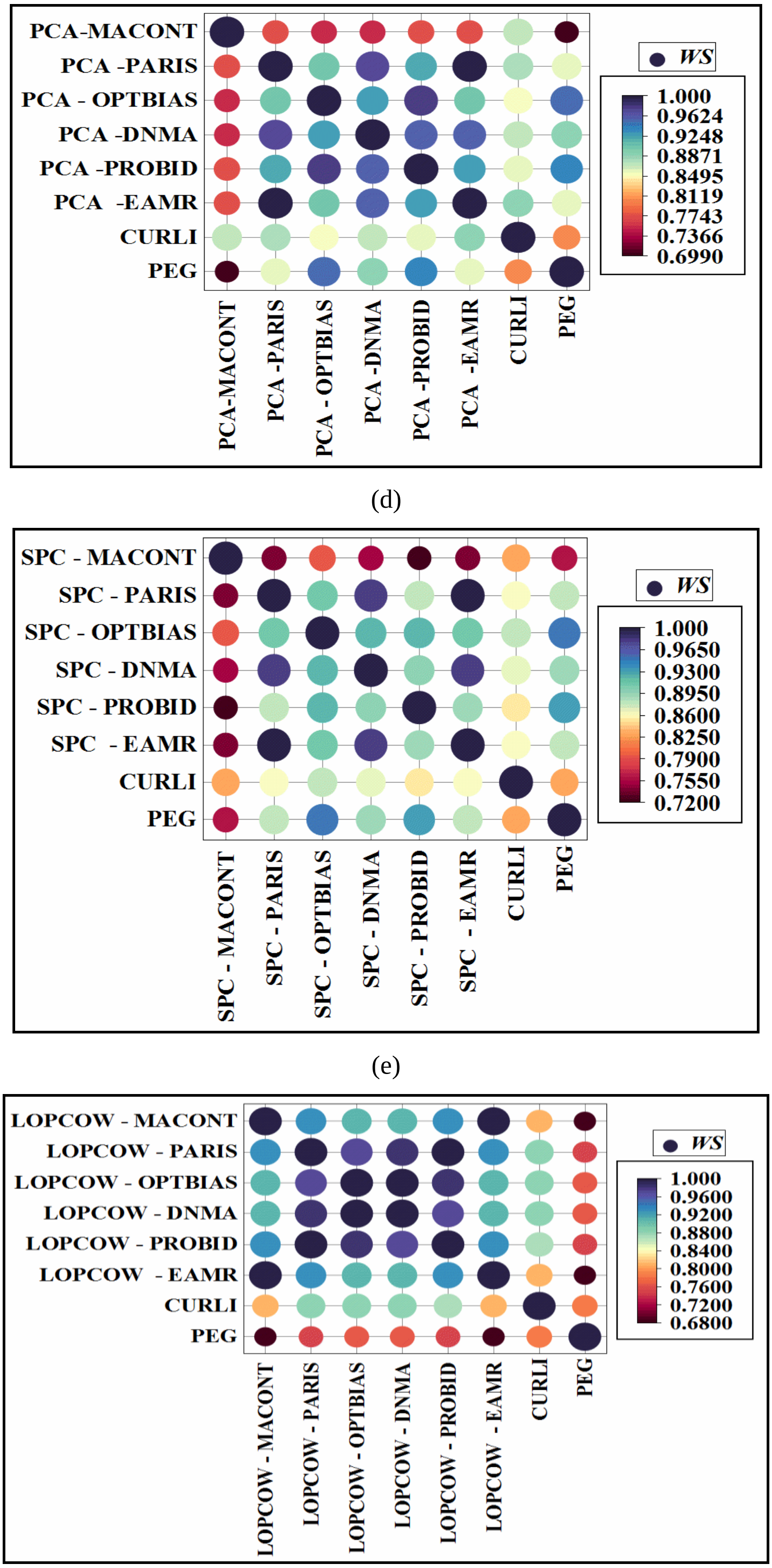


(a)

(b)

(c)

Figure 5.5 Coefficient of rank similarity (*WS*) results



(d)

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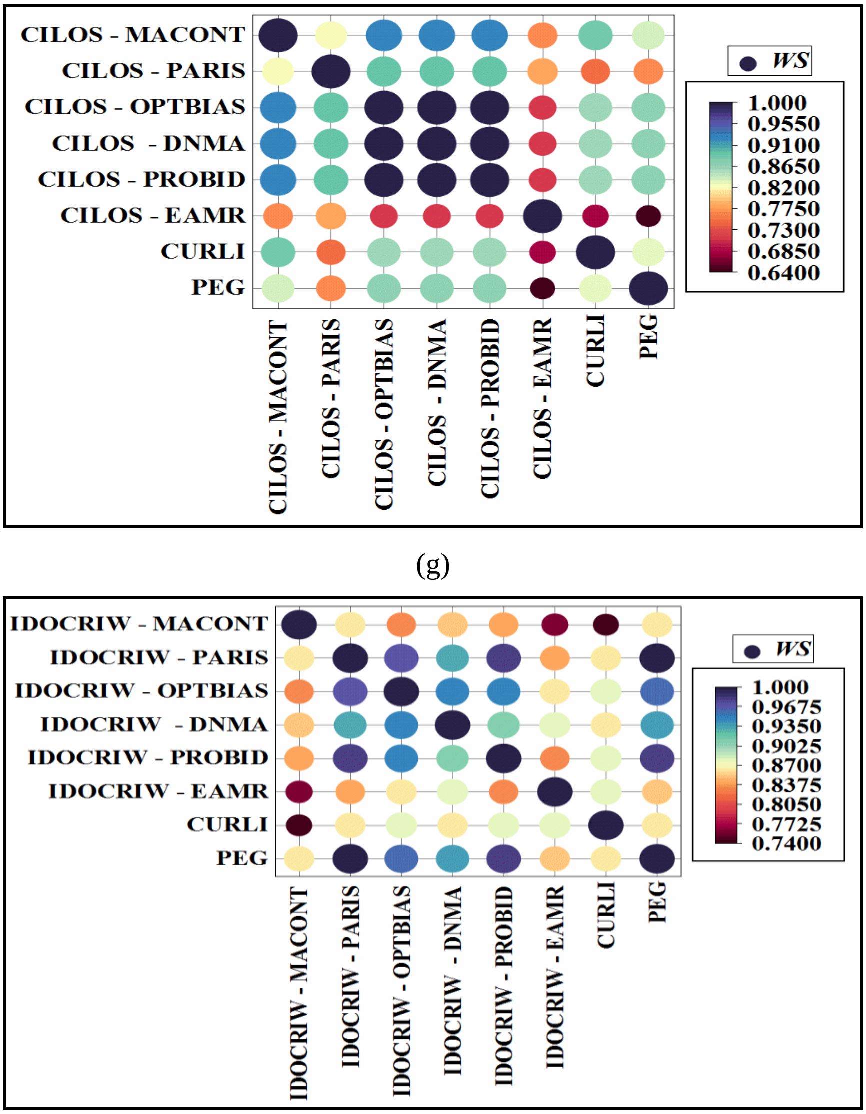
Figure 5.5 Continued



(g)

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Figure 5.5 Continued

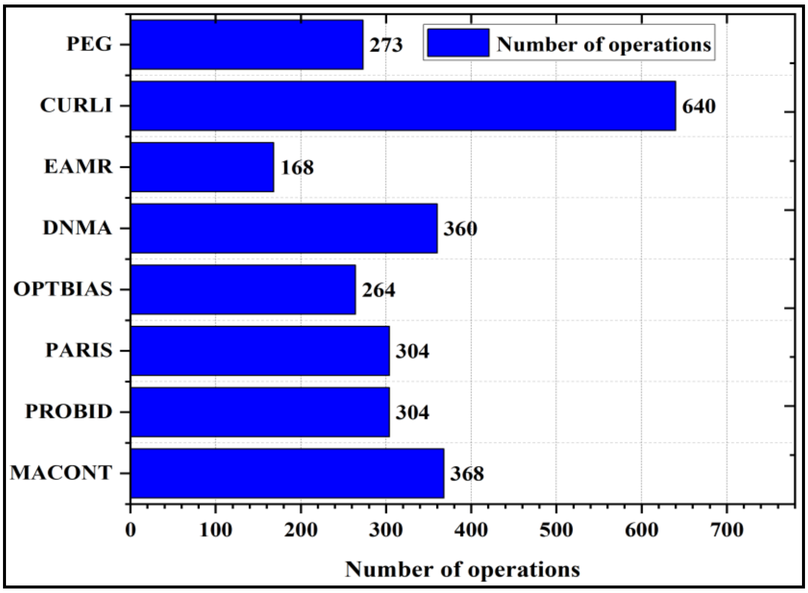


Figure 5.6 Number of operations

e) Number of operations

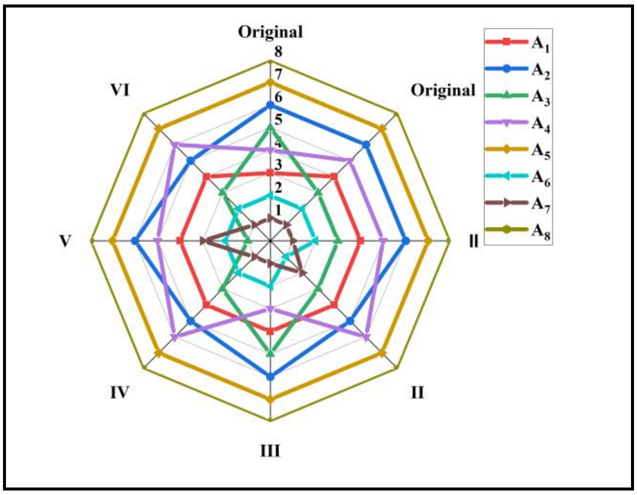
Figure 5.6 shows a comparative analysis between the considered MCDM methods with reference to the total number of mathematical operations required. From this figure, it can be unveiled that in order to solve this decision making problems, the EAMR method requires a comparatively smaller number of operations, 168, followed by OPTBIAS, 264, PEG, 273 and on the other hand PARIS and PROBID, 304, DNMA, MACONT and CURLI, requiring 360, 368 and 640 operations to get the rankings. Thus, in terms of number of operations inside the calculations, the EAMR technique outperforms all the evaluated MCDM methods.

Sensitivity Analyses

This section provides the detailed sensitivity analysis based on three scenarios, gradual removal of criterion, equal weighting condition and considering the weights of different weighting methods.

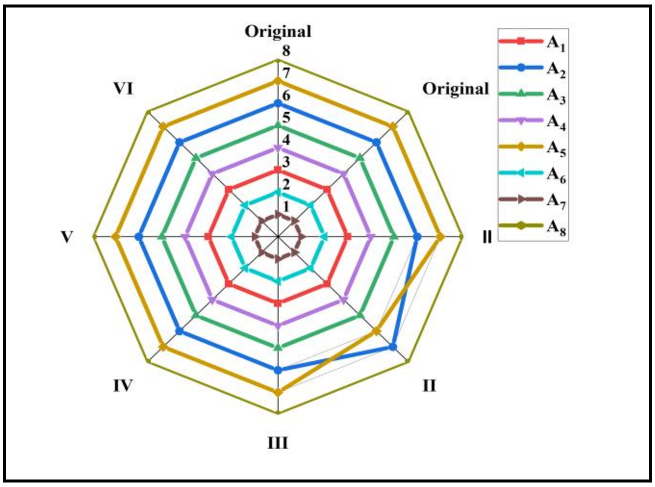
Sensitivity analysis based on gradual removal of criteria

In Figure 5.7, MACONT exhibits moderate sensitivity, with A_4 fluctuating between ranks three and six, indicating variations in performance as criteria are removed. A_7 remains consistently at rank one, while A_8 remains the worst-ranked alternative (rank eight) across all conditions (I, II, III, IV, V and VI), demonstrating its poor performance regardless of weight changes. PARIS shows high ranking stability, with A_1 and A_7 consistently maintaining their ranks two and one, respectively, while A_4 remains stable at rank three, except in the last two conditions (V and VI), where it drops to rank five. DNMA emerges as the most stable method, with A_7 consistently ranking first, A_8 ranking eighth and A_4 maintaining its rank at four across all conditions, reflecting minimal ranking fluctuations. OPTBIAS demonstrates moderate ranking sensitivity, with A_4 generally stable at rank four but shifting to rank five in condition I, while A_3 fluctuates slightly between ranks four and eight and A_8 improves in Condition V but falls back to rank eight in VI. PARIS exhibits high ranking stability, with A_7 ranking first and A_8 ranking eighth across all scenarios, while A_4 remains steady at rank 4, confirming its reliability. EAMR shows moderate sensitivity, with A_3 consistently ranked first, A_4 at rank three and A_8 at rank eight across all conditions, but A_2 and A_7 experience some fluctuations, indicating responsiveness to weight variations. Overall, DNMA, PARIS and PROBID exhibit strong ranking stability, making them more reliable for decision making, while MACONT, OPTBIAS and EAMR show moderate sensitivity to weight variations, particularly for mid-ranked alternatives. A_8 consistently ranks last in all methods, reinforcing its weak performance, whereas A_7 and A_4 frequently rank at the top across multiple methods, confirming their robustness.



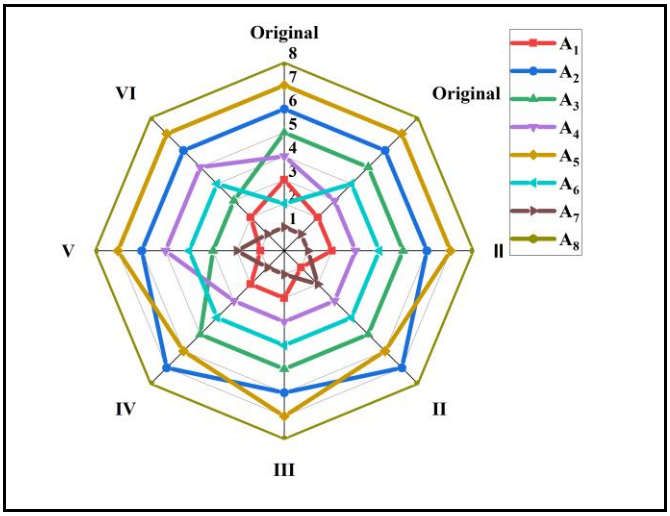
MACONT

(a)



PARIS

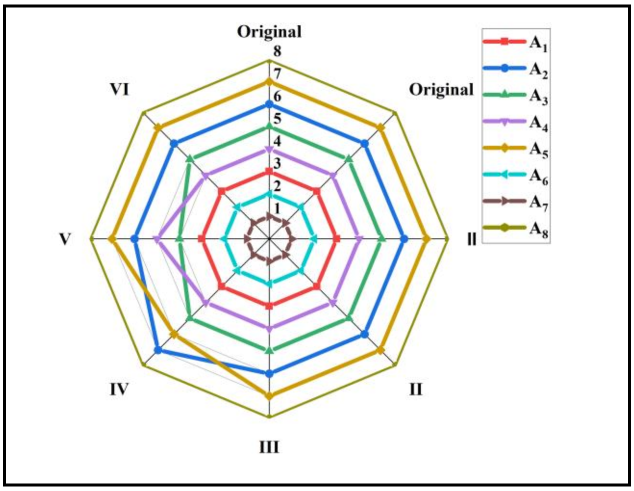
(b)



PROBID

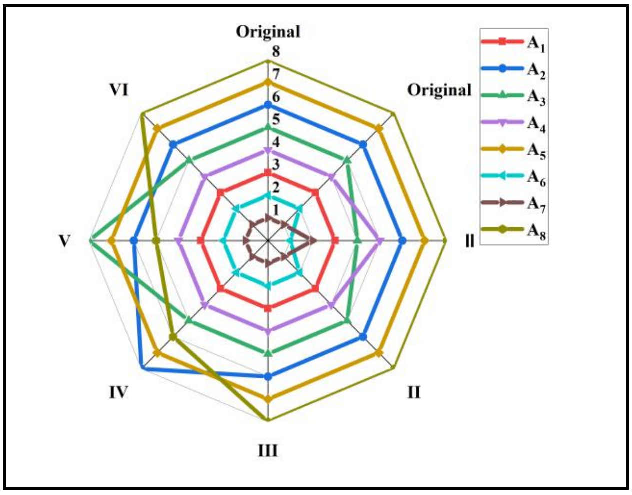
(c)

Figure 5.7 Sensitivity analyses results by gradual removal of criterion weight



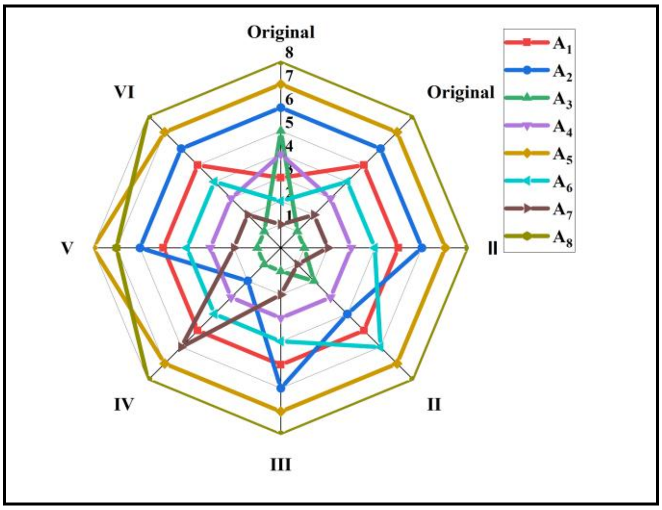
DNMA

(d)



OPTBIAS

(e)



EAMR

(f)

Figure 5.7 Continued

Sensitivity analysis based on equal weighting conditions

Figure 5.8 evaluates the stability of rankings across different weighting methods under equal weighting conditions, revealing variations in alternative performance. A_7 consistently ranks first across all methods, showing it is the best-performing alternative regardless of weighting variations, while A_8 consistently ranks last except in CURLI and PEG, where it improves slightly (fifth and fourth, respectively). A_6 remains stable at rank two in all methods, confirming its robustness. A_1 shows moderate sensitivity, ranking third under most methods but dropping to fifth in EAMR and eighth in CURLI, indicating that its ranking is affected by weight adjustments. A_2 is highly sensitive, fluctuating between ranks three and seven, suggesting that its relative performance depends heavily on the weighting approach. A_3 also shows moderate variability, moving between ranks three and eight, reflecting the impact of different weighting conditions. A_4 remains stable within ranks four to seven, with minor fluctuations, while A_5 demonstrates noticeable sensitivity, shifting between ranks three and seven, showing it is highly affected by weighting adjustments. CURLI and PEG rankings deviate from the others due to their independent ranking structures, making them useful for cross-validation. Overall, A_7 and A_6 are the most stable and best-performing alternatives, while A_8 remains consistently weak and A_2, A_3 and A_5 show the highest sensitivity to weight changes.

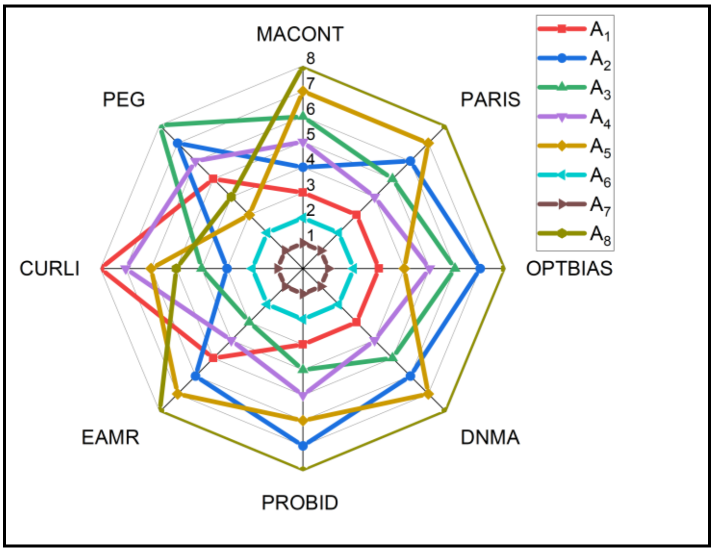
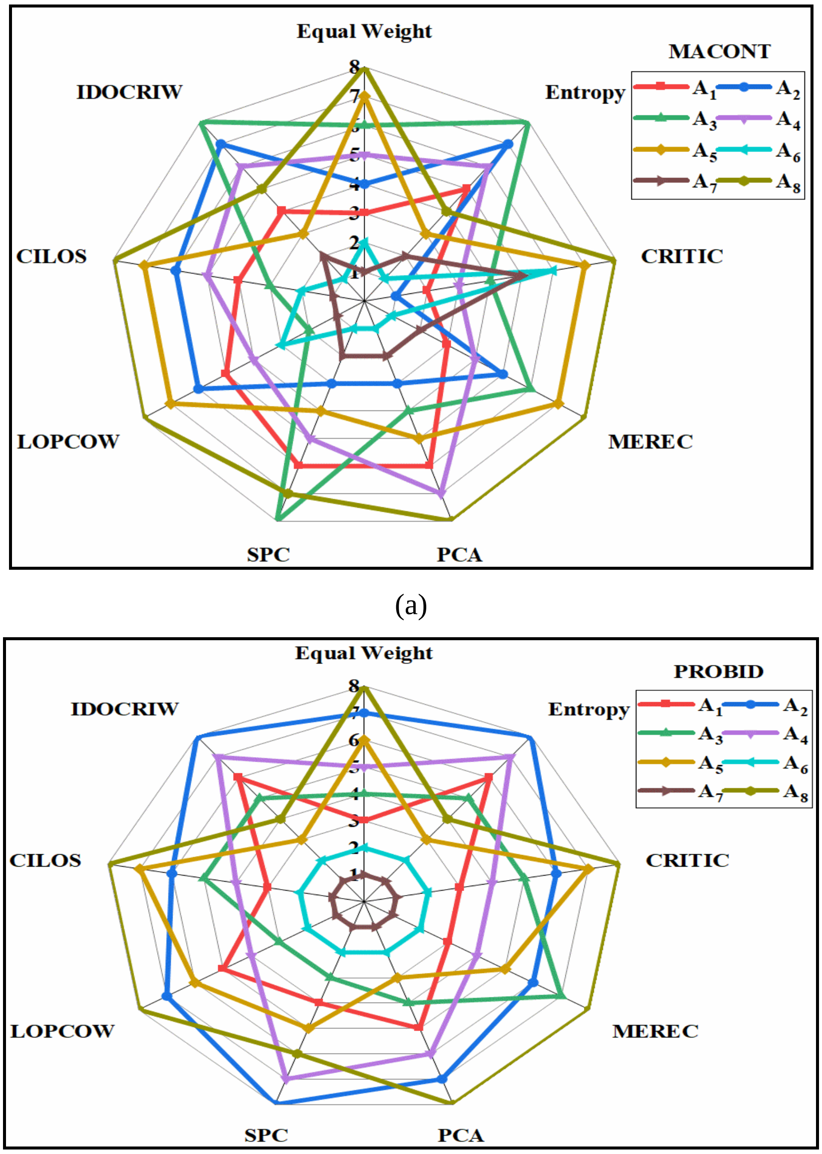


Figure 5.8 Sensitivity analyses results under equal weight condition

Sensitivity analysis based on all weighting conditions

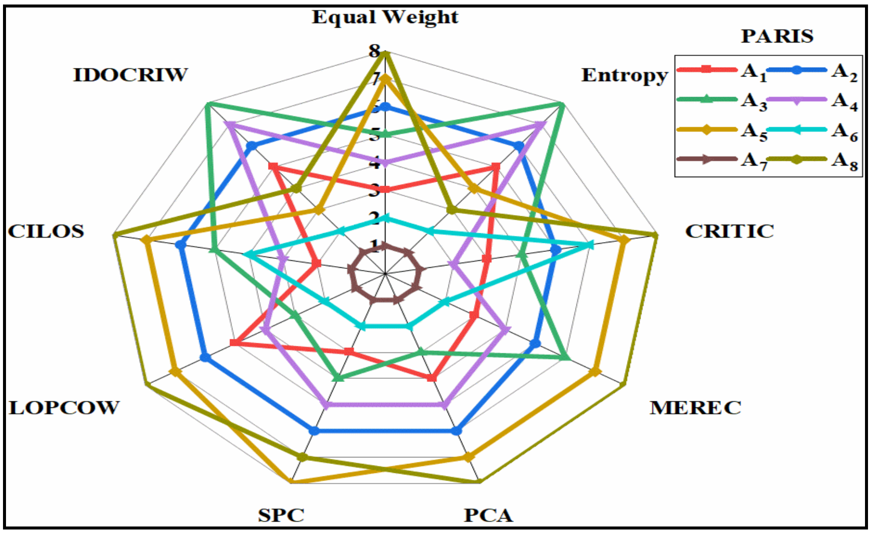
Figure 5.9 shows the sensitivity analysis results where MACONT method exhibits notable sensitivity to different weighting schemes, with significant variability in rankings, particularly for middle-tier alternatives such as A_1, A_2, A_4 and A_5. A_6 consistently performs well across various schemes, securing top rankings in methods such as entropy, MEREC, PCA, SPC and IDOCRIW, while A_8 consistently ranks lowest, demonstrating its weak performance across most weighting approaches. PROBID also shows sensitivity, with A_7 consistently ranked high and A_8 ranking at the bottom, but middle-tier alternatives such as A_3, A_4 and A_5 experience considerable fluctuation. PARIS offers stable rankings for A_7 and A_8, but middle-tier alternatives such as A_4, A_5 and A_6 show variability based on the weighting method used. OPTBIAS stands out by providing stable rankings for top and bottom performers (A_7 and A_8) while exhibiting moderate variability for middle-tier alternatives. It performs well in distinguishing clear leaders and underperformers, but its middle-tier sensitivity is more manageable compared to other methods. DNMA shares similar strengths, with stable rankings for top and bottom alternatives, but shows moderate sensitivity in the middle-tier rankings. EAMR offers consistency for top performers such as A_7 and A_6, but exhibits more variability in the middle-tier rankings. PEG and CURLI, being weight-free methods, provide simplified and stable rankings, particularly for extreme performers, though they lack nuance in distinguishing middle-tier alternatives. In conclusion, DNMA is superior to other methods because it consistently ranks top and bottom performers with high accuracy, while the middle-tier variations are less pronounced compared to methods such as PARIS and MACONT, making DNMA more reliable and suitable for decision making.



(a)

(b)

Figure 5.9 Sensitivity analyses results considering the criteria weight



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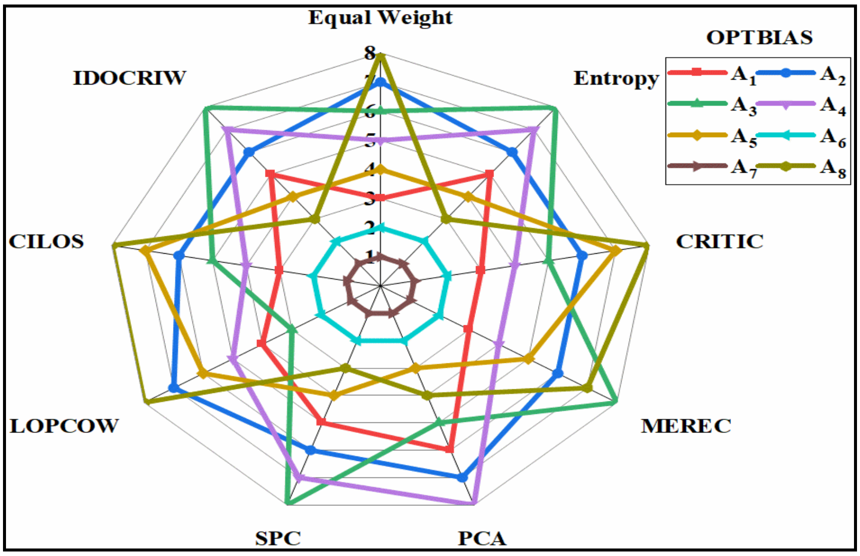
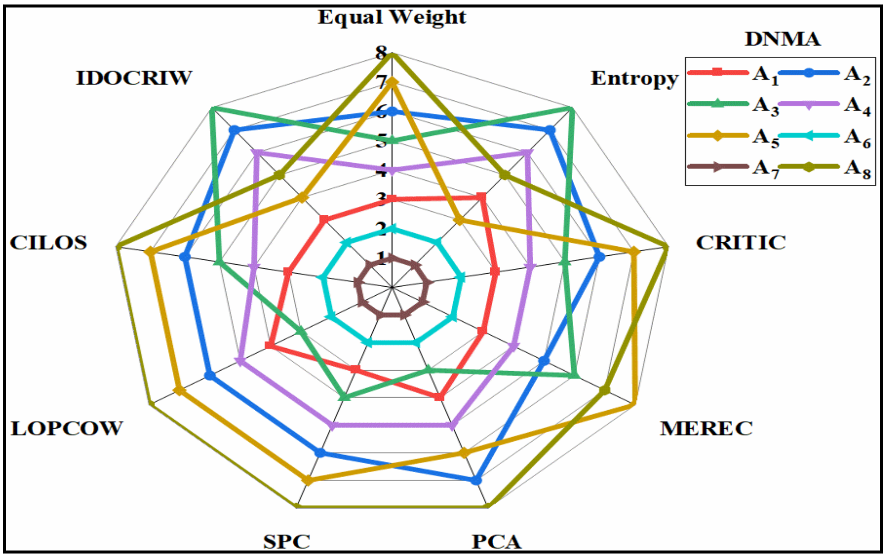
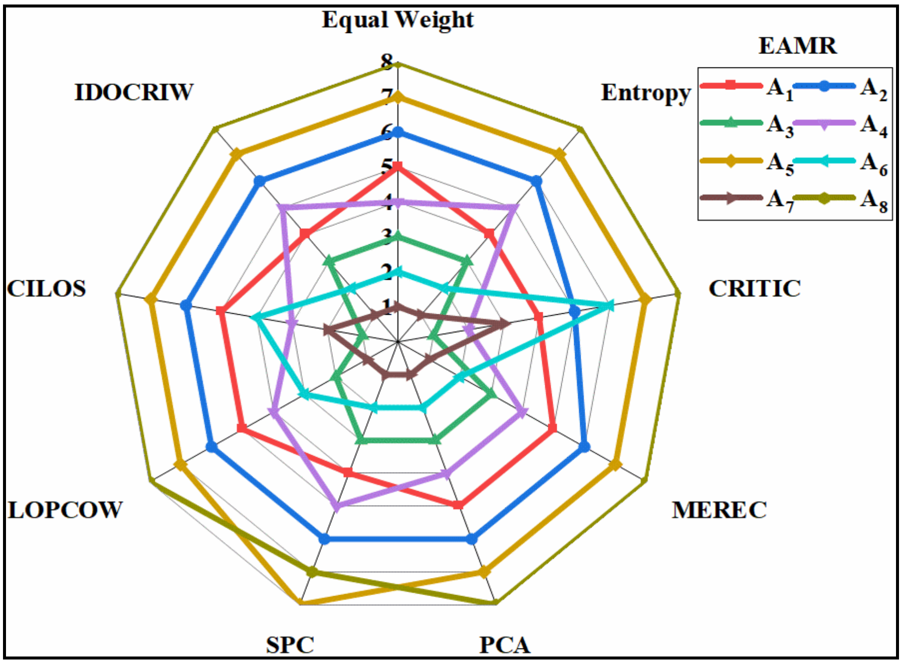


(d)



(e)

Figure 5.9 Continued



(f)

Figure 5.9 Continued

6. COBOT SELECTION

Assembly is the process of connecting individual components or sub-assemblies to develop a finished product with the help of conventional methods (like fastening, riveting, seaming, soldering etc.) or specialised equipment (such as robotic arms or assembly machines). Assembly can be performed either manually or using automated processes. Manual assembly requires human labour, whereas, automated assembly can be performed by machines with minimal human intervention. Automated assembly has become an essential step in the manufacturing process for high-volume production, where efficiency and speed are of critical issue [96]. Use of appropriate tools and equipment can make the assembly process more efficient and accurate, helping to ensure that the finished product should meet the required quality standards. However, existing manual assembly operations in a manufacturing shop floor have several limitations, including inconsistencies and variability due to differences in skill level, human error, safety risks, limited productivity and lack of flexibility. These may result in quality issues, increased waste, production delays, injuries, lost time and increased costs.

To address these constraints, several manufacturers are resorting to automated processes, including the deployment of collaborative robots or cobots, to increase efficiency, efficacy and safety in their assembly operations. Assembly cobots [97, 98] have the potential to overcome many of the current constraints of manual assembly methods on the factory shop floor. They can do tasks faster and more efficiently than humans, resulting in increased output and throughput, as well as enhanced quality and decreased waste. They are especially useful for repetitive or complicated activities that would take human workers a long time to complete. They can accomplish jobs with great accuracy and precision, maintaining consistency while minimising variability in assembly operations [99]. They can also collaborate with human operators to provide a safe and ergonomic workplace. They can carry out jobs with great accuracy and precision, maintaining consistency while minimising variability in assembly operations [99]. They can also collaborate with human operators to provide a safe and ergonomic workplace. Because cobots are very adaptable and can be programmed to do an extensive variety of jobs, they are well suited for a wide range of assembly operations. Although they may have greater upfront expenses, they can deliver a considerable long term return on investment. Assembly cobots and industrial robots are both extensively used to automate assembly operations on manufacturing shop floors. There are, nevertheless, numerous significant variations between them. Assembly cobots are engineered to collaborate with human employees, whereas industrial robots normally work alone. Assembly cobots are typically outfitted with safety features such as sensors and cameras that detect the presence of humans and alter their motions accordingly. On the other hand, industrial robots require safety barriers or cages to avoid accidents. Assembly cobots are meant to be highly flexible and versatile, allowing them to be readily reprogrammed or reconfigured to suit changing production demands. Industrial robots, on the other hand, are frequently designed for specific tasks and may be difficult to reprogramme for numerous use. Assembly cobots are often smaller and more mobile than industrial robots, which are large and immobile. This makes cobots more suitable for smaller workstations and duties requiring movement throughout the manufacturing floor [100]. Cobots are also easy to merge into prevailing production lines, requiring less advanced training to operate. Industrial robots are often built to bear larger loads than assembly cobots, which are better suited to light assembly activities. Cobots feature optimised specifications for assembly jobs, such as large payload capacity, extended reach, excellent repeatability and low weight. Overall, assembly cobots offer greater flexibility, mobility and cost-effectiveness than industrial robots. While both types of robots have their own advantages and limitations, cobots are well-suited for a variety of assembly operations and can help manufacturers to optimise their production processes and improve efficiency and quality in the shop floor.

Assembly cobots can be classified into different categories based on their design, functionality and application. Cobots can be categorised based on their payload capacity (maximum weight they can handle) into three main classes, i.e. low payload (up to 5 kg), medium payload (up to 10 kg) and high payload (up to 50 kg) [101]. They can also be classified depending on their mobility (ability to move around the manufacturing floor) into two main groups, e.g. stationary cobots (fixed at one location) and mobile cobots (can move around the shop floor). Cobots can again be classified into three groups based on their physical form factor, which refers to their shape and size, i.e., articulated cobots (having multiple joints and can move in a wide range of directions), Cartesian cobots (can move in straight lines along X, Y and Z axes) and SCARA cobots (having two parallel joints that allow them to move in a horizontal plane). Based on degree of autonomy (level of human intervention), there are semi-autonomous cobots and fully autonomous cobots. They can also be classified based on the specific task they are designed to perform, such as assembly, pick-and-place operations, welding, material handling and spray painting. Overall, the classification of assembly cobots helps the manufacturers to choose the right type of cobot for their specific needs and applications. By understanding different categories of cobots, manufacturers can optimise their assembly operations and improve productivity, quality and safety in the shop floor. As a result, the most crucial decision to make when contemplating and addressing a cobot selection problem is to determine what kind of applications and operations the cobot is utilised for. For example, when selecting an assembly cobot, some of the criteria that may be considered include payload capacity, accuracy, repeatability, power consumption and cost. Each of these criteria has a different level of importance depending on the specific requirement and objective of the assembly operation. Moreover, improving one criterion often comes at the expense of another, making it difficult to identify the best solution that satisfies all the criteria.

Hence, assembly cobot selection can be considered as a typical MCDM problem as it involves evaluation of several criteria which are often conflicting or require trade-offs. MCDM methods offer a structured way to compare alternatives and support informed, balanced decisions aligned with operational needs.

6.1 Review of MCDM in robot and cobot selection

Bahadir [102] proposed a model to aid in estimating importance weight of criteria and alternative evaluations in a single group decision making environment and applied VIKOR for final selection of cobot. Mecheri and Greene [103] first shortlisted some specific criteria for evaluating various cobots and employed an improved MCDM algorithm to select the most suitable cobot for a manufacturing/service industry. Bhalaji et al. [104] adopted decision making trial and evaluation laboratory (DEMATEL) method to evaluate the influential interaction risk factors between human-robot interaction during an assembly operation. Accorsi et al. [105] proposed a generalized methodology to support the study of technical and economic feasibility of implementing cobots in a food catering industry. Cohen et al. [106] provided a review of the concerns connected to cobot acquisition and implementation, as well as a productivity study to support the same concern. Based on a comprehensive review, Silva et al. [107] identified those evaluation criteria significantly influencing the cobot selection decision. It can be noticed that the available literature on cobot selection is notably limited, with only a handful of studies focusing on applications of MCDM techniques for the said purpose. To address this gap in knowledge, a separate review is also conducted on the applications of different MCDM tools for solving human-robot and industrial robot selection problems.

Industrial robot selection

Athawale and Chakraborty [108] analyzed the efficacy of different rankings while solving a robot selection problem and concluded that almost all the adopted approaches would result in identification of the same robot. Chatterjee et al. [109] investigated the best robots within the given manufacturing environments. Adakane and Narkhede [110] adopted three different MCDM techniques, i.e. AHP, TOPSIS and PROMETHEE to choose the best robot alternative for powder coating operation. Chakraborty et al. [111] validated the applicability and usefulness of WASPAS method as an MCDM tool for solving robot selection problems. Other studies have also employed different MCDM methods for the same purpose. Xue et al. [112] introduced QUALIFLEX method to tackle robot evaluation and selection under incomplete weight information in general industrial applications. Mirfankhradi et al. [113] applied AHP and TOPSIS for technology selection. Breaz et al. [114] and Simion et al. [115] both employed AHP for selecting industrial robots, with Breaz focusing on milling operations and Simion targeting military industry applications. Chodha et al. [116] integrated TOPSIS method with entropy weighting for selecting robots in industrial arc welding applications. Sen et al. [117] extended PROMETHEE method by incorporating objective and fuzzy subjective data. Karande et al. [118] utilized WSM, WPM, WASPAS and MOORA to evaluate the ranking performance. Yalçın and Uncu [119] applied EDAS method for selecting suitable industrial robots, while Suszyński and Rogalewicz [120] used SMART for robot selection in assembly operations. Goswami et al. [121] introduced ARAS and COPRAS, for the robot selection problem. Kumar et al. [122] applied CoCoSo for selecting spray painting robots, while Shanmugasundar et al. [123] utilized MABAC method for similar tasks. Bairagi [124] introduced TARO, to ensure accurate rankings in robot selection processes. Thus, it can be concluded that although there are applications of different MCDM tools and criteria weighting techniques for solving industrial robot and cobot selection problems, they suffer from several disadvantages, such as complicated computational steps, dependency on data, inconsistent decisions etc. To resolve these issues, this chapter proposes application of new newly developed MCDM methods for solving an assembly cobot selection problem for an automobile industry based on real-time data.

6.2 Illustrative example

To demonstrate the application of these newly developed approaches in solving an assembly cobot selection problem, an illustrative example consisting of 13 alternative cobot models is considered in this chapter, which are appraised with respect to six evaluation criteria, i.e. payload (C_1) (in kg), reach (C_2) (in mm), repeatability (C_3), weight (C_4) (in kg), power consumption (C_5) (in W) and cost (C_6) (in USD). Among them, C_1 and C_2 are beneficial in nature while C_3, C_4, C_5 and C_6 are non-beneficial (cost) attributes. Payload refers to the maximum load that a cobot can lift, carry or manipulate during a given assembly operation. It determines the type and size of the object that the cobot can handle, avoiding any potential safety hazard or limitation in the assembly process. Reach represents the distance that a cobot can outstretch from its base, including length of its arms and end-effectors. The reach of a cobot is supposed to be an important criterion determining size of the workspace and number of assembly operations that it can perform. Repeatability refers to the precision with which a cobot can perform the same assembly operation with minimum deviation from the target. It also plays a crucial role while selecting a cobot for a given assembly operation requiring higher accuracy and consistency. Repeatability enables cobots to precisely position parts on a constant basis, reducing assembly errors and maintaining integrity of the finished products. Repetitive assembly jobs also necessitate consistent execution and higher repeatability allows the cobots to complete operations with the same level of accuracy, resulting in uniform product quality and lower variation in outcomes. Weight refers to the weight of the cobot itself, affecting mobility, flexibility and its ease of operation. A lightweight cobot can always be easily moved and repositioned to different assembly stations, while a heavier cobot may be more limited in its mobility. Power consumption denotes the amount of power that a cobot consumes during its operation. It significantly affects operating cost and energy efficiency of a cobot. Cost refers to the price of cobot, including both the initial investment cost and any ongoing maintenance or operating cost. It may be treated as the most important criterion influencing overall affordability and cost-effectiveness of a specific assembly operation. Table 6.1 provides the complete initial decision matrix. The information regarding technical specifications of these assembly cobots is accumulated from various catalogues/websites of the concerned manufacturers [125, 126]. LOPCOW weighting method is used in this study. Calculation of OPTBIAS method is demonstrated in detail.

Table 6.1 Decision matrix for the assembly cobot selection problem

Cobot		Criteria					
		C_1	C_2	C_3	C_4	C_5	C_6
		Payload (kg)	Reach (mm)	Repeatability (mm)	Weight (kg)	Power consumption (W)	Cost (USD)
A_1	Universal Robots UR5	5	850	0.03	20.7	250	45000
A_2	Yaskawa Motoman HC10DP	10	1200	0.05	58	500	39000
A_3	DENSO VP6242	2.5	432	0.02	15	300	30000
A_4	F&P Robotics F&P ILD	5	900	0.1	16	200	30000
A_5	Stäubli TX2-60	4.5	670	0.02	52	700	50000
A_6	Elfin-P	3	590	0.02	19	100	15000
A_7	Fanuc CR-4Ia	4	550	0.01	48	500	30000
A_8	LBR iisy 3 R760	3	760	0.1	22.8	450	80000
A_9	Aubo-i3	3	625	0.05	16	150	20000
A_{10}	DOOSAN-M0609	6	900	0.03	27.5	850	30000
A_{11}	Techman-TM5-700	6	700	0.05	22.1	220	20000
A_{12}	CRB 15000	5	950	0.03	28	580	28000
A_{13}	KAWASAKI-RS007L	7	930	0.03	36	850	30000

OPTBIAS method

LOPCOW method is first adopted to determine criteria weights. Applying Eqs. (2.9) - (2.13), the corresponding criteria weights are determined, as provided in Table 6.2. It is noted that cost (C_6) has the maximum priority weight, followed by repeatability (C_3). Now, employing the Eqs. (3.37) - (3.47) of OPTBIAS method. The computed bi-positive ideal, bi-negative ideal and average solutions are provided in Table 6.3. Table 6.4 exhibits the corresponding values of the Euclidean distances of the alternative assembly cobots from the positive ideal solution, negative ideal solution and average solutions. This table also provides values of *B* and *PS*. Table 6.4 shows that the Elfin-P model, which has the highest performance score, is at the top of the ranking list. The Techman-TM5-700 model is next in line. On the other hand, minimum preference is assigned to LBR iisy 3 R760 model for the given assembly operation. Relatively low cost, repeatability, weight and power consumption and moderate payload and reach justify selection of Elfin P model as the most suitable assembly cobot.

Table 6.2 Criteria weights measured using LOPCOW method

Weight	C_1	C_2	C_3	C_4	C_5	C_6
	0.1023	0.1497	0.1994	0.1684	0.1442	0.2359

Table 6.3 Bi-positive ideal, bi-negative ideal and average solutions

Bi-positive ideal solution	BP(1)	0.0535	0.0624	0.0111	0.0216	0.0080	0.0258
	BP(2)	0.0374	0.0525	0.0240	0.0260	0.0157	0.0408
Bi-negative ideal solution	BN(1)	0.0134	0.0225	0.1108	0.0833	0.0680	0.1378
	BN(2)	0.0174	0.0326	0.0877	0.0733	0.0643	0.0857
Average solution	A	0.0263	0.0402	0.0460	0.0421	0.0348	0.0592

Table 6.4 Ranking of the assembly cobots using OPTBIAS method

Cobots	*RP*	*RN*	*RA*	*B*	*PS*	Rank
A_{1}	0.1071	0.2087	0.0298	1.9485	1.9157	6
A_{2}	0.1692	0.1751	0.0557	1.0347	1.4140	11
A_{3}	0.1063	0.2444	0.0406	2.2979	2.1526	3
A_{4}	0.1962	0.2033	0.0708	1.0361	1.4152	10
A_{5}	0.1835	0.1714	0.0533	0.9341	1.3673	12
A_{6}	0.0856	0.2797	0.0531	3.2677	2.9740	1
A_{7}	0.1378	0.2234	0.0467	1.6214	1.7186	7
A_{8}	0.2934	0.1380	0.1028	0.4705	1.1738	13
A_{9}	0.1096	0.2382	0.0419	2.1728	2.0648	4
A_{10}	0.1325	0.2031	0.0375	1.5330	1.6684	8
A_{11}	0.0948	0.2280	0.0339	2.4057	2.2311	2
A_{12}	0.0984	0.2098	0.0225	2.1326	2.0366	5
A_{13}	0.1384	0.1977	0.0401	1.4280	1.6112	9

MACONT method

Now MACONT method is utilized. In Table 6.1, Eqs. (3.2), (3.3) and (3.4) are first applied to obtain the normalized values. To obtain comprehensive decision matrix values Eq. (3.5) is applied. To calculate the subordinate comprehensive values, Eqs. (3.6) and (3.7) are used, considering the $\delta = 0.5$ and $\vartheta = 0.5$ respectively. Finally, the comprehensive scores are evaluated using Eq. (3.8). The ranking results are provided in Table 6.5. It is revealed that A_6, is the best cobot followed by A_{11} as they secure the first and second positions respectively.

Table 6.5 Ranking results using MACONT method

Alternative	ρ_i	Q_i	$S_1(A_i)$	$S_2(A_i)$	$S(A_i)$	Rank
A_{1}	0.0167	6.6665	0.2556	-0.0055	0.0733	7
A_{2}	-0.0182	0.2525	-0.0298	-0.0058	-0.0722	11
A_{3}	0.0209	5.5747	0.2282	0.0021	0.1352	5
A_{4}	0.0143	9.049	0.3293	-0.0122	0.0448	8
A_{5}	-0.0971	0.2882	-0.1943	-0.0104	-0.1999	12
A_{6}	0.1314	2.0111	0.3423	0.0216	0.3837	1
A_{7}	-0.0085	1.0716	0.0176	0.0152	0.1582	4
A_{8}	-0.1509	0.2613	-0.3081	-0.034	-0.4882	13
A_{9}	0.056	0.9061	0.1474	0.0088	0.1603	3
A_{10}	-0.0089	4.1545	0.1187	-0.012	-0.0587	10
A_{11}	0.0487	1.6775	0.1577	0.0088	0.1654	2
A_{12}	0.0111	3.9837	0.1551	-0.0001	0.0762	6
A_{13}	-0.0156	5.3897	0.1455	-0.0103	-0.029	9

PARIS method

Now, PARIS method is applied using LOPCOW weights. Using Eqs. (3.10) to (3.16), three weighted normalized matrices are obtained, as shown in Table 6.1. The alternatives are ranked by calculating the sum of the weighted matrix (π_i^{ω}) using Eq. (3.17). The reference ideal solution (z_j*) is determined using Eq. (3.18), followed by the computation of π_i^* and R_i using Eqs. (3.19) and (3.20). Table 6.6 presents the ranking results based on ascending R_i values, where A_6 ranks first, followed by A_{11}. The results indicate that A_6 is the most optimal choice based on the LOPCOW-weighted PARIS method, closely followed by A_{11}. This further reinforces the consistency of the ranking across different methods and provides additional confidence in the decision-making process.

Table 6.6 Ranking results using PARIS method

Alternative	R_i (WAY_1)	Rank	R_i (WAY_2)	Rank	R_i (WAY_3)	Rank
A_1	0.3143	5	0.4723	7	0.1253	4
A_2	0.3656	11	0.5099	11	0.2388	10
A_3	0.3068	4	0.4285	5	0.1624	6
A_4	0.3628	10	0.4040	4	0.2142	7
A_5	0.4312	12	0.6297	12	0.4747	12
A_6	0.2509	1	0.1584	1	0.0000	1
A_7	0.3549	9	0.4358	6	0.3068	11
A_8	0.5410	13	0.6812	13	0.6537	13
A_9	0.2979	3	0.3378	2	0.1070	3
A_{10}	0.3445	7	0.4933	9	0.2161	8
A_{11}	0.2911	2	0.3846	3	0.0813	2
A_{12}	0.3173	6	0.4785	8	0.1406	5
A_{13}	0.3513	8	0.5041	10	0.2356	9

EAMR method

While applying the EAMR method, initially the normalized and weighted normalized matrix are calculated using Eqs. (3.21) and (3.22) respectively, using LOPCOW weights. Now, employing Eqs. (3.23), (3.24) and (3.25), the related rank value and evaluation scores are evaluated and presented in Table 6.7. A_6 emerges as the best alternative. From Table, it is also observed that A_{11} is the second best, whereas, A_8 is the worst choice.

Table 6.7 Ranking results based on EAMR method

Alternative	Gi^+	Gi^-	$RV(Gi^+)$	$RV(Gi^-)$	S_i	Rank
A_1	0.1572	0.2951	0.0823	0.0662	1.2445	4
A_2	0.252	0.468	0.132	0.1049	1.2579	3
A_3	0.0795	0.2228	0.0416	0.05	0.8332	10
A_4	0.1634	0.3683	0.0856	0.0826	1.0367	9
A_5	0.1296	0.4571	0.0679	0.1025	0.6624	12

A_6	0.1043	0.1563	0.0546	0.035	1.5592	1
A_7	0.1095	0.3327	0.0574	0.0746	0.7692	11
A_8	0.1255	0.5779	0.0657	0.1296	0.5073	13
A_9	0.1087	0.2306	0.0569	0.0517	1.1008	7
A_{10}	0.1737	0.3724	0.091	0.0835	1.0894	8
A_{11}	0.1487	0.2602	0.0779	0.0583	1.3351	2
A_{12}	0.1697	0.3221	0.0889	0.0722	1.2304	5
A_{13}	0.1876	0.3971	0.0983	0.089	1.1039	6

CURLI method

On applying the CURLI method, the scoring matrix for each of the six criteria is first developed. Table 6.8 shows the calculated and rearranged processed scoring matrix, such that cells above the main diagonal are negative or 0. The alternative placed in the first row is termed as the best. Table 6.9 displays the ranking result. A_6 secures the top position followed by A_2.

Table 6.8 Processing scoring matrix after changing the positions of rows and columns

Alternative	P_6	P_2	P_{10}	P_{12}	P_4	P_{11}	P_{13}	P_7	P_9	P_1	P_8	P_3	P_5
A_6	0	0	-3	-3	-1	-4	2	-1	-4	-1	-2	1	-2
A_2	-4	0	-4	-4	0	-5	2	1	-5	0	-2	2	-2
A_{10}	3	0	0	-1	0	-3	2	-1	-4	-1	-2	1	-2
A_{12}	3	0	1	0	-1	-2	2	-2	-4	0	-2	0	-4
A_4	3	0	2	1	0	0	0	-3	-5	-3	1	-1	-4
A_{11}	4	0	3	2	0	0	2	-4	-4	0	4	-2	-4
A_{13}	6	-2	6	6	0	6	0	-2	3	-2	5	-3	-1
A_7	3	-1	3	2	3	0	2	0	-2	2	0	-1	-2
A_9	4	-1	4	4	-1	4	1	-2	0	0	5	-2	0
A_1	3	0	3	2	3	0	2	-2	-4	0	2	0	-4
A_8	2	2	2	2	5	-4	3	0	-5	6	0	2	0
A_3	5	-2	5	4	1	2	3	1	2	0	6	0	-1
A_5	2	2	2	0	4	0	1	2	-4	4	0	1	0

Table 6.9 Ranking result using CURLI method

Alternative	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}
Rank	10	2	12	5	13	1	8	11	9	3	6	4	7

PEG method

The same problem is now solved using the PEG method. The final MSE values are displayed in Table 6.10. It is noted from this table that A_6 is the top ranked alternative.

Table 6.10 Ranking results using PEG method

Alternative	x	y	x^*	y^*	MSE	Rank
A_1	0.0000	0.0690	0.2929	0.3417	863.3247	8
A_2	0.0068	0.0612	0.2977	0.3361	833.4674	9
A_3	0.0068	0.0601	0.2977	0.3354	879.9939	3
A_4	0.0068	0.0562	0.2977	0.3327	742.7509	13
A_5	0.0205	0.0530	0.3074	0.3304	886.7103	2
A_6	0.0341	0.0473	0.3170	0.3264	901.046	1
A_7	0.0273	0.0511	0.3122	0.3290	879.0726	4
A_8	0.0341	0.0443	0.3170	0.3242	747.065	12
A_9	0.0341	0.0403	0.3170	0.3214	826.3147	11
A_{10}	0.0477	0.0335	0.3267	0.3166	869.7448	6
A_{11}	0.0477	0.0259	0.3267	0.3112	827.2307	10
A_{12}	0.0614	0.0120	0.3363	0.3013	865.726	7
A_{13}	0.1023	0.0000	0.3652	0.2929	870.3363	5

PROBID method

While applying the PROBID method, Eqs. (3.48) and (3.49) are used to normalize and weighted normalize respectively. The ideal and average solutions are obtained based on Eqs. (3.50)-(3.52). The Euclidean distances ($E_{i(k)}$) and the average solutions ($E_{i(avg)}$) are computed based on Eqs. (3.53) and (3.54). Table 6.11 provides the positive ideal ($E_{i(pos\text{-}ideal)}$), negative ideal ($E_{i(neg\text{-}ideal)}$), positive-ideal or negative-ideal ratio (RA_i) and performance score (PS_i) of each of the alternatives, obtained using Eqs.(3.55)-(3.58). Table 6.11 shows that A_6 occupies the top position followed by A_3.

Table 6.11 Ranking results using PROBID method

Alternative	$E_{pos-ideal}$	$E_{neg-ideal}$	RA	PS	Rank
A_1	0.1273	0.2264	0.5624	0.7894	6
A_2	0.2164	0.2166	0.9989	0.5563	11
A_3	0.1219	0.2594	0.47	0.8597	2
A_4	0.246	0.2486	0.9896	0.5761	10
A_5	0.2261	0.203	1.1136	0.4997	12
A_6	0.1026	0.3024	0.3392	0.9499	1
A_7	0.1682	0.2445	0.6879	0.7255	7
A_8	0.3677	0.2101	1.7496	0.349	13
A_9	0.1302	0.2575	0.5055	0.8383	4
A_{10}	0.1621	0.2209	0.7339	0.6875	8
A_{11}	0.1144	0.2444	0.4681	0.8542	3
A_{12}	0.1166	0.2177	0.5356	0.7996	5
A_{13}	0.1715	0.2189	0.7838	0.6596	9

DNMA method

Employing the DNMA method, the decision matrix is normalized using linear and vector approaches based on Eqs. (3.59) and (3.60). The adjusted weight coefficients are estimated using Eqs. (3.61), (3.62) and (3.63). The utility values are then computed using CCM, UCM and ICM operators applying Eqs. (3.64)-(3.66) as shown in Table 6.12. Based on the computed values, the cobots are ranked in descending, ascending and descending orders respectively. Finally, the comprehensive utility values are calculated using Eq. (3.67). Thirteen cobots are ranked by their S_i values, with A_6 emerging as the best alternative, followed by A_{11}.

Table 6.12 Ranking results based on DNMA method

Alternative	CCM		UCM		ICM		Utility value (Si)	Rank
	$u_1(a_i)$	Rank	$u_2(a_i)$	Rank	$u_3(a_i)$	Rank		
A_1	0.6662	3	0.0869	1	0.8673	4	0.7537	3
A_2	0.5720	8	0.1743	9	0.8106	10	0.5043	8
A_3	0.6287	5	0.1359	7	0.8653	5	0.6542	5
A_4	0.5916	7	0.2027	12	0.8030	11	0.5067	7
A_5	0.4014	12	0.1500	8	0.7673	12	0.3534	12
A_6	0.7391	1	0.1143	4	0.9092	1	0.8546	1
A_7	0.5157	11	0.1338	6	0.8231	7	0.4783	10
A_8	0.3030	13	0.2027	12	0.6846	13	0.2413	13
A_9	0.6636	4	0.1143	4	0.8694	3	0.7271	4
A_{10}	0.5660	9	0.1765	10	0.8198	8	0.4963	9
A_{11}	0.6847	2	0.0901	2	0.8785	2	0.8050	2
A_{12}	0.6258	6	0.1130	3	0.8513	6	0.6391	6
A_{13}	0.5531	10	0.1765	10	0.8146	9	0.4680	11

Comparative analyses of MCDM methods

This section presents a thorough comparative analysis using various criteria weights. These weights are combined with MCDM methods, in order to evaluate and compare the ranking outcomes. Table 6.13 displays the criteria weights used in this study.

Table 6.13 Set of criteria weights

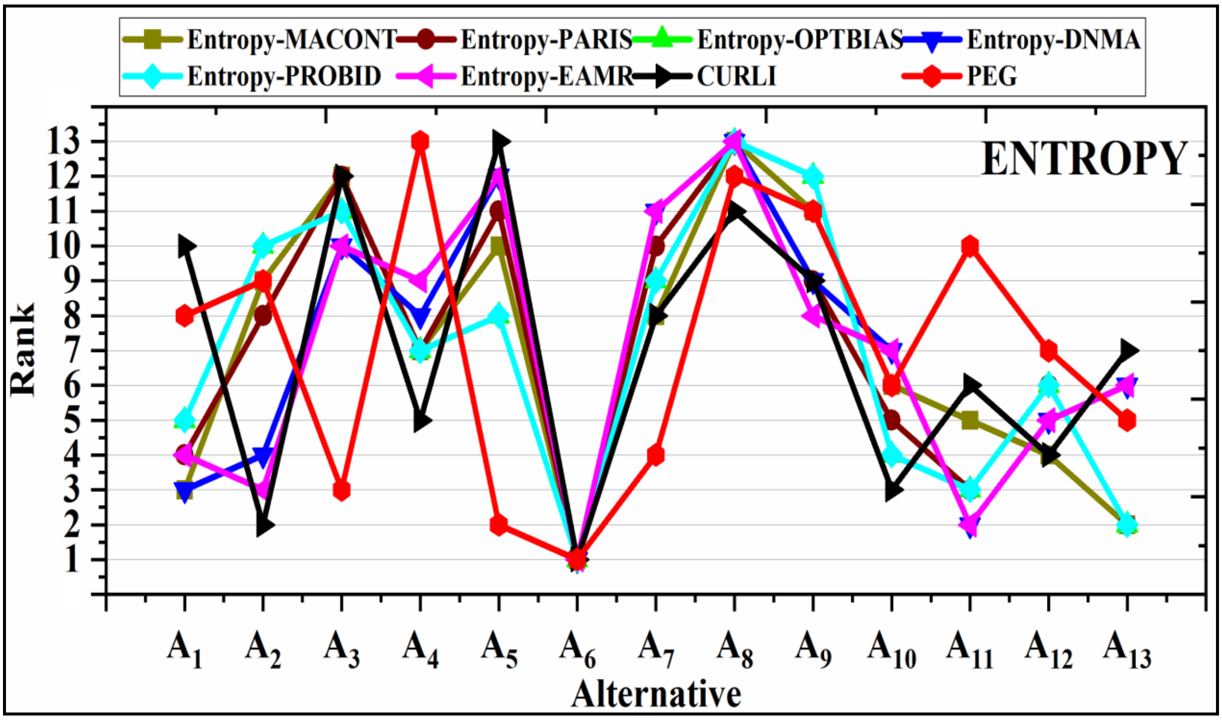
Weighting methods	C_1	C_2	C_3	C_4	C_5	C_6
Entropy	0.4283	0.1904	0.1275	0.0779	0.0968	0.0791
CRITIC	0.1505	0.1553	0.1875	0.1993	0.1916	0.1159
MEREC	0.1271	0.1156	0.2297	0.1626	0.1751	0.1899
PCA	0.1636	0.2262	0.1721	0.194	0.2211	0.3244
SPC	0.1288	0.0644	0.2648	0.1651	0.2029	0.174
LOPCOW	0.1023	0.1497	0.1994	0.1684	0.1442	0.2359
CILOS	0.167	0.209	0.1653	0.1908	0.1128	0.1551
IDOCRIW	0.4196	0.2335	0.1237	0.0872	0.0641	0.072

a) Based on rank comparison

Figure 6.1 clearly indicates that alternative A_6 consistently secures the top rank across nearly all methods, followed occasionally by A_1 and A_{13}. Alternatives A_1, A_2, A_3 and A_7 also frequently achieve high ranks, reflecting their relative strengths. In contrast, A_8 and A_{12} often rank lowest, indicating weaker performance. The variations in rankings demonstrate the differing prioritization mechanisms. A_6 emerges as the most dependable choice under various weighting scenarios. Both DNMA and PARIS consistently prioritize alternatives like A_1, A_3 and A_6, ensuring reliable rankings.

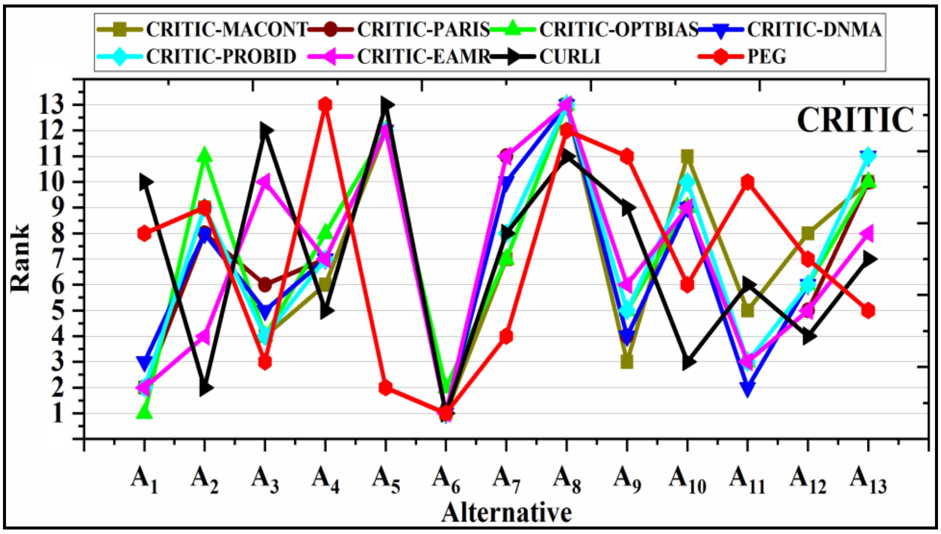
b) Based on Spearman correlation

Figure 6.2 presents the Spearman correlation among various MCDM methods. CURLI and PEG consistently perform poorly, while most other methods show strong correlations across different weighting schemes. Under entropy weighting, OPTBIAS-PROBID shows perfect correlation of 1 and DNMA-EAMR reaches 0.99. With CRITIC and MEREC, DNMA-PARIS and OPTBIAS-PROBID exhibit high correlations, up to 0.99, while PEG and CURLI remain weak. PCA and SPC also yield high correlations for DNMA-PARIS and OPTBIAS-PROBID, with EAMR, PEG and CURLI underperforming. OPTBIAS-PROBID and DNMA-PARIS again demonstrate strong agreement.

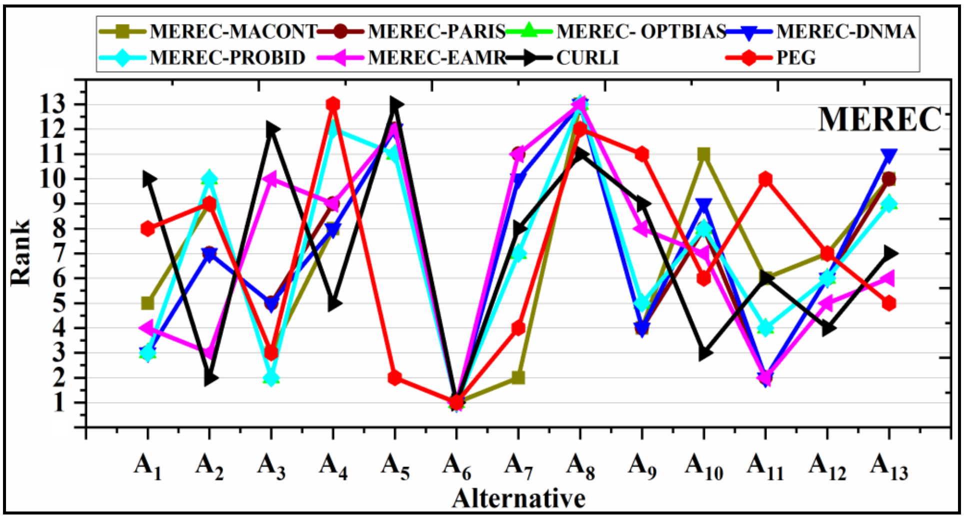


(a)

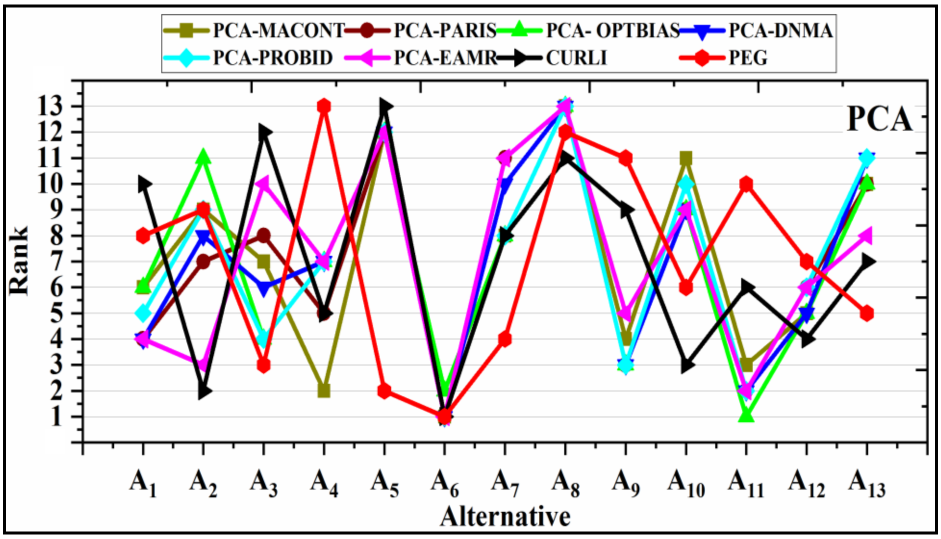
Figure 6.1 Weight wise ranking results



(b)

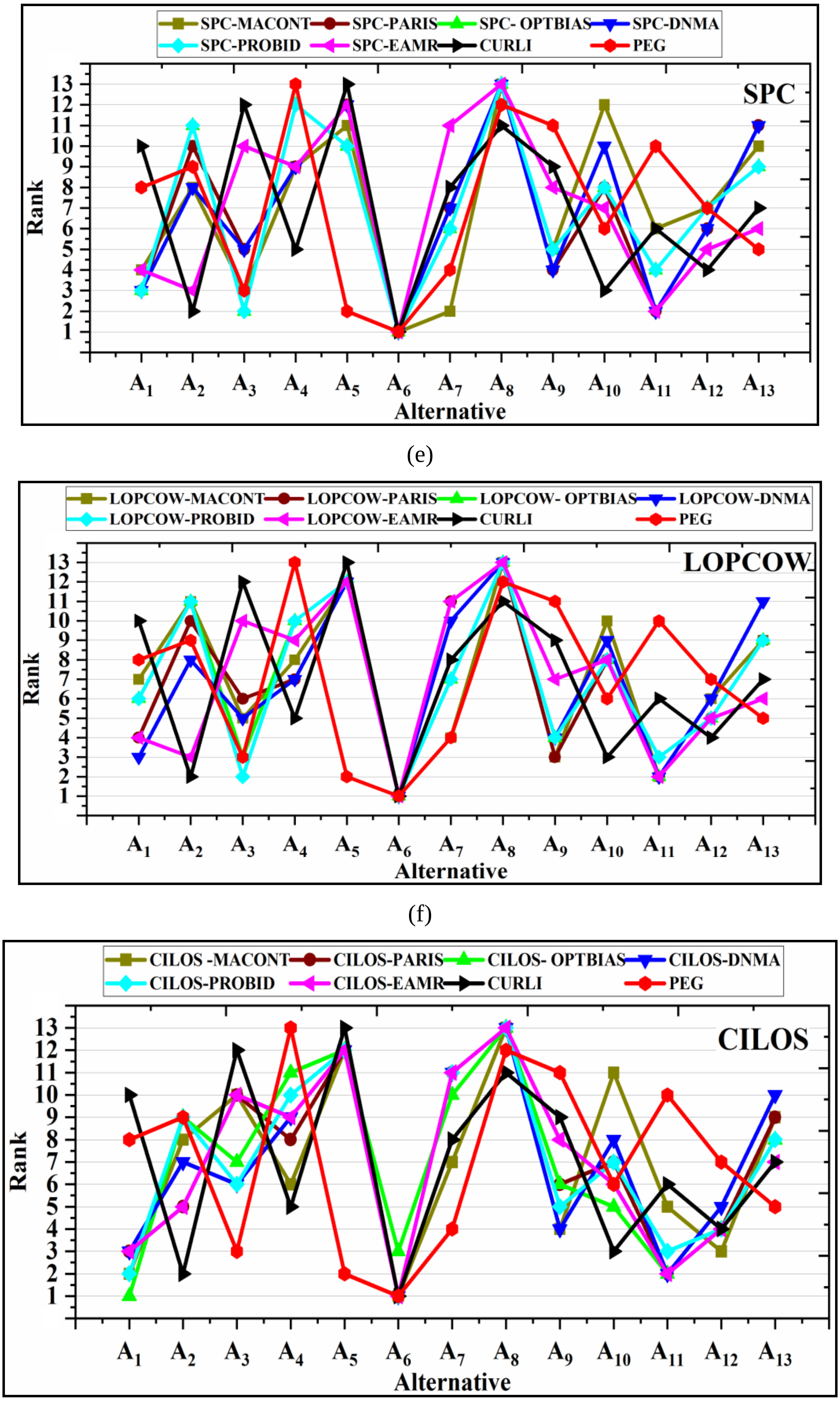


(c)



(d)

Figure 6.1 Continued

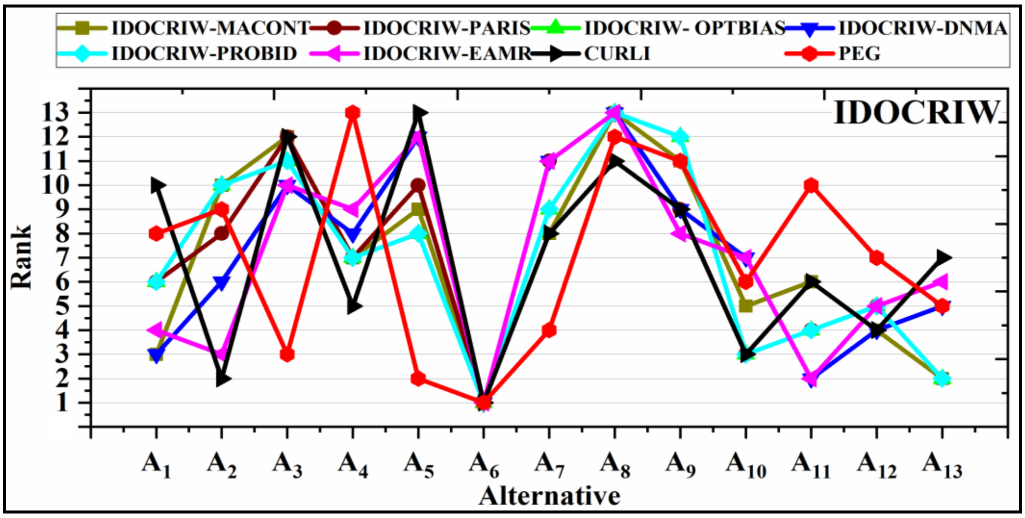


(e)

(f)

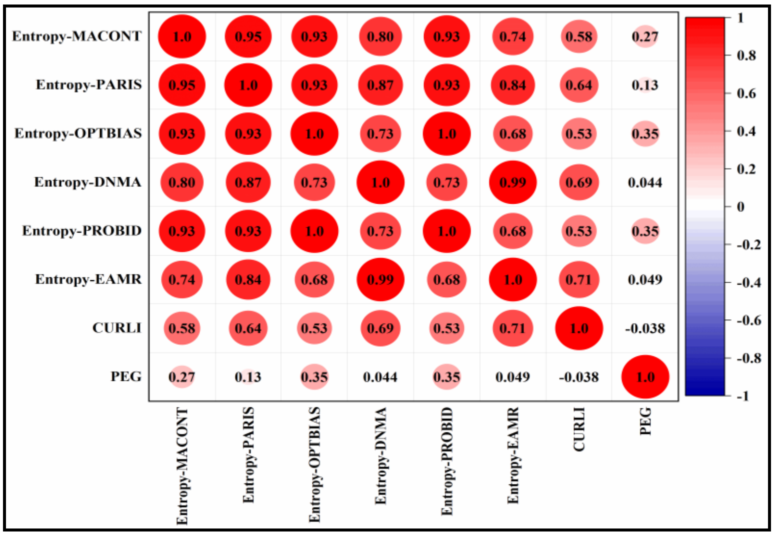
(g)

Figure 6.1 Continued



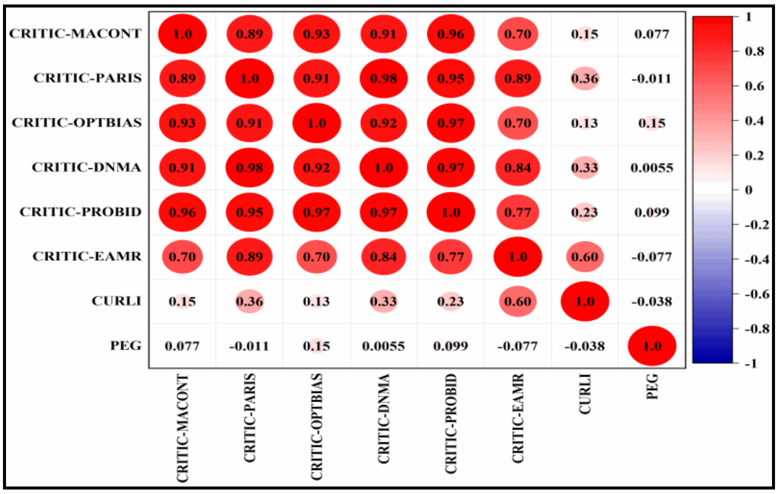
(h)

Figure 6.1 Continued



	Entropy-MACONT	Entropy-PARIS	Entropy-OPTBIAS	Entropy-DNMA	Entropy-PROBID	Entropy-EAMR	CURLI	PEG
Entropy-MACONT	1.0	0.95	0.93	0.80	0.93	0.74	0.58	0.27
Entropy-PARIS	0.95	1.0	0.93	0.87	0.93	0.84	0.64	0.13
Entropy-OPTBIAS	0.93	0.93	1.0	0.73	1.0	0.68	0.53	0.35
Entropy-DNMA	0.80	0.87	0.73	1.0	0.73	0.99	0.69	0.044
Entropy-PROBID	0.93	0.93	1.0	0.73	1.0	0.68	0.53	0.35
Entropy-EAMR	0.74	0.84	0.68	0.99	0.68	1.0	0.71	0.049
CURLI	0.58	0.64	0.53	0.69	0.53	0.71	1.0	-0.038
PEG	0.27	0.13	0.35	0.044	0.35	0.049	-0.038	1.0

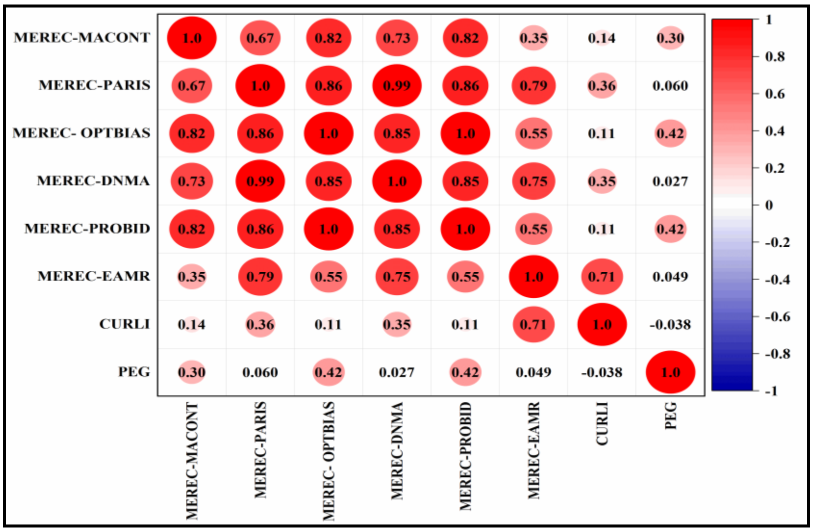
(a)



	CRITIC-MACONT	CRITIC-PARIS	CRITIC-OPTBIAS	CRITIC-DNMA	CRITIC-PROBID	CRITIC-EAMR	CURLI	PEG
CRITIC-MACONT	1.0	0.89	0.93	0.91	0.96	0.70	0.15	0.077
CRITIC-PARIS	0.89	1.0	0.91	0.98	0.95	0.89	0.36	-0.011
CRITIC-OPTBIAS	0.93	0.91	1.0	0.92	0.97	0.70	0.13	0.15
CRITIC-DNMA	0.91	0.98	0.92	1.0	0.97	0.84	0.33	0.0055
CRITIC-PROBID	0.96	0.95	0.97	0.97	1.0	0.77	0.23	0.099
CRITIC-EAMR	0.70	0.89	0.70	0.84	0.77	1.0	0.60	-0.077
CURLI	0.15	0.36	0.13	0.33	0.23	0.60	1.0	-0.038
PEG	0.077	-0.011	0.15	0.0055	0.099	-0.077	-0.038	1.0

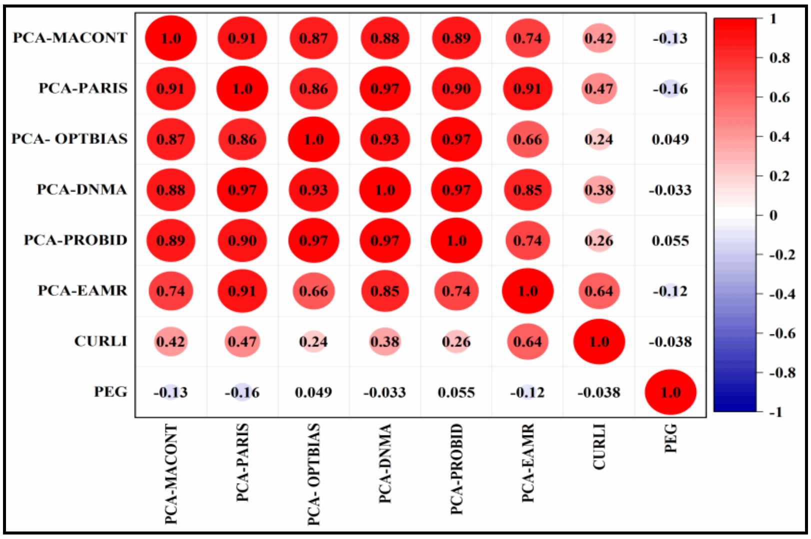
(b)

Figure 6.2 Spearman correlation coefficient result



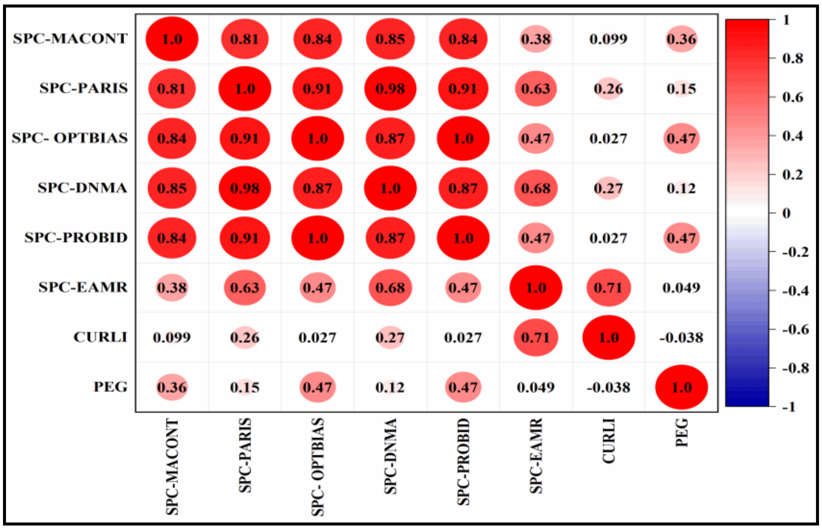
	MEREC-MACONT	MEREC-PARIS	MEREC- OPTBIAS	MEREC-DNMA	MEREC-PROBID	MEREC-EAMR	CURLI	PEG
MEREC-MACONT	1.0	0.67	0.82	0.73	0.82	0.35	0.14	0.30
MEREC-PARIS	0.67	1.0	0.86	0.99	0.86	0.79	0.36	0.060
MEREC- OPTBIAS	0.82	0.86	1.0	0.85	1.0	0.55	0.11	0.42
MEREC-DNMA	0.73	0.99	0.85	1.0	0.85	0.75	0.35	0.027
MEREC-PROBID	0.82	0.86	1.0	0.85	1.0	0.55	0.11	0.42
MEREC-EAMR	0.35	0.79	0.55	0.75	0.55	1.0	0.71	0.049
CURLI	0.14	0.36	0.11	0.35	0.11	0.71	1.0	-0.038
PEG	0.30	0.060	0.42	0.027	0.42	0.049	-0.038	1.0

(c)



	PCA-MACONT	PCA-PARIS	PCA- OPTBIAS	PCA-DNMA	PCA-PROBID	PCA-EAMR	CURLI	PEG
PCA-MACONT	1.0	0.91	0.87	0.88	0.89	0.74	0.42	-0.13
PCA-PARIS	0.91	1.0	0.86	0.97	0.90	0.91	0.47	-0.16
PCA- OPTBIAS	0.87	0.86	1.0	0.93	0.97	0.66	0.24	0.049
PCA-DNMA	0.88	0.97	0.93	1.0	0.97	0.85	0.38	-0.033
PCA-PROBID	0.89	0.90	0.97	0.97	1.0	0.74	0.26	0.055
PCA-EAMR	0.74	0.91	0.66	0.85	0.74	1.0	0.64	-0.12
CURLI	0.42	0.47	0.24	0.38	0.26	0.64	1.0	-0.038
PEG	-0.13	-0.16	0.049	-0.033	0.055	-0.12	-0.038	1.0

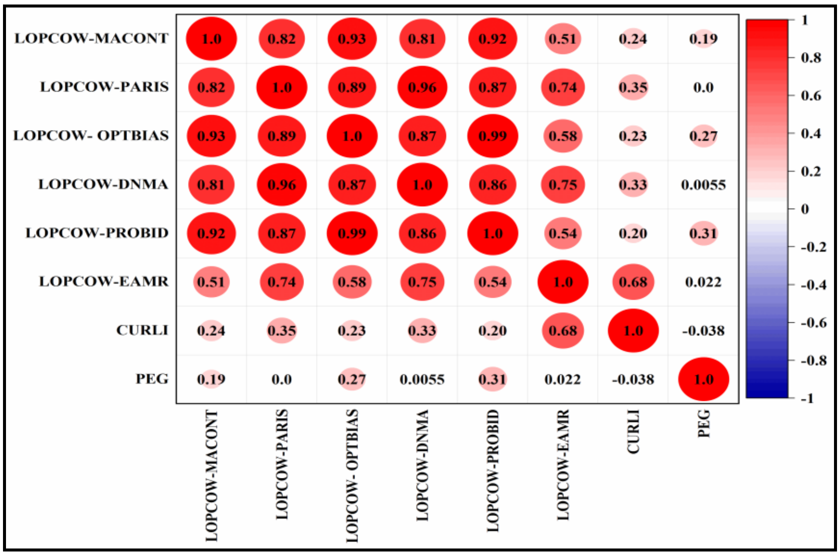
(d)



	SPC-MACONT	SPC-PARIS	SPC- OPTBIAS	SPC-DNMA	SPC-PROBID	SPC-EAMR	CURLI	PEG
SPC-MACONT	1.0	0.81	0.84	0.85	0.84	0.38	0.099	0.36
SPC-PARIS	0.81	1.0	0.91	0.98	0.91	0.63	0.26	0.15
SPC- OPTBIAS	0.84	0.91	1.0	0.87	1.0	0.47	0.027	0.47
SPC-DNMA	0.85	0.98	0.87	1.0	0.87	0.68	0.27	0.12
SPC-PROBID	0.84	0.91	1.0	0.87	1.0	0.47	0.027	0.47
SPC-EAMR	0.38	0.63	0.47	0.68	0.47	1.0	0.71	0.049
CURLI	0.099	0.26	0.027	0.27	0.027	0.71	1.0	-0.038
PEG	0.36	0.15	0.47	0.12	0.47	0.049	-0.038	1.0

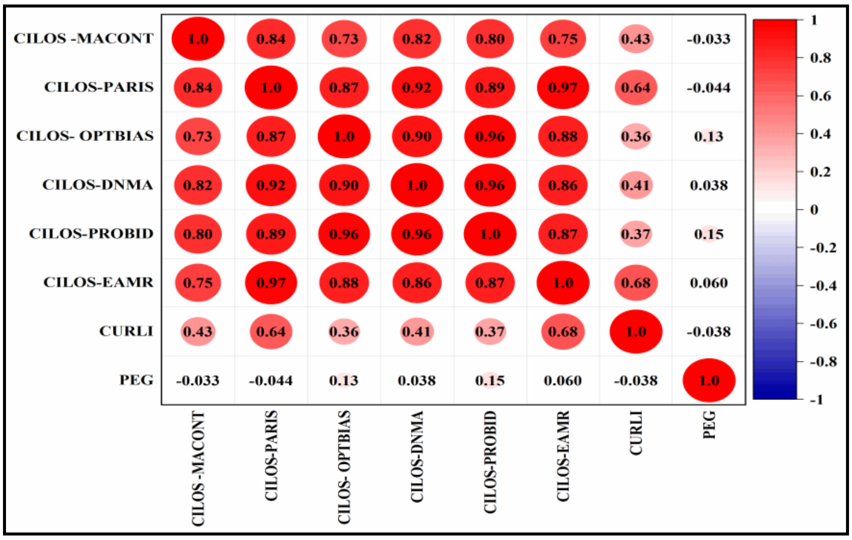
(e)

Figure 6.2 Continued



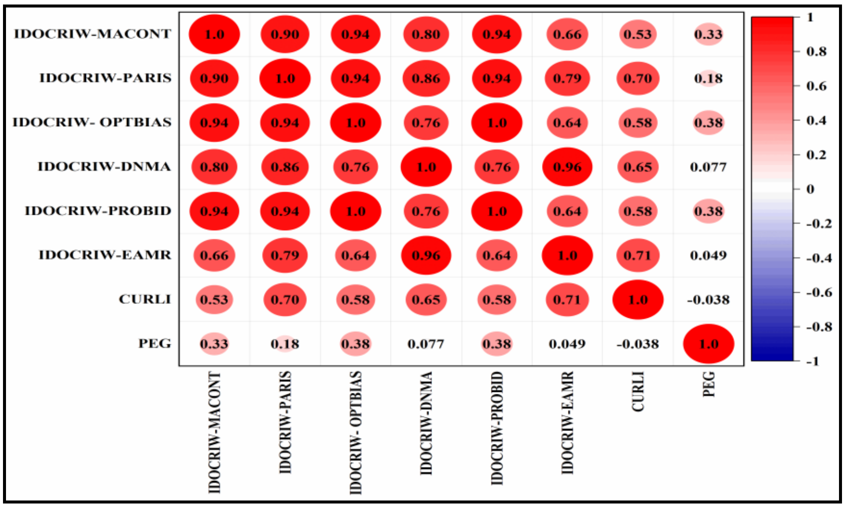
	LOPCOW-MACONT	LOPCOW-PARIS	LOPCOW- OPTBIAS	LOPCOW-DNMA	LOPCOW-PROBID	LOPCOW-EAMR	CURLI	PEG
LOPCOW-MACONT	1.0	0.82	0.93	0.81	0.92	0.51	0.24	0.19
LOPCOW-PARIS	0.82	1.0	0.89	0.96	0.87	0.74	0.35	0.0
LOPCOW- OPTBIAS	0.93	0.89	1.0	0.87	0.99	0.58	0.23	0.27
LOPCOW-DNMA	0.81	0.96	0.87	1.0	0.86	0.75	0.33	0.0055
LOPCOW-PROBID	0.92	0.87	0.99	0.86	1.0	0.54	0.20	0.31
LOPCOW-EAMR	0.51	0.74	0.58	0.75	0.54	1.0	0.68	0.022
CURLI	0.24	0.35	0.23	0.33	0.20	0.68	1.0	-0.038
PEG	0.19	0.0	0.27	0.0055	0.31	0.022	-0.038	1.0

(f)



	CILOS -MACONT	CILOS-PARIS	CILOS- OPTBIAS	CILOS-DNMA	CILOS-PROBID	CILOS-EAMR	CURLI	PEG
CILOS -MACONT	1.0	0.84	0.73	0.82	0.80	0.75	0.43	-0.033
CILOS-PARIS	0.84	1.0	0.87	0.92	0.89	0.97	0.64	-0.044
CILOS- OPTBIAS	0.73	0.87	1.0	0.90	0.96	0.88	0.36	0.13
CILOS-DNMA	0.82	0.92	0.90	1.0	0.96	0.86	0.41	0.038
CILOS-PROBID	0.80	0.89	0.96	0.96	1.0	0.87	0.37	0.15
CILOS-EAMR	0.75	0.97	0.88	0.86	0.87	1.0	0.68	0.060
CURLI	0.43	0.64	0.36	0.41	0.37	0.68	1.0	-0.038
PEG	-0.033	-0.044	0.13	0.038	0.15	0.060	-0.038	1.0

(g)



	IDOCRIW-MACONT	IDOCRIW-PARIS	IDOCRIW- OPTBIAS	IDOCRIW-DNMA	IDOCRIW-PROBID	IDOCRIW-EAMR	CURLI	PEG
IDOCRIW-MACONT	1.0	0.90	0.94	0.80	0.94	0.66	0.53	0.33
IDOCRIW-PARIS	0.90	1.0	0.94	0.86	0.94	0.79	0.70	0.18
IDOCRIW- OPTBIAS	0.94	0.94	1.0	0.76	1.0	0.64	0.58	0.38
IDOCRIW-DNMA	0.80	0.86	0.76	1.0	0.76	0.96	0.65	0.077
IDOCRIW-PROBID	0.94	0.94	1.0	0.76	1.0	0.64	0.58	0.38
IDOCRIW-EAMR	0.66	0.79	0.64	0.96	0.64	1.0	0.71	0.049
CURLI	0.53	0.70	0.58	0.65	0.58	0.71	1.0	-0.038
PEG	0.33	0.18	0.38	0.077	0.38	0.049	-0.038	1.0

(h)

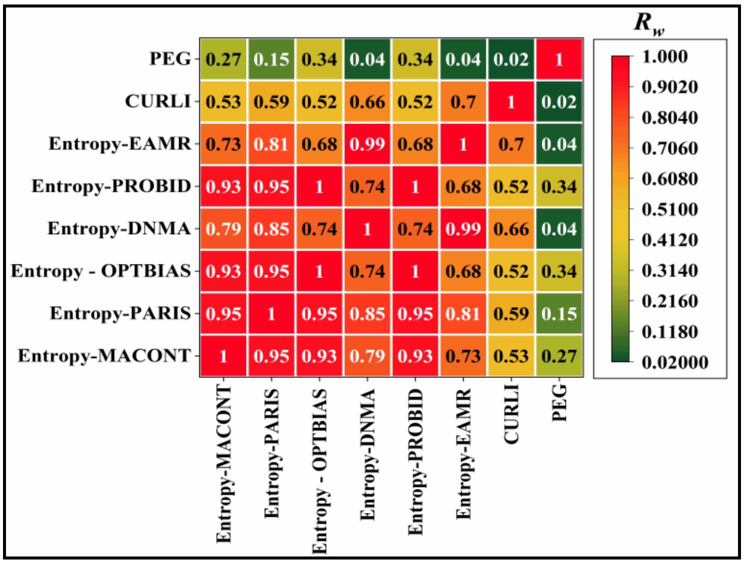
Figure 6.2 Continued

c) Based on weighted Spearman rank correlation coefficient

To analyze the impact of higher ranked alternatives R_w is computed as it provides larger significance to higher ranked alternatives. Figure 6.3 presents an overall result, where in entropy combined conditions, the R_w value is 1 for OPTBIAS-PROBID, DNMA-EAMR at 0.99, while CURLI and PEG struggle with other MCDM methods. CRITIC weighting shows high correlations for OPTBIAS-PROBID and DNMA-PARIS at 0.98. MEREC weighting results indicate that PROBID-OPTBIAS achieves a perfect correlation of 1 and DNMA-PARIS both at 0.99. PCA weighting shows high correlations for DNMA-PARIS at 0.97 and PROBID-OPTBIAS at 1. SPC weighting highlights DNMA-PARIS at 0.99, while many other methods perform poorly. LOPCOW weighting sees OPTBIAS-PROBID at 0.99. Under CILOS weighting, EAMR-PARIS shows a correlation of 0.97. Finally, IDOCRIW weighting indicates that OPTBIAS-PROBID achieves a perfect correlation of 1 again.

d) Based on coefficient of ranking similarity (*WS*)

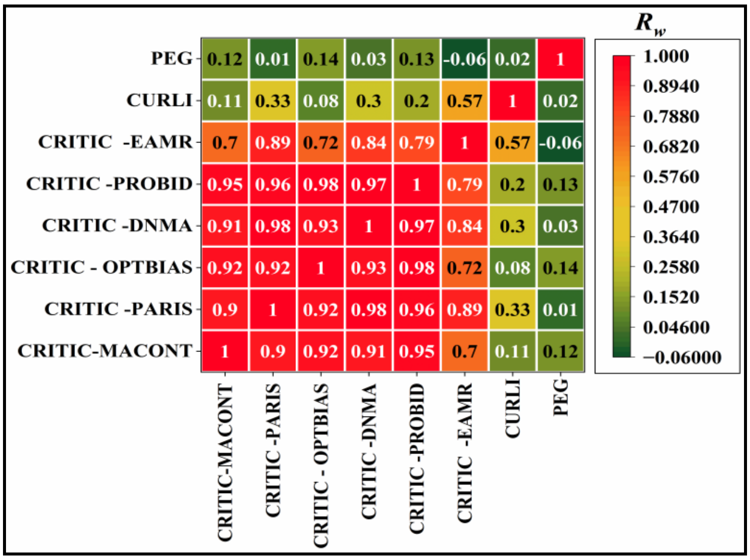
To analyze the impact of rank positions in correlation results, *WS* values are computed. Figure 6.4 shows the result of *WS* values of all the rankings. Under entropy-based conditions, the *WS* value is a perfect 1 between PROBID-OPTBIAS. The CRITIC weighting method highlights PROBID and PARIS performed very well in terms of above 0.95 value. Similarly, under the MEREC, PROBID and OPTBIAS again achieved 1, while under PCA, PROBID-DNMA achieved 0.98 and SPC weighting method, OPTBIAS-PROBID and PARIS-DNMA achieved 1. The LOPCOW and CILOS weighting method show high similarity, except PEG and CURLI. Finally, the IDOCRIW weighting method demonstrates PARIS-PROBID and PARIS-OPTBIAS with perfect 1. This study reveals that PARIS, DNMA, OPTBIAS and PROBID performed better than other MCDM methods, often achieving perfect score of 1 and many close to 1 under different weighting methods.



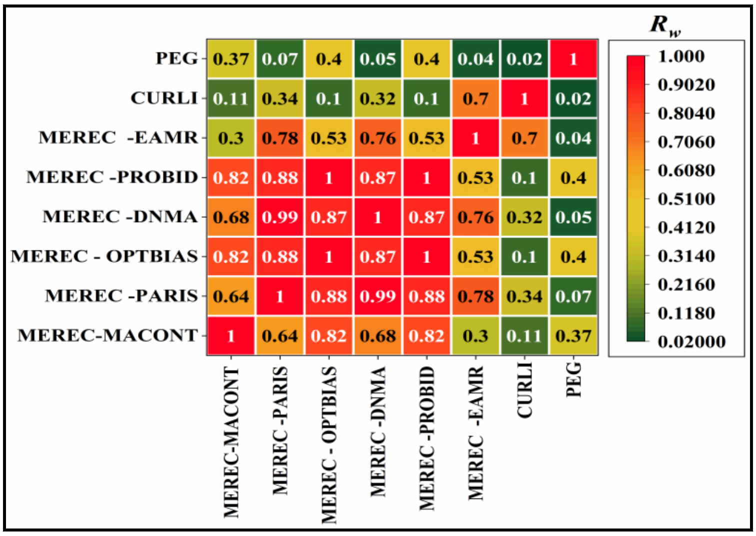
	Entropy-MACONT	Entropy-PARIS	Entropy - OPTBIAS	Entropy-DNMA	Entropy-PROBID	Entropy-EAMR	CURLI	PEG
PEG	0.27	0.15	0.34	0.04	0.34	0.04	0.02	1
CURLI	0.53	0.59	0.52	0.66	0.52	0.7	1	0.02
Entropy-EAMR	0.73	0.81	0.68	0.99	0.68	1	0.7	0.04
Entropy-PROBID	0.93	0.95	1	0.74	1	0.68	0.52	0.34
Entropy-DNMA	0.79	0.85	0.74	1	0.74	0.99	0.66	0.04
Entropy - OPTBIAS	0.93	0.95	1	0.74	1	0.68	0.52	0.34
Entropy-PARIS	0.95	1	0.95	0.85	0.95	0.81	0.59	0.15
Entropy-MACONT	1	0.95	0.93	0.79	0.93	0.73	0.53	0.27

(a)

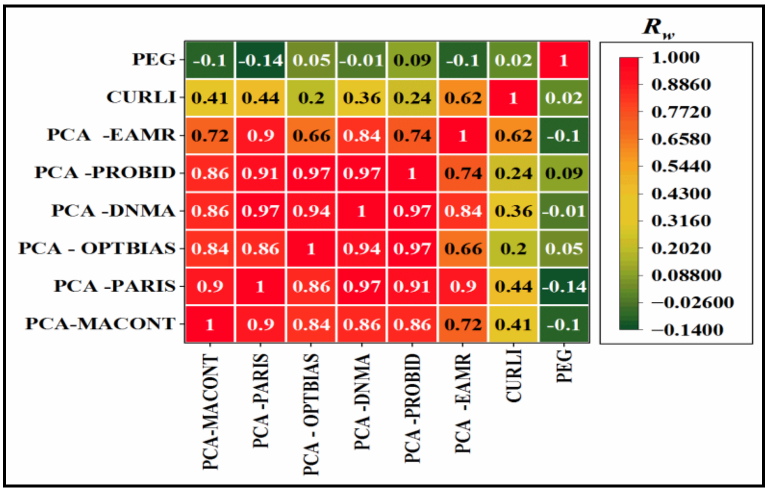
Figure 6.3 Weighted Spearman correlation coefficient (R_w)



(b)

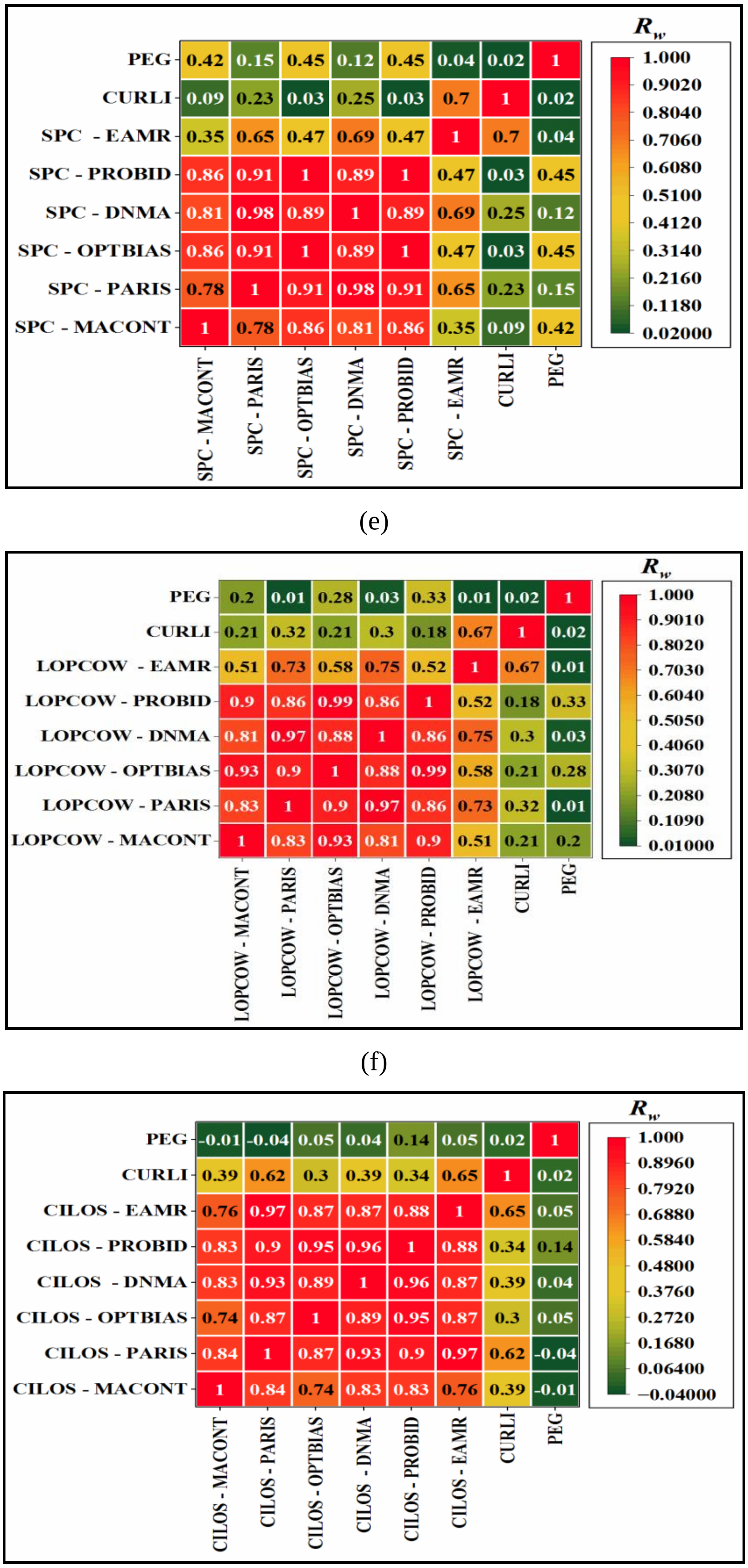


(c)



(d)

Figure 6.3 Continued



	SPC - MACONT	SPC - PARIS	SPC - OPTBIAS	SPC - DNMA	SPC - PROBID	SPC - EAMR	CURLI	PEG
PEG	0.42	0.15	0.45	0.12	0.45	0.04	0.02	1
CURLI	0.09	0.23	0.03	0.25	0.03	0.7	1	0.02
SPC - EAMR	0.35	0.65	0.47	0.69	0.47	1	0.7	0.04
SPC - PROBID	0.86	0.91	1	0.89	1	0.47	0.03	0.45
SPC - DNMA	0.81	0.98	0.89	1	0.89	0.69	0.25	0.12
SPC - OPTBIAS	0.86	0.91	1	0.89	1	0.47	0.03	0.45
SPC - PARIS	0.78	1	0.91	0.98	0.91	0.65	0.23	0.15
SPC - MACONT	1	0.78	0.86	0.81	0.86	0.35	0.09	0.42

(e)

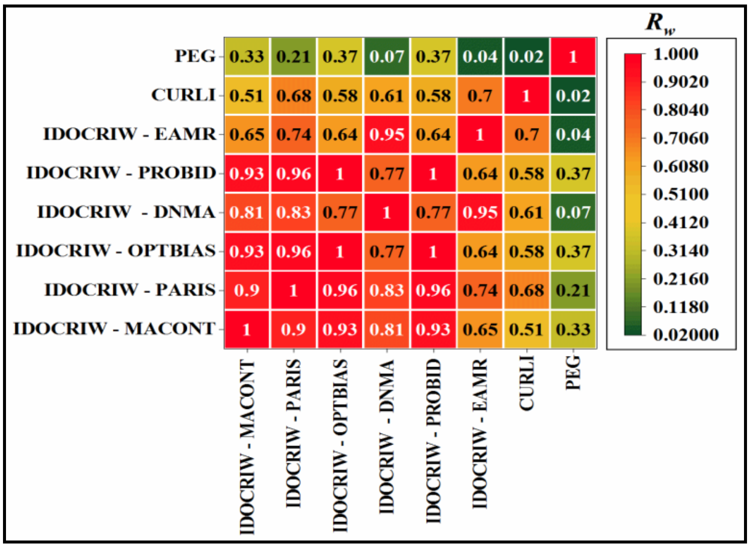
	LOPCOW - MACONT	LOPCOW - PARIS	LOPCOW - OPTBIAS	LOPCOW - DNMA	LOPCOW - PROBID	LOPCOW - EAMR	CURLI	PEG
PEG	0.2	0.01	0.28	0.03	0.33	0.01	0.02	1
CURLI	0.21	0.32	0.21	0.3	0.18	0.67	1	0.02
LOPCOW - EAMR	0.51	0.73	0.58	0.75	0.52	1	0.67	0.01
LOPCOW - PROBID	0.9	0.86	0.99	0.86	1	0.52	0.18	0.33
LOPCOW - DNMA	0.81	0.97	0.88	1	0.86	0.75	0.3	0.03
LOPCOW - OPTBIAS	0.93	0.9	1	0.88	0.99	0.58	0.21	0.28
LOPCOW - PARIS	0.83	1	0.9	0.97	0.86	0.73	0.32	0.01
LOPCOW - MACONT	1	0.83	0.93	0.81	0.9	0.51	0.21	0.2

(f)

	CILOS - MACONT	CILOS - PARIS	CILOS - OPTBIAS	CILOS - DNMA	CILOS - PROBID	CILOS - EAMR	CURLI	PEG
PEG	-0.01	-0.04	0.05	0.04	0.14	0.05	0.02	1
CURLI	0.39	0.62	0.3	0.39	0.34	0.65	1	0.02
CILOS - EAMR	0.76	0.97	0.87	0.87	0.88	1	0.65	0.05
CILOS - PROBID	0.83	0.9	0.95	0.96	1	0.88	0.34	0.14
CILOS - DNMA	0.83	0.93	0.89	1	0.96	0.87	0.39	0.04
CILOS - OPTBIAS	0.74	0.87	1	0.89	0.95	0.87	0.3	0.05
CILOS - PARIS	0.84	1	0.87	0.93	0.9	0.97	0.62	-0.04
CILOS - MACONT	1	0.84	0.74	0.83	0.83	0.76	0.39	-0.01

(g)

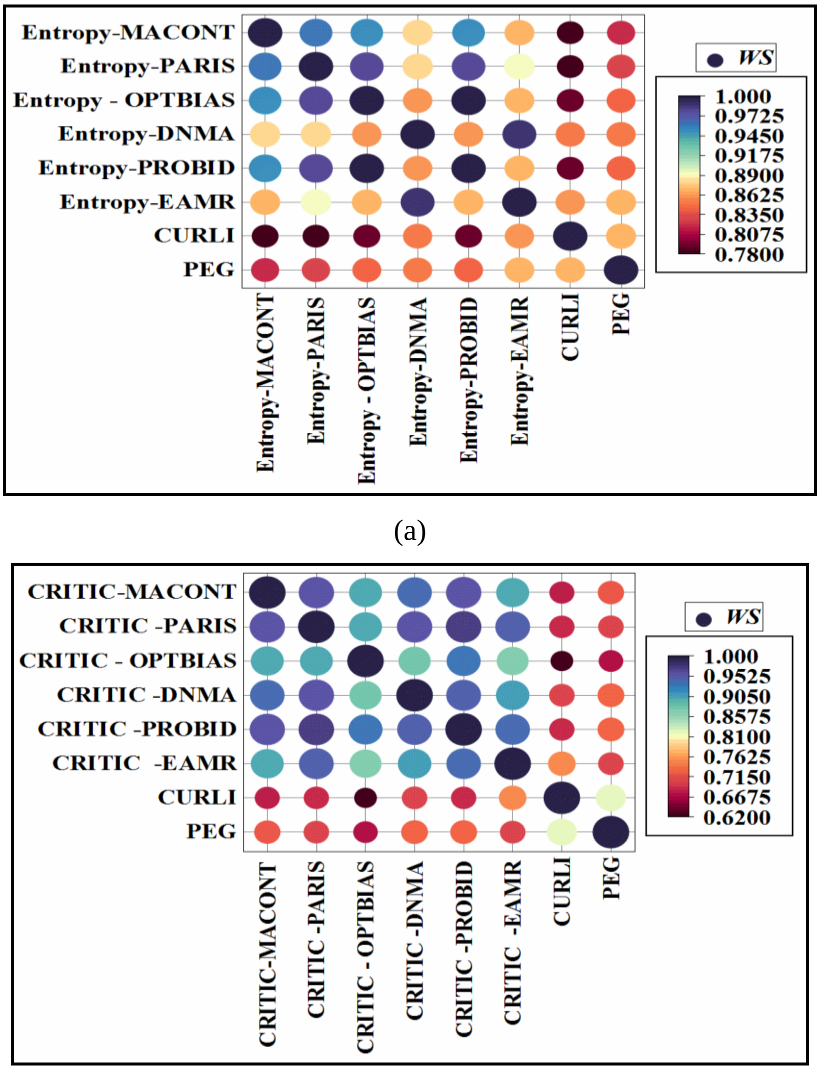
Figure 6.3 Continued



	IDOCRIW - MACONT	IDOCRIW - PARIS	IDOCRIW - OPTBIAS	IDOCRIW - DNMA	IDOCRIW - PROBID	IDOCRIW - EAMR	CURLI	PEG
PEG	0.33	0.21	0.37	0.07	0.37	0.04	0.02	1
CURLI	0.51	0.68	0.58	0.61	0.58	0.7	1	0.02
IDOCRIW - EAMR	0.65	0.74	0.64	0.95	0.64	1	0.7	0.04
IDOCRIW - PROBID	0.93	0.96	1	0.77	1	0.64	0.58	0.37
IDOCRIW - DNMA	0.81	0.83	0.77	1	0.77	0.95	0.61	0.07
IDOCRIW - OPTBIAS	0.93	0.96	1	0.77	1	0.64	0.58	0.37
IDOCRIW - PARIS	0.9	1	0.96	0.83	0.96	0.74	0.68	0.21
IDOCRIW - MACONT	1	0.9	0.93	0.81	0.93	0.65	0.51	0.33

(h)

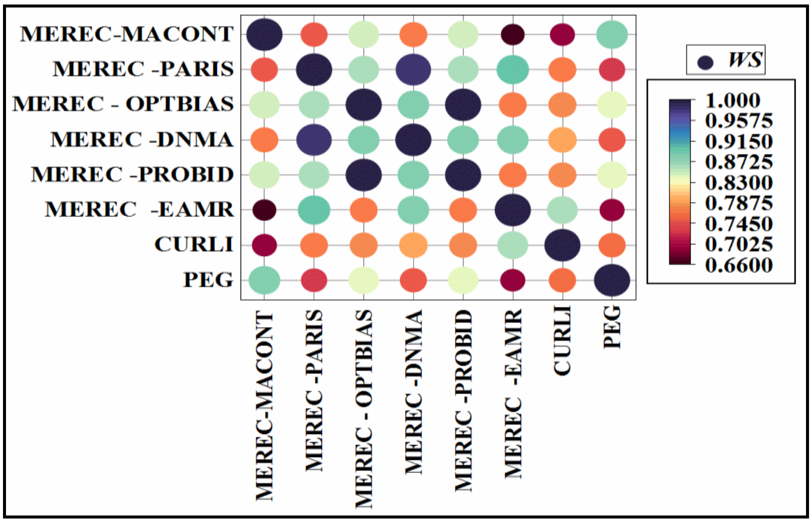
Figure 6.3 Continued



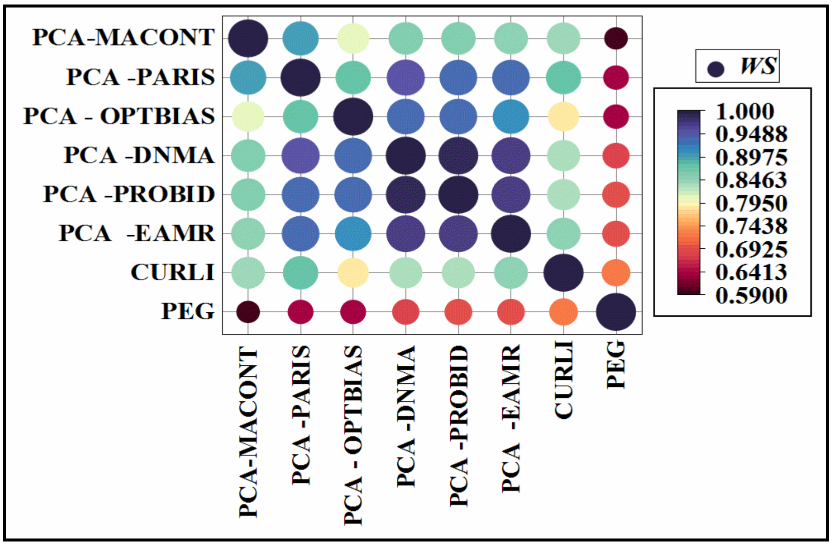
(a)

(b)

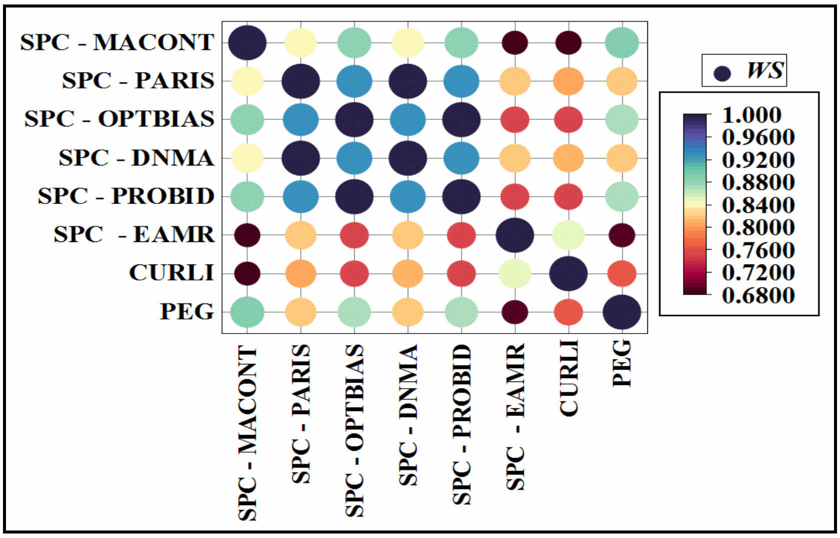
Figure 6.4 Coefficient of rank similarity (*WS*) results



(c)

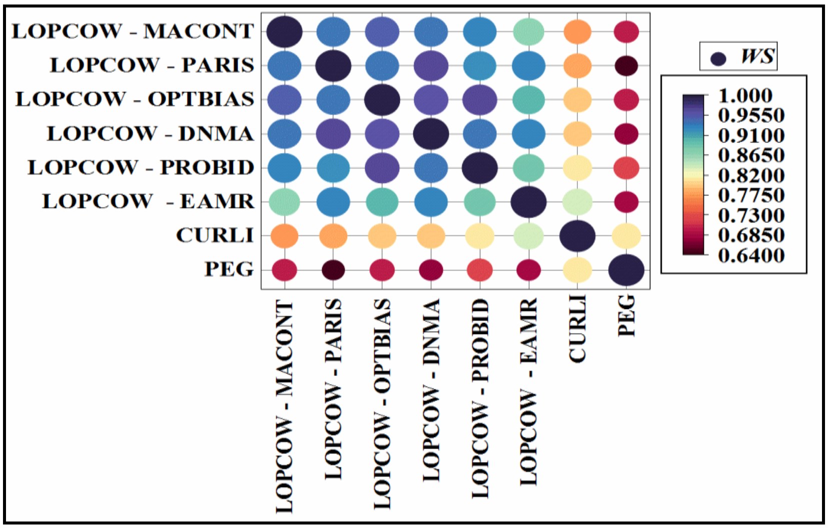


(d)

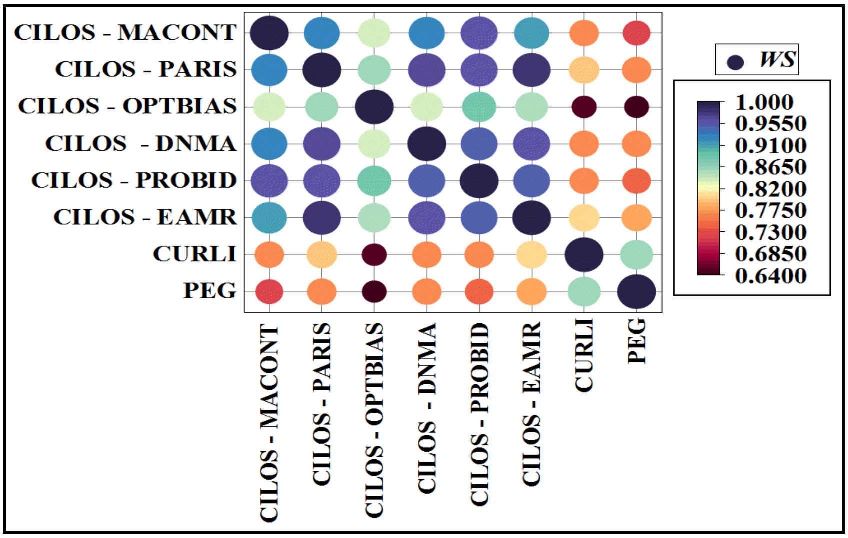


(e)

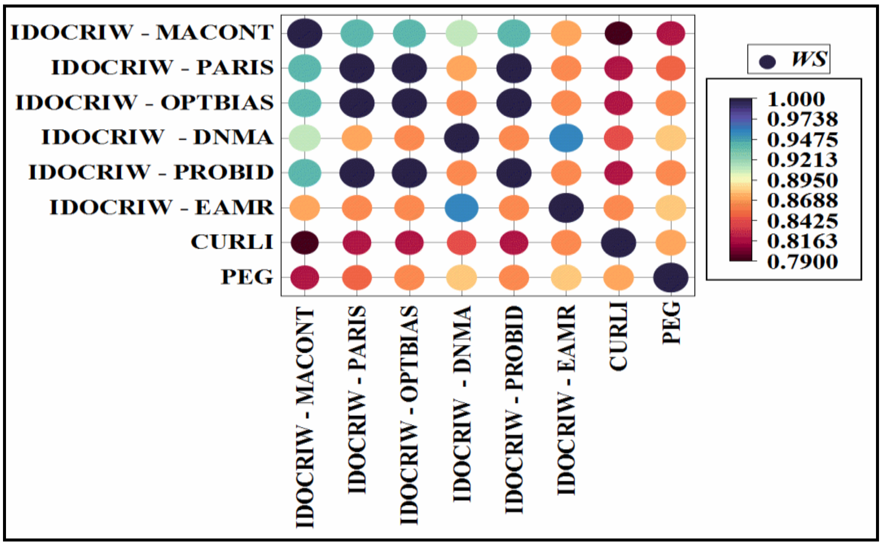
Figure 6.4 Continued



(f)



(g)



(h)

Figure 6.4 Continued

e) Based on number of operations

Figure 6.5 shows a comparative analysis between the considered MCDM methods with reference to the total number of mathematical operations required. From this figure, it is unveiled that in order to solve this decision making problem, the EAMR method requires comparatively less number of operations, 221, followed by PARIS, 383 and on the other hand CURLI requires 1352 number of operations to get the rankings.

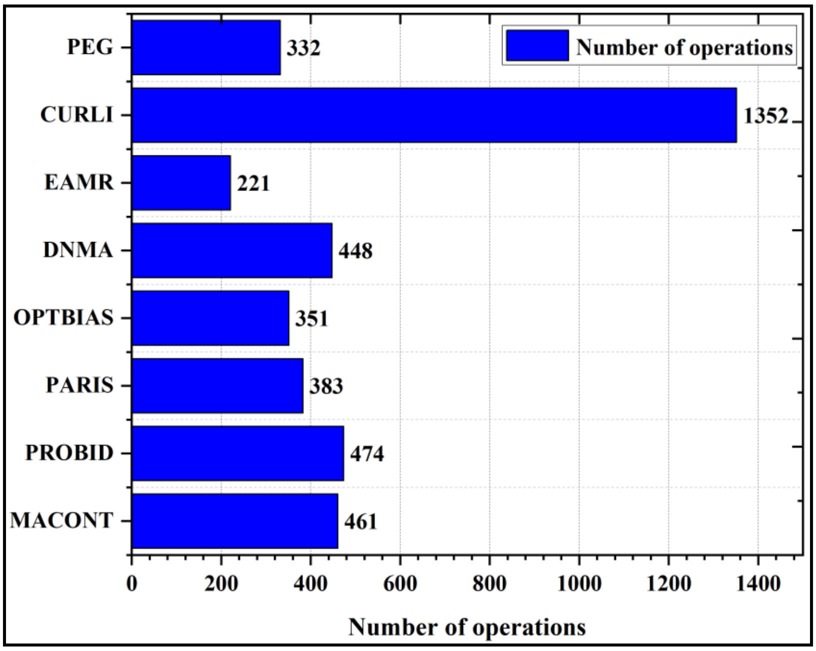


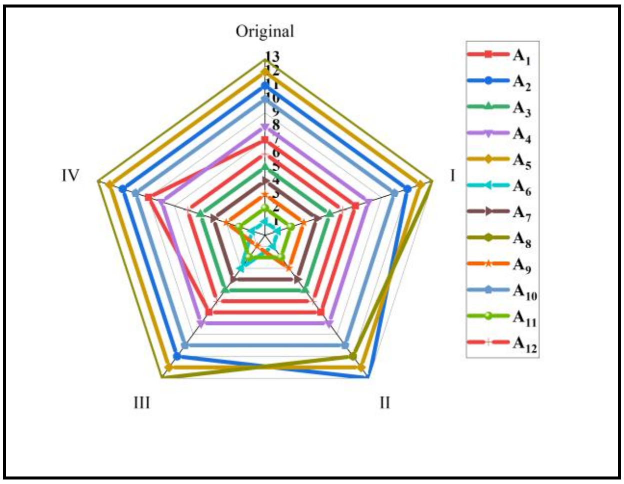
Figure 6.5 Number of operations

Sensitivity analysis

This section presents a detailed sensitivity analysis based on three scenarios: the gradual elimination of criteria, the equal weighting condition and the application of weights from various weighting methods.

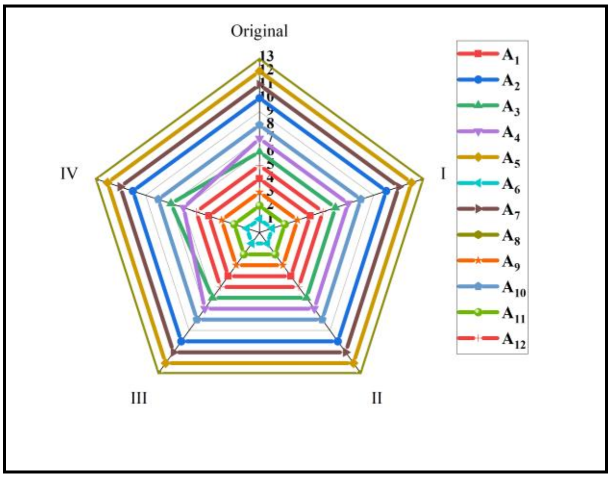
Sensitivity analysis based on gradual removal of criteria

Figure 6.6 reveals that A_6 remains the most stable and top-ranked alternative (ranking 1 in almost all cases), confirming its robustness regardless of the weighting method used. A_8 consistently ranks last (thirteenth) across all methods, except in MACONT (where it improves to eleventh in scenario II) and EAMR (where A_7 drops slightly), indicating that A_8 is the weakest alternative overall. A_9, A_{11} and A_1 demonstrate relatively stable rankings across different methods, suggesting moderate sensitivity to weight changes, while A_2, A_3 and A_{12} exhibit minor fluctuations but remain in similar rank clusters. A_5 and A_7 show moderate sensitivity, with A_5 consistently ranking low, but with some variations in PARIS and MACONT. EAMR introduces slight shifts, such as A_2 jumping to rank one in scenario III, showing its susceptibility to certain weight structures. Overall, A_6 is the most stable and best-performing alternative, A_8 is the weakest and A_2 and A_5 are the most sensitive to weighting changes, highlighting the impact of different methods on decision making consistency.



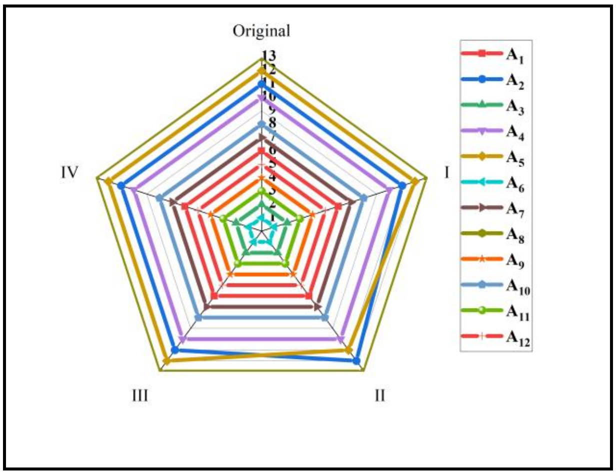
MACONT

(a)



PROBID

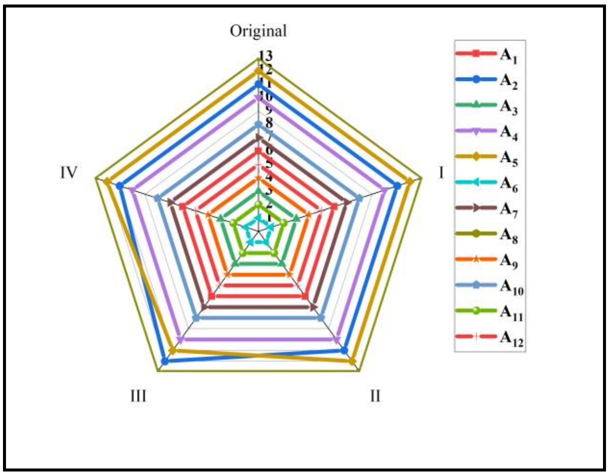
(b)



PARIS

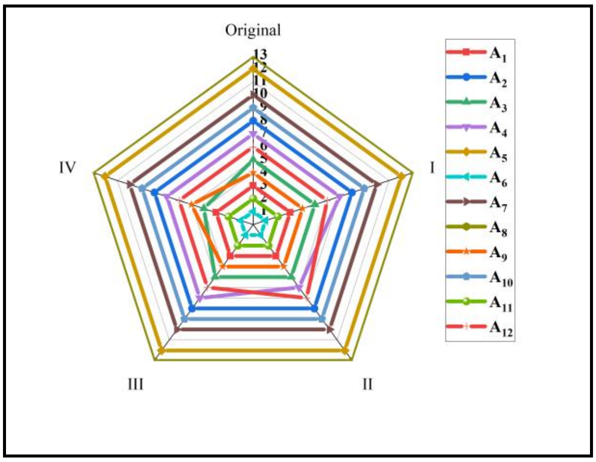
(c)

Figure 6.6 Sensitivity analyses results by gradually removal of criterion weight



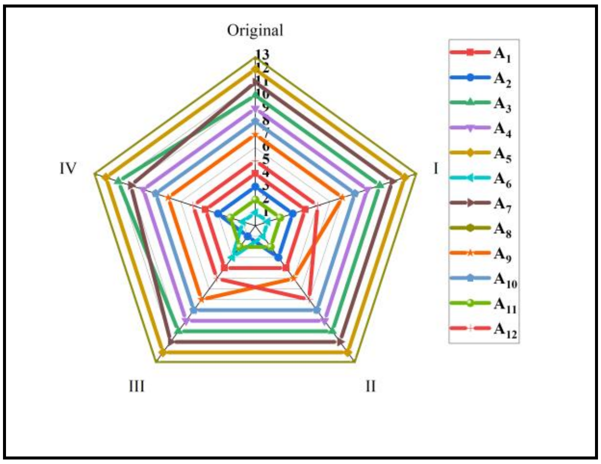
DNMA

(d)



OPTBIAS

(e)



EAMR

(f)

Figure 6.6 Continued

Sensitivity analysis based on equal weighting conditions

Under the equal weighting condition, the ranking results demonstrate the stability and variability of alternatives across different MCDM methods. Figure 6.7 shows that A_6 consistently maintains the top rank across all methods, indicating its robustness in decision making regardless of the weighting approach. Conversely, A_8 consistently holds the lowest rank, reinforcing its weaker standing. The middle-ranked alternatives (A_1 to A_{13}, excluding A_6 and A_8) exhibit moderate variations, with some fluctuations observed across different methods. These variations highlight the sensitivity of rankings to changes in normalization and aggregation techniques, emphasizing the importance of selecting an appropriate MCDM method based on the specific decision making context.

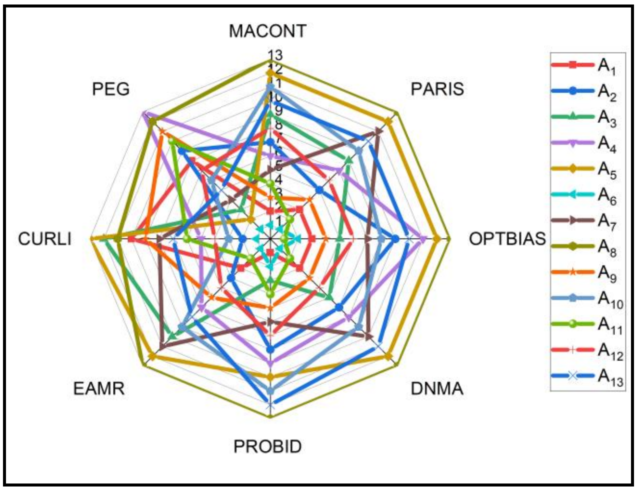
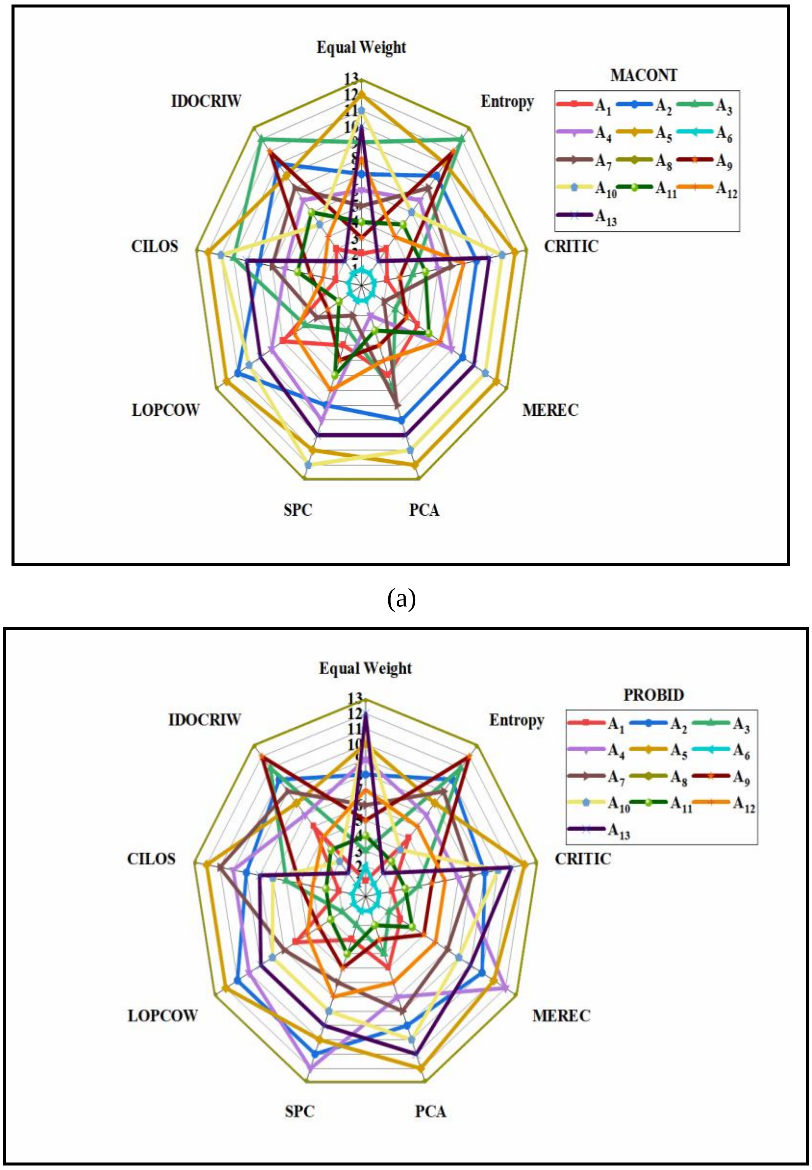


Figure 6.7 Sensitivity analyses results under equal weight condition

Sensitivity analysis based on all weighting conditions

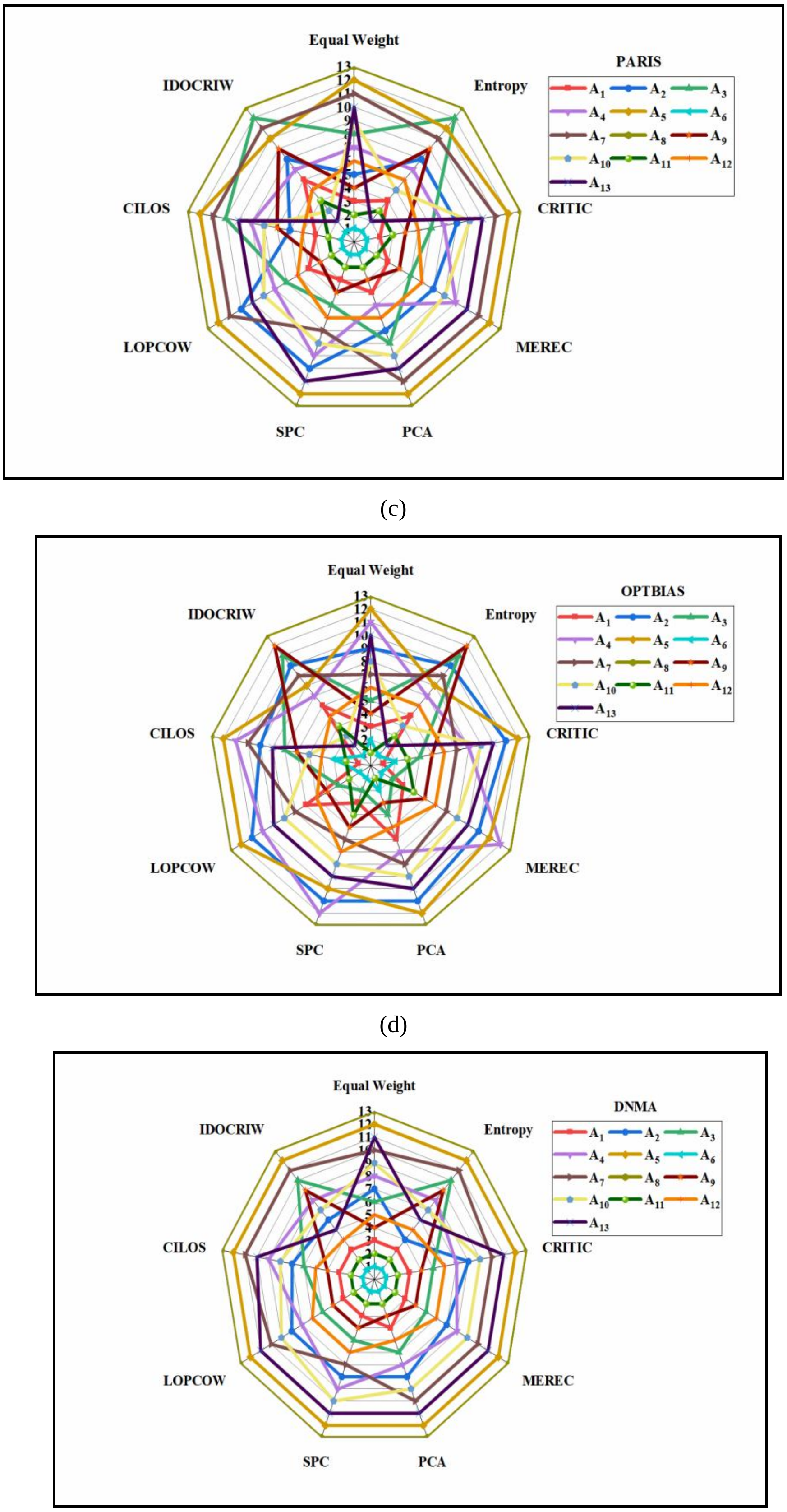
Figure 6.8 indicates that A_6 remains top choice in most of the cases. The performance of various MCDM methods reveals notable patterns in their sensitivity to weighting schemes. Across most methods, A_6 consistently emerges as a top performer, highlighting its robustness and stability, particularly under methods such as MACONT, PARIS, DNMA and EAMR where it ranks first. A_{13} persistently ranks at the bottom across nearly all methods, highlighting its weak performance. Middle-tier alternatives such as A_3, A_4, A_7 and A_{10} exhibit significant variability depending on the weighting method, with A_3 achieving ranks as high as second in some schemes (e.g., MEREC and SPC under PROBID) but dropping to eleventh in others (e.g., entropy under OPTBIAS). A_8 and A_{13} show consistent underperformance, ranking last or near the bottom across most methods. CURLI and PEG, independent of weighting schemes, maintain unique ranking structures, with PEG emphasizing strong rankings for A_2 and A_3 while consistently positioning A_{13} near the bottom. PARIS provides robust rankings for extremes (A_6 and A_8) but demonstrates sensitivity for middle-tier alternatives, which frequently shift depending on the weighting. EAMR stabilizes extreme ranks effectively but shows moderate variability in middle alternatives such as A_9 and A_8. DNMA stands out for its balanced stability, where top performers such as A_6 and A_{11} retain their positions consistently and middle-tier rankings are less volatile compared to other methods. DNMA outperforms other MCDM methods due to its superior balance between robustness and sensitivity. It consistently identifies top performers, such as A$_6$ and A$_{11}$, while maintaining reasonable stability across middle-tier alternatives. Unlike other methods, which excel at distinguishing extreme performers but exhibit notable variability in the middle ranks, DNMA offers a more even distribution of sensitivity, ensuring reliability across all tiers of alternatives. Compared to PARIS, which is prone to sensitivity in middle-tier ranks and PROBID, which demonstrates variability across certain middle and lower-ranked alternatives, DNMA provides a more consistent and reliable framework for decision making. Its ability to balance the nuanced prioritization of middle-tier performers with stable differentiation of top and bottom alternatives makes it a more effective method.



(a)

(b)

Figure 6.8 Sensitivity analyses results considering the criteria weight

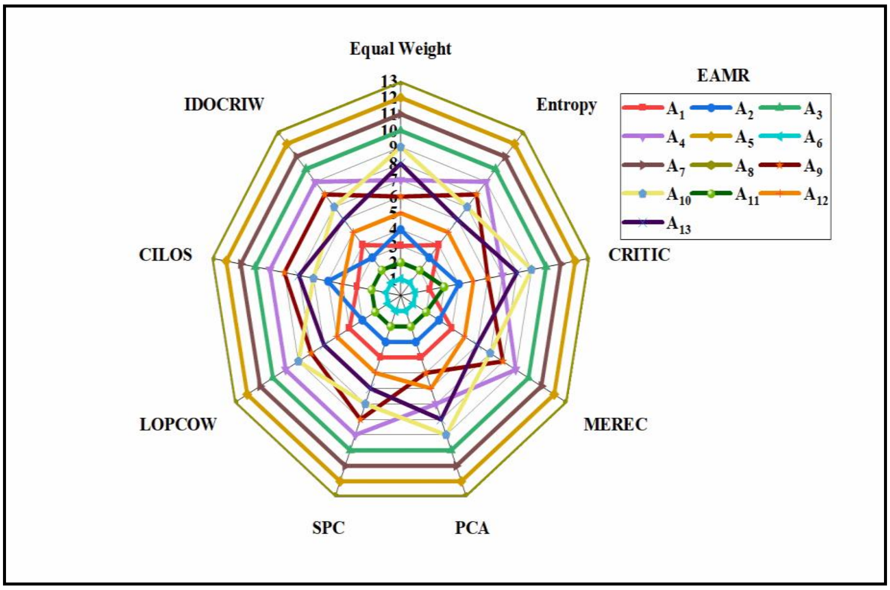


(c)

(d)

(e)

Figure 6.8 Continued



(f)

Figure 6.8 Continued

7. DRONE SELECTION

Delivery operation within a manufacturing unit is a critical component of logistics of manufacturing and assembly line processes. It involves movement of raw materials, semi-finished components and finished products within a factory or assembly line. It also requires coordination of multiple departments and personnel, including inventory management, production planning and logistics. The first step in delivery operation is inventory control, which ensures that materials and components are readily available as and when required and finished products are prepared to be delivered to the customers. At the point when inventories are distributed, the next stage is production planning through coordination of the production processes. It takes into account production capacity of the facilities as well as availability of materials and components. Finally, logistics deal with movement of raw materials, semi-finished items and finished products throughout the facility. Transportation of materials and products securely and within the premises of the manufacturing unit is the target of planned operations. Successfully overseeing the stock levels inside any manufacturing/ assembly unit is one of the challenges that a delivery task often faces. This requires thorough planning and coordination to ensure that the right materials and components are available as and when required. Inadequate inventory management may lead to production delays and increased costs [127]. It is also necessary to ensure that materials and components are transported within the facility in a safe and efficient manner. Maintaining production schedules, cutting costs and increasing customer satisfaction require efficient delivery operations. In manufacturing facilities, conventional modes of transportation, such as forklifts and conveyors have been utilized for a considerable period of time. However, in modern manufacturing units, they pose a number of challenges, including lack of flexibility and safety, constant monitoring, higher handling cost, limited automation, requirements for maintenance and repair and impact on environment.

To address these issues, numerous manufacturing facilities have looked into novel transportation alternatives, such as drones for delivery purpose. To effectively resolve the current transportation issues arising within the manufacturing facilities, drones are gaining popularity. They outperform the conventional modes of transportation in a number of ways, including increased flexibility, reduced costs, enhanced safety and increased efficiency. Drones can transport raw materials to assembly lines, finished products to storage areas or parts/com ponents between various assembly zones [128, 129]. Moreover, stock administration can be computerized with transportation drones [130]. Drones for delivery operation are able to automate the restocking process, keep track of inventory levels and alert the inventory manager when stocks are running low by scanning the shelves and storage areas on a regular basis. They can also be used to make repairs and maintenance more efficient, saving time and cutting down the need for manual labor. These drones can be effectively employed to transport and dispose waste resulting in sustainable green manufacturing environment. Drones are reforming how products and materials are being shipped inside the assembly/manufacturing units [131]. They can be divided into two fundamental classes based on the kind of transportation they are intended for. Ground-based drones have wheels or tracks that make them easy to move around the manufacturing units, facilitating effective material transportation, waste and inventory management. They can move heavy/bulky products to those regions that may be challenging for the human labors or forklifts to access. On the other hand, aerial drones are dedicated to transport materials/products from one location to another while hovering above the manufacturing shop floor. They can also transport mate rials between various production, storage and shipping areas [132]. Aerial drones can also be deployed for inspection, such as checking inventory levels or monitoring machine condition [133]. They are capable of moving lighter, smaller items and are especially useful in reaching those areas that may be inaccessible for the ground-based drones [134]. Hybrid drones, which can alternate between ground based and aerial modes of transportation, are more flexible. From material transportation and inventory management to inspection and maintenance, these hybrid drones are capable to perform a wider range of tasks within the manufacturing units. They are able to adjust to the needs of the manufacturing process, while boosting productivity and efficiency.

Availability of various categories of drones offers a scope of choices for transportation inside the manufacturing/assembly units. They offer more adaptability and flexibility contrasted to the conventional transportation strategies, making them an important expansion to the present day manufacturing processes. Due to their higher efficiency and adaptability, drones have emerged out as a popular alternative for meeting the current transportation and delivery needs of the manufacturing units. However, the selection process is quite challenging due to availability of numerous drone alternatives with varying configurations and complexities. End-users may frequently be drawn towards a particular drone without considering whether a less expensive alternative can complete the delivery task more quickly and afford ably. Therefore, it is essential to take into consideration various characteristics and capabilities of drones, including their payload capacity, flight range, speed, cost, requirements for maintenance, ease of integration with the existing delivery system and impact on environment while searching for a feasible alternative. Moreover, choice of the most apposite drone from a pool of candidate alternatives with conflicting assessment standards appears as a MCDM problem.

To ensure that the selected drone can meet the desired performance requirements of the manufacturing unit, a comprehensive analysis of the available drone alternatives for delivery purpose is ardently required. As the delivery drone selection problem is deemed to be a complex decision making task involving multiple conflicting criteria, such as cost, flight time, weight carrying capacity, flight range, type of compatibility etc., it has thus garnered considerable attention from the researchers.

7.1 Review of MCDM in drone selection

In the field of drone technology, there is a need for a rigorous methodology to appropriately evaluate and select drones that are suitable for specific applications and environments. Researchers have therefore explored the use of MCDM techniques to address this problem. Hamurcu and Eren [135] proposed an approach integrating AHP and TOPSIS to assess unmanned aerial vehicle alternatives in defense applications. Nur er al. [136] adopted interval-valued inferential fuzzy TOPSIS for last mile delivery operations. Merkepçi et al. [137] proposed the application of neutrosophic evaluation of mixed data (EVAMIX) along with CRITIC method for drone selection, while Khan et al. [138] applied TOPSIS method for drone selection based on cost aspect. Radovanović et al. [139] proposed a hybrid MCDM model based on fuzzy AHP-VIKOR to select unmanned aerial vehicles for tactical units. Aktas and Kabak [140] employed interval-valued Pythagorean fuzzy (IVPF)-WASPAS method for last mile delivery drone selection. In the similar direction, Göktekin and Şimşek [141] utilized VIKOR in drone selection to be used in self-training of volunteers and rescue teams. Kim et al. [142] proposed a geographic information system-based multi-criteria model for selecting take-off and landing sites for firefighter drones in urban areas. Banik et al. [143] adopted graph theory and matrix approach to select the most suitable drones for specific medical supply delivery scenarios in urban and rural/remote areas. MOORA and its full multiplicative form (MULTIMOORA) were adopted by Abdulvahitoğlu et al. [144] to assist decision makers in unmanned aerial vehicle selection. These past researches thus strengthen the importance of MCDM techniques in drone selection and also provide a range of available methods for evaluating and selecting drones for different applications and environments.

According to the literature review, the use of MCDM approaches has already been the subject of numerous research, such as defense, last mile delivery, self-training of volunteers and rescue teams, firefighting and medical supply delivery. Conversely, there is a lack of research on the application of MCDM approaches in selecting drones for delivery purpose, specifically in manufacturing facilities. As per authors' knowledge and based on the previous study, there has been no information related to MCDM applications for drone selection for delivery operations in a manufacturing unit. Additionally, there is always a need to develop a robust methodology that can distinguish drones according to the requirements, specifically within the context of manufacturing shop floors. Therefore, there is a research gap in development of a comprehensive and systematic MCDM approach to evaluate suitability of drones for delivery operations in manufacturing applications. A methodical approach in selecting drones that are best suited for their particular requirements would be provided to the decision makers while establishing a stringent selection procedure for drones used for delivery operations. This would help optimize operations and enhance productivity by reducing delivery times, human errors and improving safety.

It can be noticed that a number of MCDM approaches, including TOPSIS, VIKOR, WASPAS, EVAMIX etc. and subjective criteria weighting techniques, such as AHP, have been considered to solve drone selection problems. However, there has not been any comparative analysis on different MCDM methods for selecting drones for delivery purpose and the previous studies have not found suitable drones for performing delivery operations in manufacturing industries. To address the identified research gaps, this chapter for the first time applies newly developed approaches in delivery drone domain.

7.2 Case study

Eight newly developed mcdm methods are applied in this chapter, considering eight alternative drone models and eight evaluation criteria. These eight criteria consist of flight time (C_1) (in min), maximum takeoff weight (C_2) (in kg), maximum speed (C_3) (in km/h), maximum flight altitude (C_4) (in km), average operating temperature (C_5) (in °C), remote controller distance range (C_6) (in km), camera resolution (C_7) (in mega pixel) and approximate cost (C_8) (in USD). Except criterion C_8, all the remaining attributes are beneficial in nature requiring their higher values. Flight time is a critical criterion as it determines how long a particular drone can operate before needing to recharge or replace its battery. It is also important in ensuring that the drone can complete its tasks efficiently and effectively without the need for frequent downtime. The takeoff weight allows the drone to carry larger and heavier packages/loads. Use of a drone having higher takeoff weight is always recommended. Another important criterion is the maximum speed, responsible for quick transportation/movement of the parts/products in a manufacturing/assembly unit, subsequently enhancing productivity. The maximum flight altitude determines the maximum height a drone can fly. It helps in getting around the obstacles and avoiding collisions with other facilities inside a shop floor. Average operating temperature decides the recommended temperature for the drone to efficiently work in. For use within a manufacturing unit having temperature variations, a drone that can operate in a wider range of temperatures is more suitable. In order to consider the operating temperature, average of the higher and lower working temperatures is considered in this paper. The distance over which the drone can be controlled is determined by the range of the remote controller. This criterion is responsible in guaranteeing that the drone can be controlled from a protected distance and utilized to transport parts/products starting from one region of the manufacturing unit then onto the next. Camera resolution is additionally significant as it decides the nature of pictures grabbed by the drone, which can be subsequently utilized to monitor placement of parts/products inside the shop floor. Finally, cost is the most important criterion influencing the drone selection decision in a major way.

Based on the considered criteria, a set of eight feasible alternatives, i.e. Parrot Anafi USA (A_1), Power Vision Power Eye (A_2), Yuneec H520 (A_3), Airdog ADII (A_4), Skydio 2+(A_5), Autel EVO II Pro V3 (A_6), DJI Phantom 4 Pro (A_7) and Aurelia X4 Standard (A_8) is shortlisted from a pool of available choices in the market. These delivery drone alternatives possess unique specialities in their applications areas. Each of them has distinct characteristics and benefits making them appropriate for various other purposes. Parrot Anafi USA is a lightweight drone that can be employed in any area, having the capability of capturing aerial photos and video clips. Professional photographers and videographers would appreciate its unique zoom capability and built-in camera controls. Power Vision Power Eye is a commercial-grade drone, perfect for inspection, surveying and mapping purposes. It has advanced flying characteristics, including obstacle avoidance. Because of its lengthy flight time and range, it is perfect for industrial applications. Yuneec H520 is a commercial drone built for industrial inspection and mapping. It has a good quality camera, obstacle avoidance capability and retractable landing gear. Due to its accurate flight control and extended flying length, it is an ideal choice for inspection tasks. Airdog ADII is designed for sports videography and it excels in obstacle avoidance and tracking skills, making it quite popular among the professionals. Skydio 2+ is an intelligent drone that incorporates strong AI algorithms to shoot high-quality images. Its advanced obstacle avoidance and tracking capabilities make it an excellent choice for outdoor applications. DJI Phantom 4 Pro is a high-performance drone, ideal for professional photography and cinematography. It has advanced flying characteristics, including obstacle avoidance. Because of its lengthy flight period and fast speed, it is a perfect candidate for various applications. Aurelia X4 Standard is a commercial drone, also intended for industrial inspections and mapping. It has a high-resolution camera, obstacle avoidance capabilities and a lengthy flying time. It is a good choice for inspection activity because to its accurate flight control and sophisticated features.

With respect to delivery of tools and components within a shop floor, each of the eight drones offers distinct benefits depending on the parameters listed. Parrot Anafi USA, for example, can be easily transported about the shop floor due to its foldable and portable form and its powerful camera functions, such as zoom and built-in camera controls may assist in more precisely recognizing tools and components. With its lengthy flight time, complex flight functions and high-resolution camera, Power Vision Power Eye may be utilized for mapping and scanning the shop floor for improved inventory management. Similarly, having precise flight control, obstacle avoidance and retractable landing gear, Yuneec H520 can assist in accessing constrained areas and securely delivering tools and supplies. Airdog ADII, with its excellent tracking and obstacle avoidance features, can assist the workers in navigating the shop floor and delivering supplies with ease. The powerful AI algorithms, obstacle avoidance and tracking characteristics of Skydio 2+ can be beneficial in mapping and scanning the work floor, as well as locating tools and components. Autel EVO II Pro V3 having superior camera functions can assist in collecting high-quality images of tools and components for improved identification. DJI Phantom 4 Pro has high-performance camera, obstacle avoidance capability and lengthy flying time, which are beneficial for examining the shop floor and locating tools and components. Finally, with its lengthy flight time, obstacle avoidance ability and accurate flight control, Aurelia X4 Standard can be utilized for inspection purposes and safely transporting tools and components. Overall, based on the criteria outlined, each drone has its own set of benefits and effectiveness in delivering tools and components inside the shop floor. The photographs of two typical delivery drones are provided in Figure 7.1.

Table 7.1 provides the initial decision matrix for solving the drone selection problem for delivery operation using eight newly developed MCDM method.

The catalogues and websites of the relevant drone manufacturers are the source of the information about the technical specifications of the drones under consideration.

Parrot Anafi USA
(https://www.parrot.com/en/drones/anafi-usa)

Power vision power eye
(https://www.powervision.me/en/product/powereye)

Figure 7.1 Photographs of two typical delivery drones

Table 7.1 Decision matrix of drone selection

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	32	0.644	54	5	42	5	21	7000
A_2	29.5	3.95	64.8	4	25	5	12	1999
A_3	30	2.5	48.6	4	20	7	20	1650
A_4	18	2.146	72	3.5	22.5	5	12	1500
A_5	27	0.8	58	4.5	22.5	6	12.3	1099
A_6	40	2	72	7	25	15	20	2500
A_7	30	1.7	72	2	20	7	20	1527.27
A_8	25	5.315	56	3	32.5	2.4	12	3300

PROBID method

Before applying the PROBID method, criteria weights are evaluated. To estimate objective weights of the considered criteria, the SPC method is first employed. For this purpose, the symmetry points of those criteria (SPC_j) are determined using Eq. (2.15), as shown in Table 7.2. The matrix of absolute distances (V) is derived employing Eq. (2.16) and is shown in Table 7.3. Table 7.4 provides the moduli of symmetry (S), calculated employing Eq. (2.17). The modulus of symmetry of the criteria (T), determined based on Eq. (2.18), is exhibited in Table 7.5. Finally, Table 7.6 displays the criteria weights, computed applying Eq.(2.19), indicating that 'cost' (C_8) has the maximum priority, followed by maximum takeoff weight (C_2).

Table 7.2 Symmetry point of criterion

Criterion	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
Min	18	0.644	48.6	2	20	2.4	12	1099
Max	40	5.315	72	7	42	15	21	7000
Symmetry point	29	2.9795	60.3	4.5	31	8.7	16.5	4049.5

Table 7.3 Resulting matrix of absolute distances (*V*)

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	3	2.335	6.3	0.5	11	3.7	4.5	2950.5
A_2	0.5	0.970	4.5	0.5	6	3.7	4.5	2050.5
A_3	1	0.479	11.7	0.5	11	1.7	3.5	2399.5
A_4	11	0.833	11.7	1	8.5	3.7	4.5	2549.5
A_5	2	2.180	2.3	0	8.5	2.7	4.2	2950.5
A_6	11	0.980	11.7	2.5	6	6.3	3.5	1549.5
A_7	1	1.280	11.7	2.5	11	1.7	3.5	2522.2
A_8	4	2.336	4.3	1.5	1.5	6.3	4.5	749.5

Table 7.4 Matrix of the moduli of symmetry (*S*)

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.1309	2.2114	0.1486	0.2250	0.1890	0.7450	0.1946	0.3165
A_2	0.1419	0.3605	0.1238	0.2813	0.3175	0.7450	0.3406	1.1082
A_3	0.1396	0.5697	0.1651	0.2813	0.3969	0.5321	0.2044	1.3426
A_4	0.2326	0.6636	0.1115	0.3214	0.3528	0.7450	0.3406	1.4768
A_5	0.1551	1.7802	0.1384	0.2500	0.3528	0.6208	0.3323	2.0157
A_6	0.1047	0.7121	0.1115	0.1607	0.3175	0.2483	0.2044	0.8861
A_7	0.1396	0.8377	0.1115	0.5625	0.3969	0.5321	0.2044	1.4504
A_8	0.1675	0.2679	0.1433	0.3750	0.2442	1.5521	0.3406	0.6713

Table 7.5 Modulus of symmetry of criterion (*T*)

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
T	0.1515	0.9254	0.1317	0.3071	0.3209	0.7151	0.2702	1.1584

Table 7.6 Criteria weight using SPC

C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
0.0381	0.2325	0.0331	0.0772	0.0806	0.1796	0.0679	0.2910

Following the procedural steps involved in the PROBID method, the normalized and weighted normalized decision matrices are computed using Eqs. (3.48)-(3.49) and are shown in Table 7.7 and Table 7.8 respectively. The ideal (Z_k) and average ($\bar{Z}$) solutions are obtained based on Eqs. (3.50)-(3.52), as provided in Table 7.9. In Table 7.10, the Euclidean distances ($E_{i(k)}$) (most PIS, second PIS,...,eighth PIS) and the average solutions ($E_{i(avg)}$) are computed based on Eqs. (3.53) and (3.54). Table 7.11 provides the positive ideal ($E_{i(pos\text{-}ideal)}$), negative ideal ($E_{i(neg\text{-}ideal)}$), positive-ideal or negative-ideal ratio (RA_i) and performance score (PS_i) of each of the alternatives, obtained using Eqs.(3.55)-(3.58). It can be clearly noticed from Table 7.11 that Power Vision Power Eye secures the top position with the highest performance score followed by Yuneec H520 model. On the other hand, the minimum preference is assigned to the Parrot Anafi USA model for the given delivery operation. Relatively low cost, higher camera resolution and moderate to fair performance with respect to other criteria justify its selection as the most suitable drone for the said application.

Table 7.7 Normalized matrix

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.3832	0.0814	0.3041	0.4062	0.5476	0.2384	0.4453	0.7893
A_2	0.3533	0.4990	0.3649	0.3250	0.3259	0.2384	0.2544	0.2254

A_3	0.3593	0.3158	0.2737	0.3250	0.2608	0.3338	0.4241	0.1861
A_4	0.2156	0.2711	0.4055	0.2844	0.2934	0.2384	0.2544	0.1691
A_5	0.3234	0.1011	0.3266	0.3656	0.2934	0.2861	0.2608	0.1239
A_6	0.4790	0.2527	0.4055	0.5687	0.3259	0.7153	0.4241	0.2819
A_7	0.3593	0.2148	0.4055	0.1625	0.2608	0.3338	0.4241	0.1722
A_8	0.2994	0.6715	0.3154	0.2437	0.4237	0.1144	0.2544	0.3721

Table 7.8 Weighted normalized matrix

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.0146	0.0189	0.0101	0.0313	0.0442	0.0428	0.0302	0.2297
A_2	0.0134	0.1160	0.0121	0.0251	0.0263	0.0428	0.0173	0.0656
A_3	0.0137	0.0734	0.0091	0.0251	0.0210	0.0600	0.0288	0.0541
A_4	0.0082	0.0630	0.0134	0.0219	0.0237	0.0428	0.0173	0.0492
A_5	0.0123	0.0235	0.0108	0.0282	0.0237	0.0514	0.0177	0.0361
A_6	0.0182	0.0587	0.0134	0.0439	0.0263	0.1285	0.0288	0.0820
A_7	0.0137	0.0499	0.0134	0.0125	0.0210	0.0600	0.0288	0.0501
A_8	0.0114	0.1561	0.0104	0.0188	0.0342	0.0206	0.0173	0.1083

Table 7.9 Ideal and average solutions of the drone selection problem

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
Most PIS	0.0182	0.1561	0.0134	0.0439	0.0442	0.1285	0.0302	0.0361
2nd PIS	0.0146	0.1160	0.0134	0.0313	0.0342	0.0600	0.0288	0.0492
3rd PIS	0.0137	0.0734	0.0134	0.0282	0.0263	0.0600	0.0288	0.0501
4th PIS	0.0137	0.0630	0.0121	0.0251	0.0263	0.0514	0.0288	0.0541
5th PIS	0.0134	0.0587	0.0108	0.0251	0.0237	0.0428	0.0177	0.0656
6th PIS	0.0123	0.0499	0.0104	0.0219	0.0237	0.0428	0.0173	0.0820
7th PIS	0.0114	0.0235	0.0101	0.0188	0.0210	0.0428	0.0173	0.1083
8th PIS (Most NIS)	0.0082	0.0189	0.0091	0.0125	0.0210	0.0206	0.0173	0.2297
Average	0.0132	0.0700	0.0116	0.0259	0.0275	0.0561	0.0233	0.0844

Table 7.10 Euclidean distances of each solution to the ideal solutions and average solutions

Alternative	Most PIS	2nd PIS	3rd PIS	4th PIS	5th PIS	6th PIS	7th PIS	8th PIS	Average
A_1	0.2527	0.2059	0.1894	0.1822	0.1707	0.1531	0.1250	0.0399	0.1557
A_2	0.1034	0.0283	0.0499	0.0561	0.0574	0.0683	0.1023	0.1926	0.0519
A_3	0.1131	0.0455	0.0085	0.0148	0.0278	0.0422	0.0768	0.1889	0.0320
A_4	0.1317	0.0589	0.0247	0.0167	0.0182	0.0357	0.0713	0.1874	0.0394
A_5	0.1562	0.0952	0.0539	0.0451	0.0469	0.0541	0.0734	0.1968	0.0676
A_6	0.1092	0.0964	0.0787	0.0844	0.0901	0.0899	0.1006	0.1905	0.0759
A_7	0.1331	0.0700	0.0287	0.0212	0.0301	0.0394	0.0676	0.1870	0.0430
A_8	0.1335	0.0834	0.1099	0.1131	0.1093	0.1122	0.1351	0.1838	0.0969

Table 7.11 Ranking of the drone alternatives using PROBID method

Alternative	$E_{pos\text{-}deal}$	$E_{neg\text{-}ideal}$	*RA*	*PS*	Rank
A_1	0.4643	0.1962	2.3670	0.3072	8
A_2	0.1482	0.2808	0.5276	0.8341	1
A_3	0.1424	0.2483	0.5735	0.7845	2

A_3	0.1424	0.2483	0.5735	0.7845	2
A_4	0.1736	0.2396	0.7246	0.6952	5
A_5	0.2330	0.2633	0.8850	0.6284	7
A_6	0.2047	0.2933	0.6978	0.7484	3
A_7	0.1829	0.2414	0.7578	0.6782	6
A_8	0.2401	0.3161	0.7596	0.7310	4

MACONT method

The drone selection problem is now solved using the MACONT method with SPC weights. In Table 7.1, Eqs. (3.2), (3.3) and (3.4) are first applied to obtain the normalized values. To obtain the comprehensive decision matrix values Eq. (3.5) is applied. To calculate the subordinate comprehensive values, Eqs. (3.6) and (3.7) are used, considering the $\delta = 0.5$ and $\vartheta = 0.5$ respectively. Finally, the comprehensive scores are evaluated using Eq. (3.8). The ranking results are provided in Table 7.12. It is revealed that A_2, is the best drone followed by A_5 as they secure the first and second positions respectively.

Table 7.12 Ranking results using MACONT method

Alternative	ρ_i	Q_i	$S_1(A_i)$	$S_2(A_i)$	$S(A_i)$	Rank
A_1	0.0074	0.5415	0.214	0.0085	0.1844	4
A_2	0.0395	0.8176	0.4234	0.0221	0.4138	1
A_3	0.0057	0.2398	0.1034	0.0075	0.1205	7
A_4	0.0049	0.3732	0.1468	0.0149	0.2093	3
A_5	0.0294	0.7308	0.3574	0.0142	0.3083	2
A_6	-0.1259	0.4791	-0.2791	-0.0425	-0.5279	8
A_7	-0.001	0.2282	0.0754	0.0109	0.1376	6
A_8	0.04	0.3227	0.2534	0.0054	0.1757	5

PARIS method

In Table 7.1, Eqs. (3.10) to (3.16) are first applied to obtain the three weighted normalized matrices. π_i^{ω} is calculated using Eq. (3.17). Eq. (3.18) is applied to determine the reference ideal solution (z_j*). Eqs. (3.19) and (3.20) are used to calculate R_i. Table 7.13 presents the ranking results based on ascending order of R_i. It is unveiled that A_6 is the best drone followed by A_2 as they secure the first and second positions respectively.

Table 7.13 Ranking results using PARIS method

Alternative	*Ri* (WAY_1)	Rank	*Ri* (WAY_2)	Rank	*Ri* (WAY_3)	Rank
A_1	0.4986	8	0.4625	8	0.6114	8
A_2	0.2229	2	0.1368	4	0.2203	2
A_3	0.2356	3	0.1317	2	0.2295	3
A_4	0.2804	6	0.1976	7	0.3501	6
A_5	0.2927	7	0.1349	3	0.3777	7
A_6	0.1692	1	0.04	1	0	1
A_7	0.2701	5	0.1744	5	0.2741	4
A_8	0.2559	4	0.1918	6	0.279	5

EAMR method

Following the procedure of the EAMR method, the evaluation score is displayed in Table 7.14. A_2 emerges as the best alternative. From this table, it is also observed that A_3 is the second best, whereas, A_1 is the worst choice.

Table 7.14 Ranking results based on EAMR method

Alternative	G_i^+	G_i^-	$RV(G_i^+)$	$RV(G_i^-)$	S_i	Rank
A_1	0.3470	0.2910	0.1121	0.3402	0.3296	8
A_2	0.2918	0.0457	0.0943	0.0534	1.7655	1
A_3	0.3913	0.0686	0.1264	0.0802	1.5768	2
A_4	0.3246	0.0624	0.1049	0.0729	1.4388	4
A_5	0.4214	0.0831	0.1362	0.0972	1.4019	6
A_6	0.5281	0.1039	0.1707	0.1215	1.4048	5
A_7	0.3450	0.0635	0.1115	0.0742	1.5019	3
A_8	0.4450	0.1372	0.1438	0.1604	0.8968	7

CURLI method

The CURLI method is applied to solve this selection problem. Table 7.15 displays the processing matrix, obtained by summing the scoring matrix values. Further this matrix is rearranged, so that the upper section of the main diagonal contains the negative and 0 values. Final ranks are displayed in Table 7.16. A_2 secures the top position followed by A_1.

Table 7.15 Processing scoring matrix after changing the positions of rows and columns

Alternative	P_2	P_1	P_7	P_3	P_5	P_6	P_4	P_8
A_2	0	-4	-4	-3	-6	-3	-3	-4
A_1	4	0	0	-2	0	-1	-1	-2
A_7	4	0	0	0	-2	-2	1	-2
A_3	3	2	0	0	0	-1	-2	-2
A_5	6	0	2	0	0	0	-3	-4
A_6	3	1	2	1	0	0	-2	-3
A_4	3	1	-1	2	3	2	0	-1
A_8	4	2	2	2	4	3	1	0

Table 7.16 Rank result using CURLI method

Alternative	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
Rank	2	1	4	7	5	6	3	8

PEG method

The same problem is now solved using the PEG method. The final MSE values are presented in Table 7.17, revealing that A_2 is the top ranked alternative. This ranking highlights superior performance of A_2 compared to other alternatives.

Table 7.17 Ranking results using PEG method

Alternative	x	y	x∗	y∗	MSE	Rank
A_1	0	0.875	0.2929	0.9116	1.1793	2

A_2	0.5455	0.2406	0.6786	0.463	1.288	1
A_3	0.4091	0.5383	0.5822	0.6735	0.5992	6
A_4	0.5227	0.4653	0.6625	0.6219	0.443	8
A_5	0.5455	0.2866	0.6786	0.4956	0.4695	7
A_6	0.3182	0.6327	0.5179	0.7403	0.6453	4
A_7	0.6364	0.1622	0.7429	0.4076	0.6153	5
A_8	1	0	1	0.2929	0.7743	3

DNMA method

Applying the steps of DNMA method, the decision matrix is normalized using Eqs. (3.59) and (3.60). In the next step, using Eqs. (3.61), (3.62) and (3.63) the adjusted weight coefficients are estimated. Based on the computed utility values, the alternative drones are subsequently ranked. Finally, the comprehensive utility values for each of the alternatives are calculated using Eq.(3.67), considering values of different tuning parameters as φ = 0.5, $\overline{\omega}_1$= 0.6, $\overline{\omega}_2$= 0.1 and $\overline{\omega}_3$= 0.3. Eight drones are subsequently ranked in decreasing order of their S_i values. Table 7.18 shows A_6 as the best followed by A_3.

Table 7.18 Ranking results using DNMA method

Alternative	CCM $u_1(a_i)$	Rank	UCM $u_2(a_i)$	Rank	ICM $u_3(a_i)$	Rank	Utility value (S_i)	Rank
A_1	0.3349	8	0.2232	8	0.6136	8	0.2588	8
A_2	0.4999	3	0.1323	2	0.811	2	0.6618	3
A_3	0.5029	2	0.1249	1	0.8059	3	0.6898	2
A_4	0.4019	6	0.1406	3	0.7687	6	0.4398	6
A_5	0.3879	7	0.2003	7	0.7568	7	0.3583	7
A_6	0.716	1	0.1471	4	0.8616	1	0.8415	1
A_7	0.4833	4	0.1604	5	0.7772	4	0.5557	4
A_8	0.4571	5	0.1667	6	0.7767	5	0.4879	5

OPTBIAS method

The OPTBIAS method is applied, and the decision matrix is normalized using the vector normalization approach. The bi-positive ideal, bi-negative ideal, and average solutions are calculated using Eqs. (3.43)-(3.45). Table 7.19 shows the Euclidean distances of the alternatives from the positive ideal, negative ideal, and average solutions, along with *B* and *PS* values using Eqs. (3.46) and (3.47). A_2, with the highest performance score, ranks first.

Comparative analyses of MCDM methods

A detailed comparative analysis is performed in this section using the set of criteria weights presented in Table 7.20.

a) Based on rank comparison

In Figure 7.1, entropy-based results show that A_6 maintains high ranks, reflecting its robust performance, while A_8 continues to perform poorly. For the CRITIC method, alternative A_2 consistently secures the top position, showcasing strong preference, while A_8 ranks lowest. In

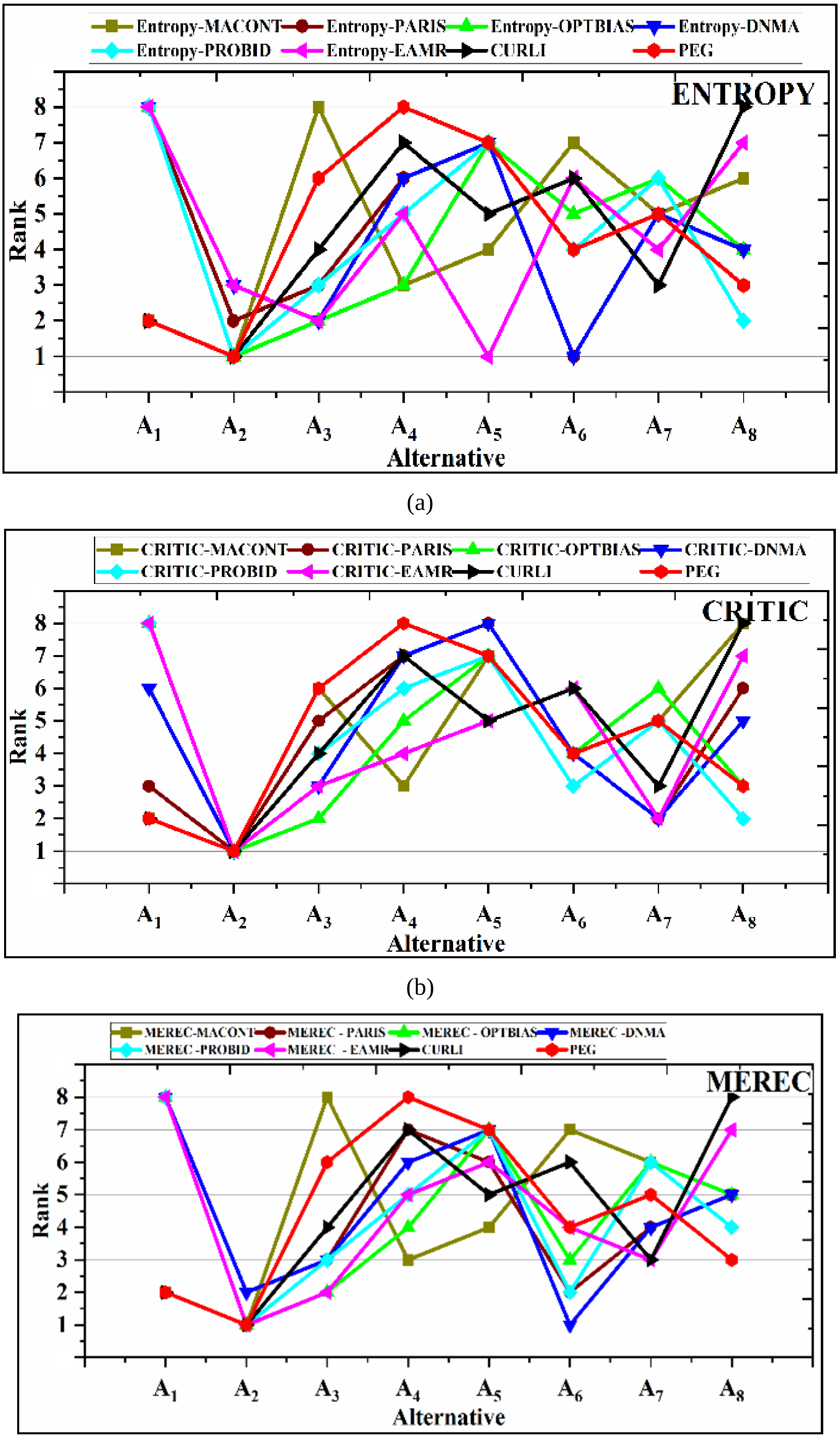
MEREC, alternative A_2 consistently secures top ranks, with A_8 frequently at the bottom. PCA-based results highlight A_2 dominance, with A_8 consistently performing poorly. SPC rankings also place A_2 at the top across most methods, with A_8 at the bottom. The LOPCOW method reveals similar trends, with A_2 maintaining strong performance and A_8 ranking low. Under CILOS, A_2 consistently secures top ranks, while A_8 ranks lowest. Finally, IDOCRIW-based results highlight A_2 strong preference across methods and A_8 poor performance. Overall, A_2 consistently secures top ranks across various weighting methods, while A_8 consistently performs poorly. The results indicate differing prioritization criteria inherent in each method, with A_2 and A_6 often emerging as robust performers, while A_8 frequently ranks lowest. MACONT and PARIS exhibit some variability but generally align with other methods in ranking top alternatives. DNMA and EAMR show strong performance in ranking alternatives such as A_1 and A_2, reflecting their reliability. CURLI and PEG present more fluctuations in their rankings, highlighting their sensitivity to different prioritization criteria. DNMA and PARIS provide consistent rankings but CURLI and PEG require careful consideration due to their variability.

Table 7.19 Ranking results based on OPTBIAS method

Alternative	*RP*	*RN*	*RA*	*B*	*PS*	Rank
A_1	0.4649	0.2230	0.1543	0.4797	1.1830	8
A_2	0.1772	0.3027	0.0501	1.7081	1.7703	1
A_3	0.1617	0.2672	0.0311	1.6519	1.7363	2
A_4	0.1622	0.2474	0.0369	1.5248	1.6647	3
A_5	0.2013	0.2421	0.0673	1.2028	1.4974	7
A_6	0.2286	0.3191	0.0227	1.3961	1.5940	5
A_7	0.1770	0.2471	0.0423	1.3959	1.5951	4
A_8	0.2641	0.3405	0.0899	1.2894	1.5426	6

Table 7.20 Set of criteria weights

Weighting Methods	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
Entropy	0.032	0.2836	0.0151	0.0851	0.0507	0.1865	0.0498	0.2971
CRITIC	0.0797	0.1497	0.1432	0.0904	0.1489	0.0798	0.1653	0.1431
MEREC	0.0879	0.2232	0.0455	0.1314	0.0491	0.1736	0.0514	0.2379
PCA	0.2716	0.0214	0.0771	0.2227	0.1201	0.309	0.1452	0.0876
SPC	0.0381	0.2325	0.0331	0.0772	0.0806	0.1796	0.0679	0.291
LOPCOW	0.1744	0.0953	0.115	0.129	0.0573	0.072	0.1	0.2571
CILOS	0.1086	0.0705	0.2606	0.0662	0.1097	0.0444	0.2579	0.082
IDOCRIW	0.0413	0.2378	0.0468	0.067	0.0662	0.0984	0.1527	0.2898

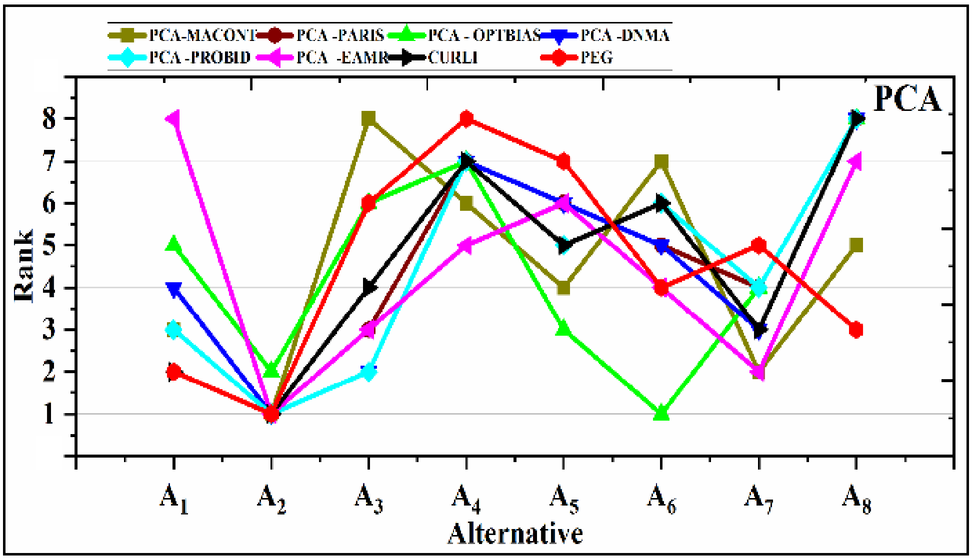


(a)

(b)

(c)

Figure 7.1 Weight wise ranking result



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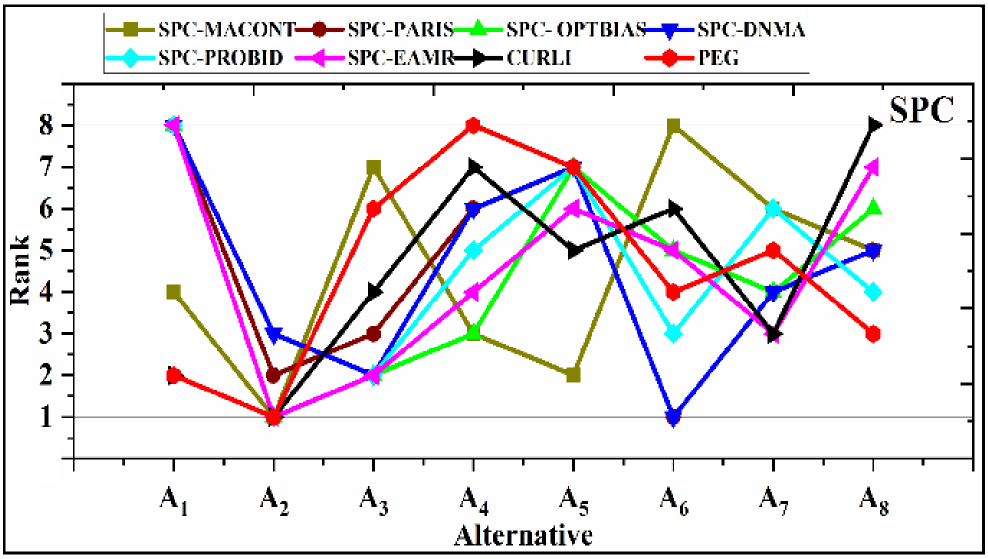

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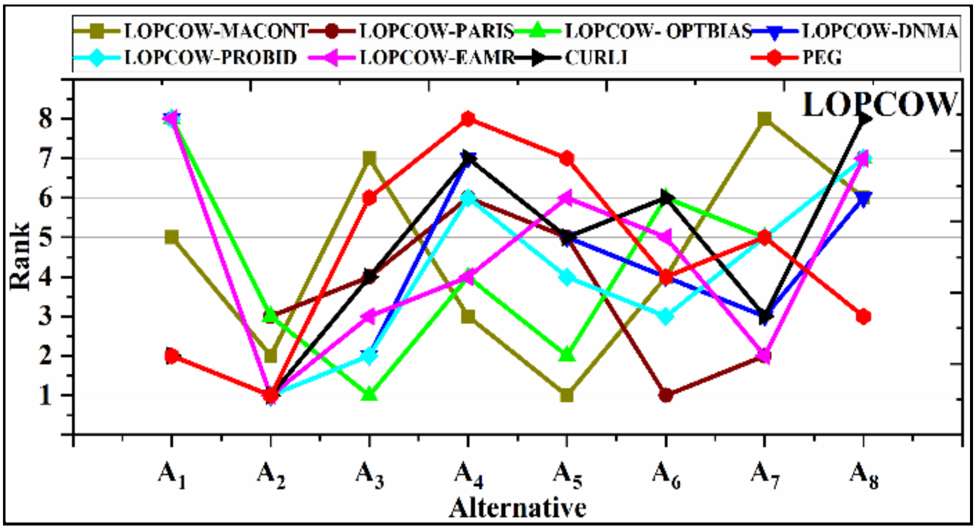

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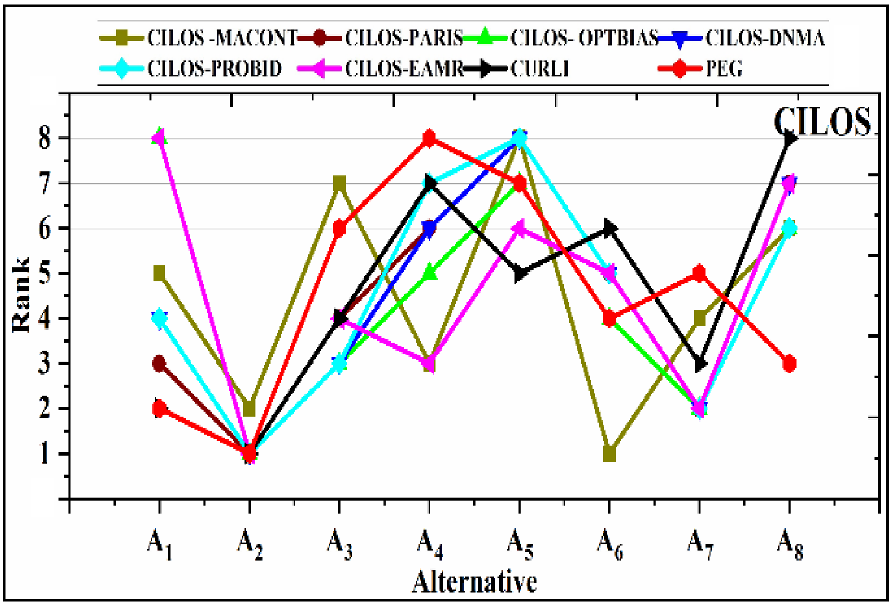
Figure 7.1 Continued



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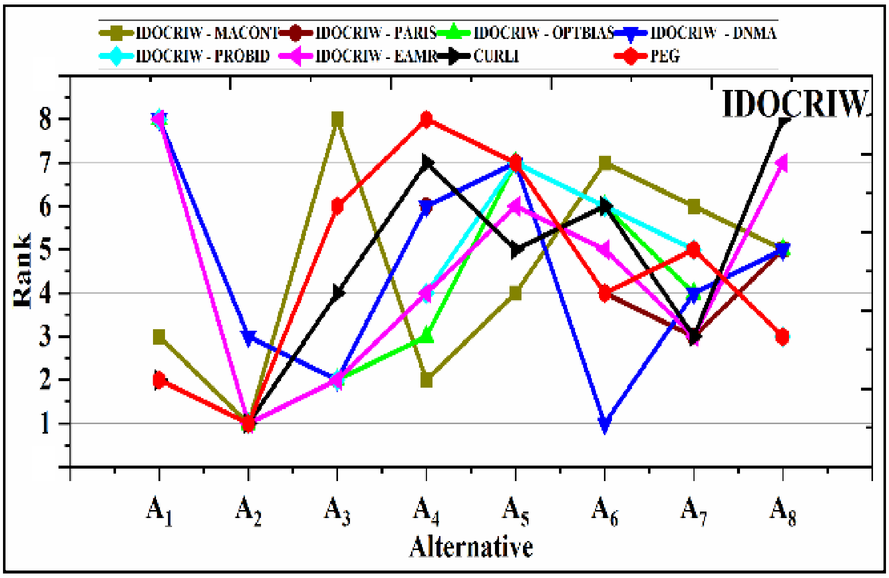
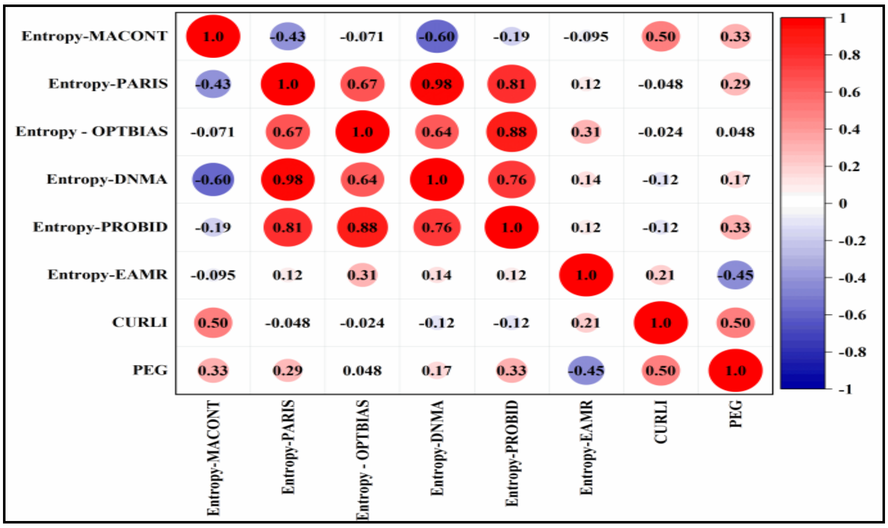


(h)

Figure 7.1 Continued

b) Based on Spearman co-relation coefficients

Figure 7.2 discloses that with entropy based methods, PARIS-DNMA exhibit a strong correlation of 0.98. Under CRITIC weighting, PROBID-OPTBIAS achieve a correlation of 0.90. MEREC weighting results show that DNMA-PARIS both have a correlation of 0.95. PCA weighting highlights high correlations for PARIS-PROBID and PARIS-CURLI at 0.95. SPC weighting sees PARIS-DNMA at 0.98. Under LOPCOW weighting, DNMA-PROBID achieve a correlation of 0.90. CILOS weighting also sees PARIS-DNMA with a high correlation of 0.98. Finally, IDOCRIW weighting shows OPTBIAS-PROBID at 0.93, with high correlations among most methods except PEG and CURLI. This study reveals that PARIS and DNMA consistently show high correlation values.



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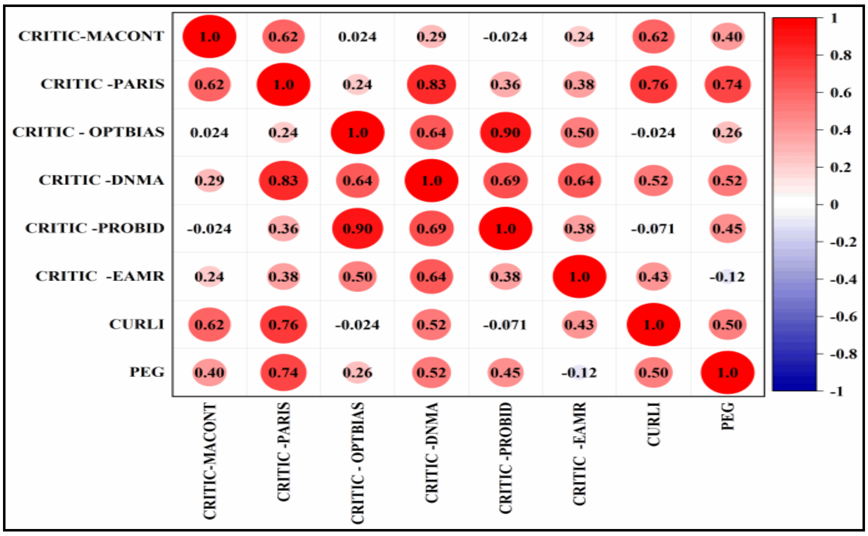

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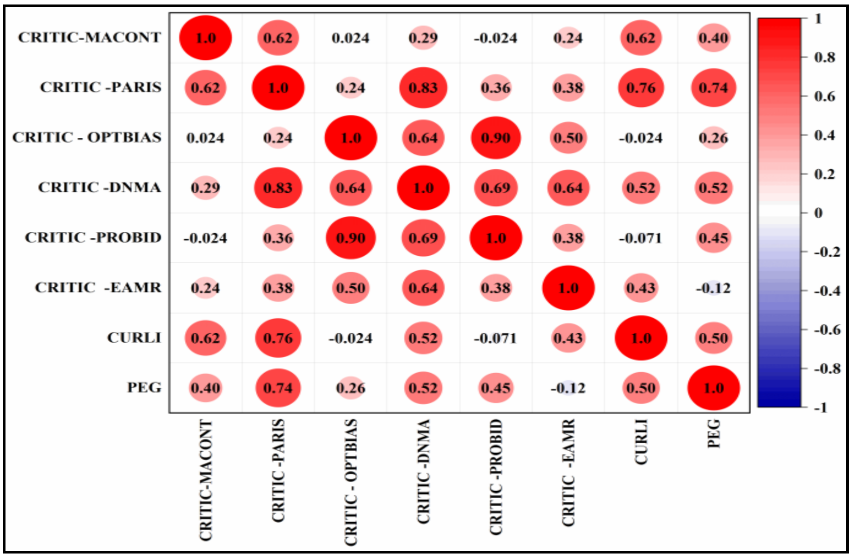
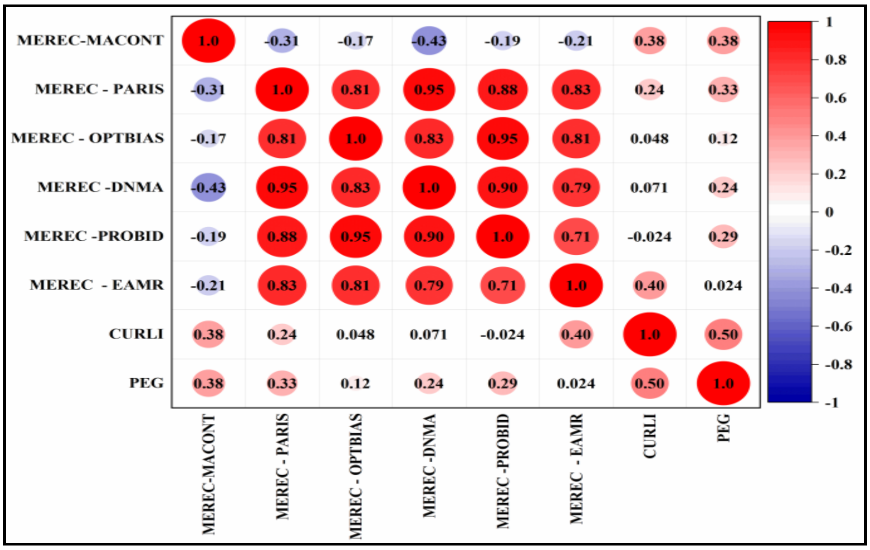


(c)

Figure 7.2 Spearman correlation coefficient result



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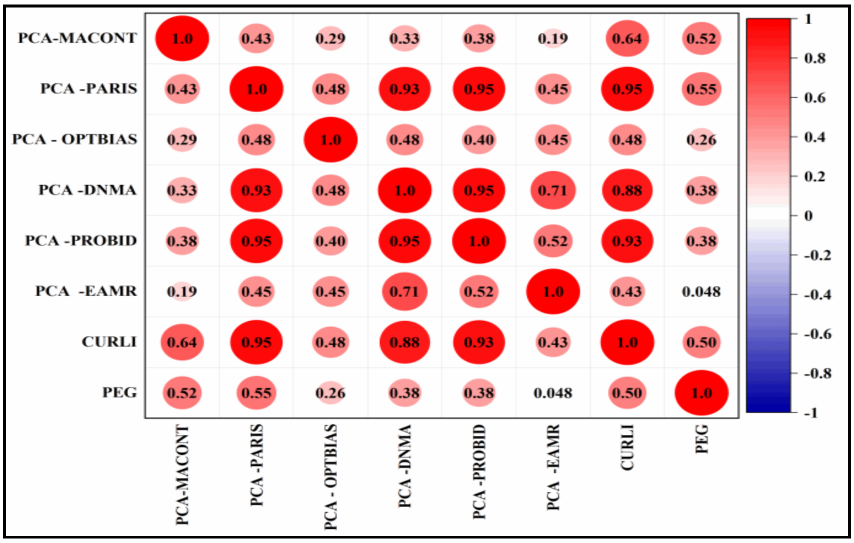

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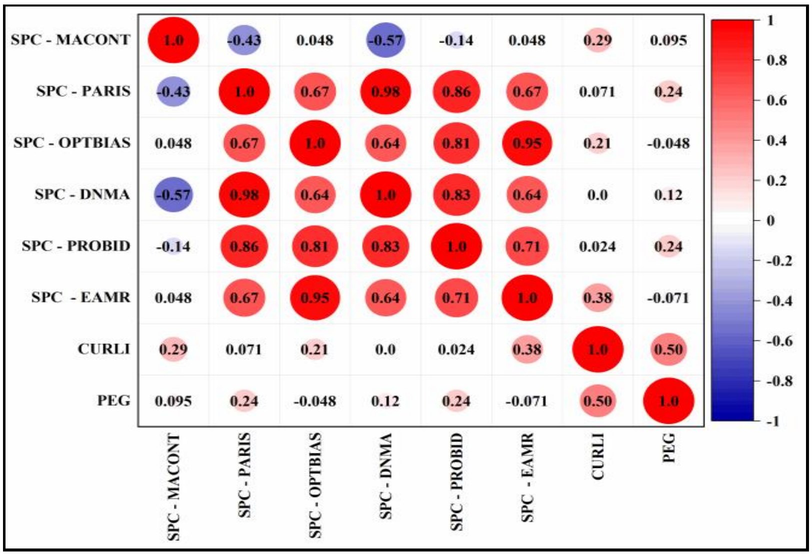

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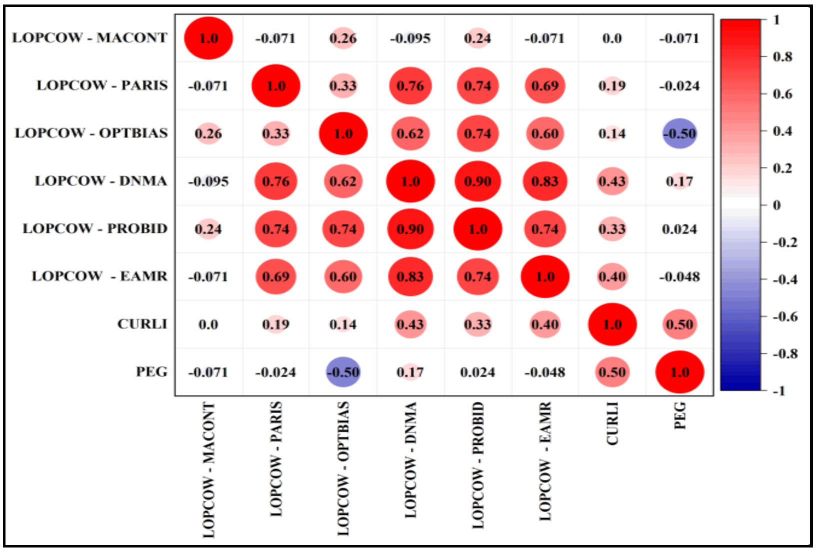
Figure 7.2 Continued



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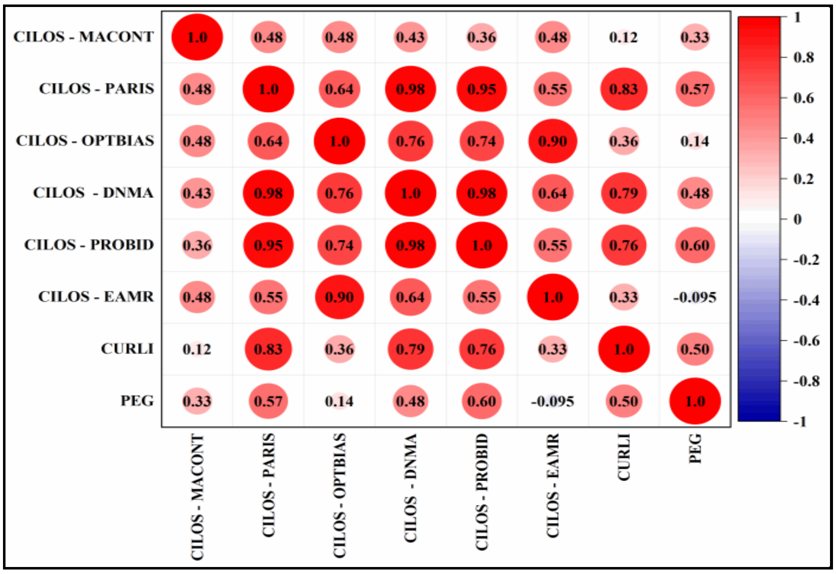
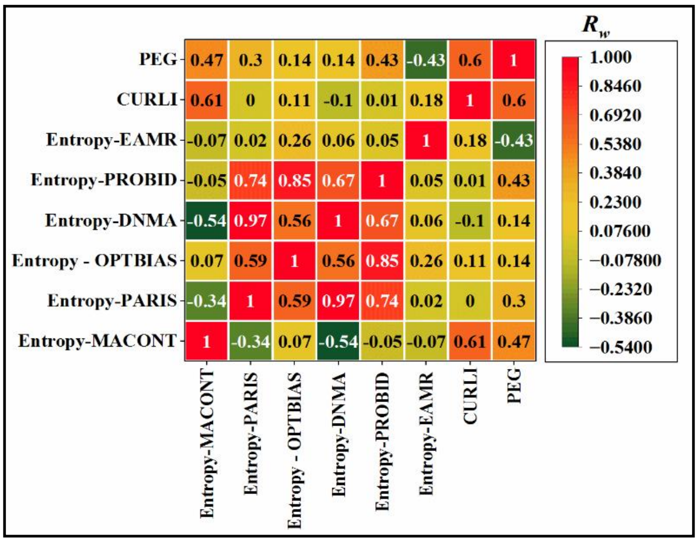


(h)

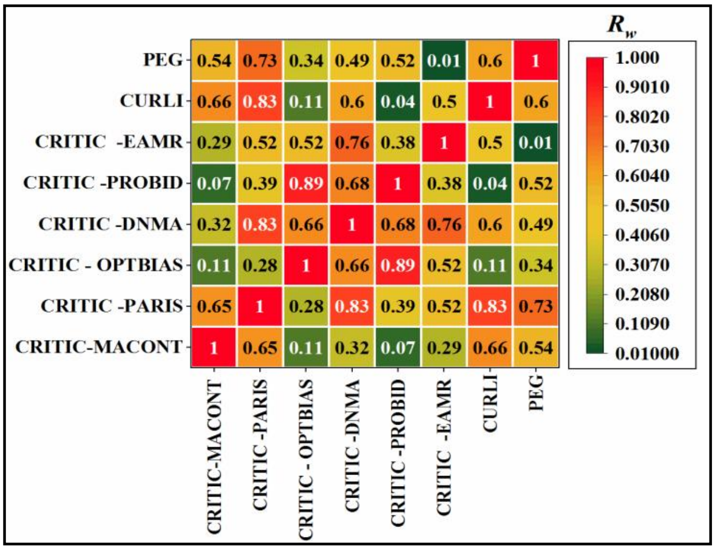
Figure 7.2 Continued

c) Based on weighted Spearman rank co-relation coefficient (R_w)

Figure 7.3 presents an overall result, where for entropy combined conditions, DNMA-PARIS shows value of 0.97, while EAMR, CURLI and PEG struggle with other MCDM methods. CRITIC weighting reveals high correlations for OPTBIAS-PROBID at 0.89 and DNMA-PARIS and CURLI-PARIS both at 0.83. MEREC weighting indicates that PROBID-OPTBIAS achieves 0.94 and DNMA-PARIS 0.95. PCA weighting shows high correlations for PARIS-CURLI, PARIS-PROBID and DNMA-PROBID all at 0.95. SPC weighting highlights DNMA-PARIS at 0.97 and OPTBIAS-EAMR at 0.96. LOPCOW weighting sees PROBID-DNMA at 0.91. CILOS weighting shows DNMA-PROBID with a correlation of 0.99. Finally, IDOCRIW weighting indicates that OPTBIAS-PROBID and OPTBIAS-EAMR both achieve 0.92. Clearly, PEG and CURLI do not perform well compared to the other MCDM methods.



(a)



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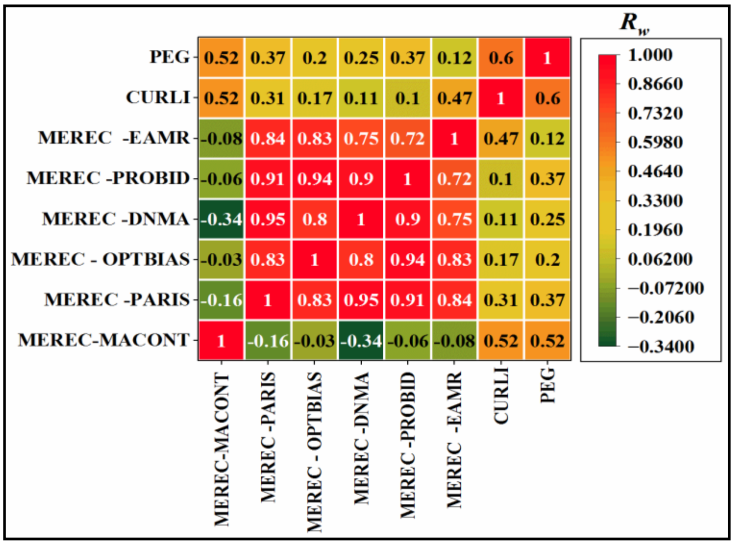
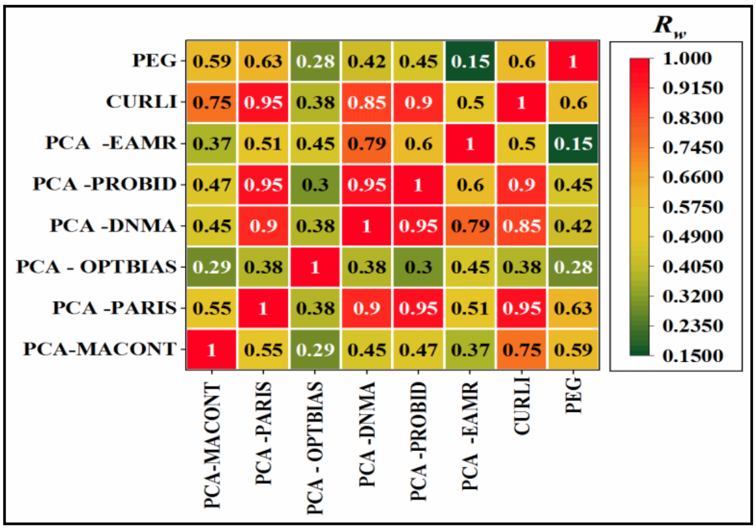


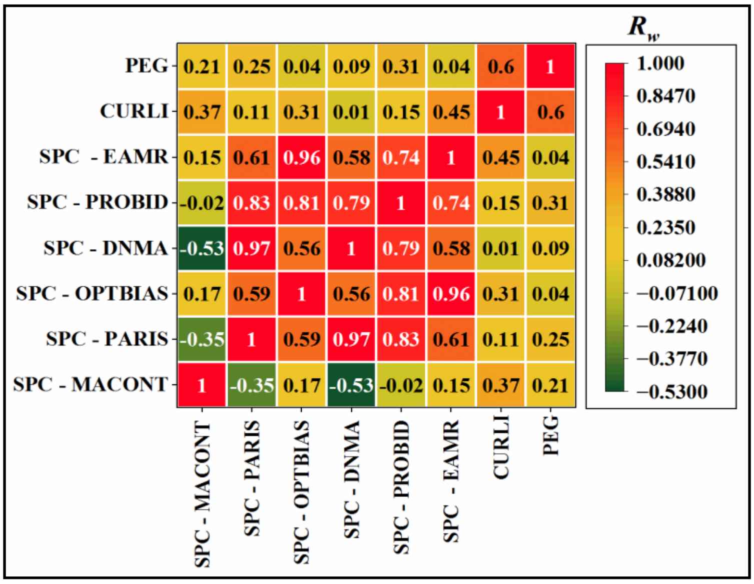
(c)

Figure 7.3 Weighted spearman correlation coefficient (R_w)



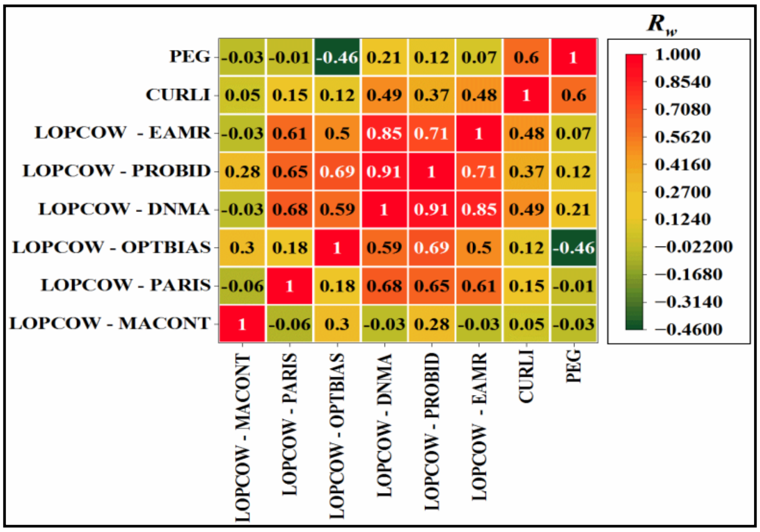
	PCA-MACONT	PCA -PARIS	PCA - OPTBIAS	PCA -DNMA	PCA -PROBID	PCA -EAMR	CURLI	PEG
PEG	0.59	0.63	0.28	0.42	0.45	0.15	0.6	1
CURLI	0.75	0.95	0.38	0.85	0.9	0.5	1	0.6
PCA -EAMR	0.37	0.51	0.45	0.79	0.6	1	0.5	0.15
PCA -PROBID	0.47	0.95	0.3	0.95	1	0.6	0.9	0.45
PCA -DNMA	0.45	0.9	0.38	1	0.95	0.79	0.85	0.42
PCA - OPTBIAS	0.29	0.38	1	0.38	0.3	0.45	0.38	0.28
PCA -PARIS	0.55	1	0.38	0.9	0.95	0.51	0.95	0.63
PCA-MACONT	1	0.55	0.29	0.45	0.47	0.37	0.75	0.59

(d)



	SPC - MACONT	SPC - PARIS	SPC - OPTBIAS	SPC - DNMA	SPC - PROBID	SPC - EAMR	CURLI	PEG
PEG	0.21	0.25	0.04	0.09	0.31	0.04	0.6	1
CURLI	0.37	0.11	0.31	0.01	0.15	0.45	1	0.6
SPC - EAMR	0.15	0.61	0.96	0.58	0.74	1	0.45	0.04
SPC - PROBID	-0.02	0.83	0.81	0.79	1	0.74	0.15	0.31
SPC - DNMA	-0.53	0.97	0.56	1	0.79	0.58	0.01	0.09
SPC - OPTBIAS	0.17	0.59	1	0.56	0.81	0.96	0.31	0.04
SPC - PARIS	-0.35	1	0.59	0.97	0.83	0.61	0.11	0.25
SPC - MACONT	1	-0.35	0.17	-0.53	-0.02	0.15	0.37	0.21

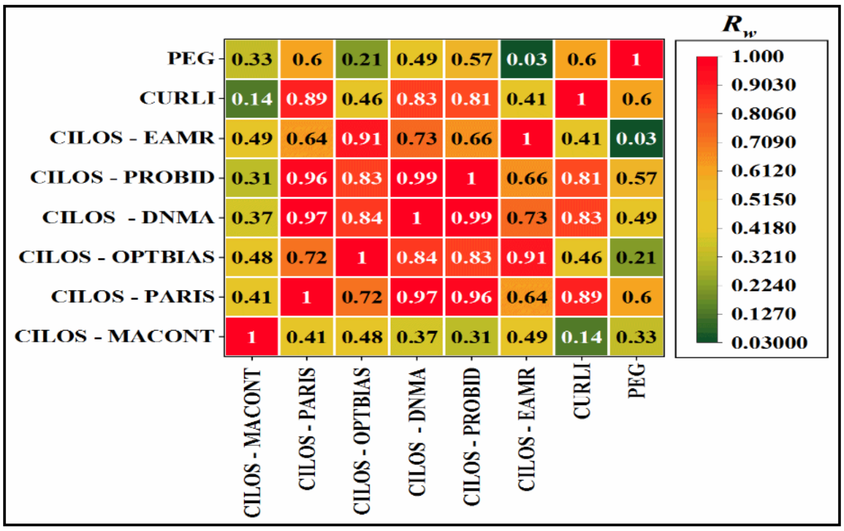
(e)



	LOPCOW - MACONT	LOPCOW - PARIS	LOPCOW - OPTBIAS	LOPCOW - DNMA	LOPCOW - PROBID	LOPCOW - EAMR	CURLI	PEG
PEG	-0.03	-0.01	-0.46	0.21	0.12	0.07	0.6	1
CURLI	0.05	0.15	0.12	0.49	0.37	0.48	1	0.6
LOPCOW - EAMR	-0.03	0.61	0.5	0.85	0.71	1	0.48	0.07
LOPCOW - PROBID	0.28	0.65	0.69	0.91	1	0.71	0.37	0.12
LOPCOW - DNMA	-0.03	0.68	0.59	1	0.91	0.85	0.49	0.21
LOPCOW - OPTBIAS	0.3	0.18	1	0.59	0.69	0.5	0.12	-0.46
LOPCOW - PARIS	-0.06	1	0.18	0.68	0.65	0.61	0.15	-0.01
LOPCOW - MACONT	1	-0.06	0.3	-0.03	0.28	-0.03	0.05	-0.03

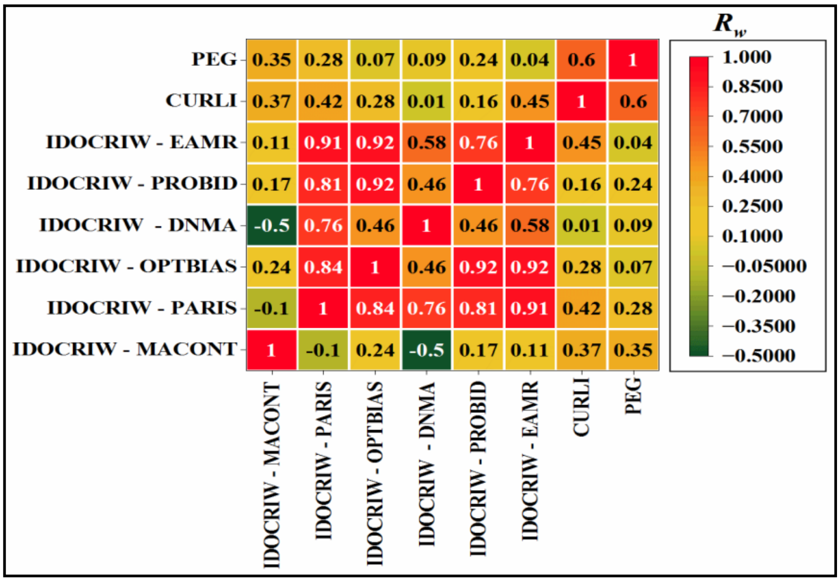
(f)

Figure 7.3 Continued



	CILOS - MACONT	CILOS - PARIS	CILOS - OPTBIAS	CILOS - DNMA	CILOS - PROBID	CILOS - EAMR	CURLI	PEG
PEG	0.33	0.6	0.21	0.49	0.57	0.03	0.6	1
CURLI	0.14	0.89	0.46	0.83	0.81	0.41	1	0.6
CILOS - EAMR	0.49	0.64	0.91	0.73	0.66	1	0.41	0.03
CILOS - PROBID	0.31	0.96	0.83	0.99	1	0.66	0.81	0.57
CILOS - DNMA	0.37	0.97	0.84	1	0.99	0.73	0.83	0.49
CILOS - OPTBIAS	0.48	0.72	1	0.84	0.83	0.91	0.46	0.21
CILOS - PARIS	0.41	1	0.72	0.97	0.96	0.64	0.89	0.6
CILOS - MACONT	1	0.41	0.48	0.37	0.31	0.49	0.14	0.33

(g)



	IDOCRIW - MACONT	IDOCRIW - PARIS	IDOCRIW - OPTBIAS	IDOCRIW - DNMA	IDOCRIW - PROBID	IDOCRIW - EAMR	CURLI	PEG
PEG	0.35	0.28	0.07	0.09	0.24	0.04	0.6	1
CURLI	0.37	0.42	0.28	0.01	0.16	0.45	1	0.6
IDOCRIW - EAMR	0.11	0.91	0.92	0.58	0.76	1	0.45	0.04
IDOCRIW - PROBID	0.17	0.81	0.92	0.46	1	0.76	0.16	0.24
IDOCRIW - DNMA	-0.5	0.76	0.46	1	0.46	0.58	0.01	0.09
IDOCRIW - OPTBIAS	0.24	0.84	1	0.46	0.92	0.92	0.28	0.07
IDOCRIW - PARIS	-0.1	1	0.84	0.76	0.81	0.91	0.42	0.28
IDOCRIW - MACONT	1	-0.1	0.24	-0.5	0.17	0.11	0.37	0.35

(h)

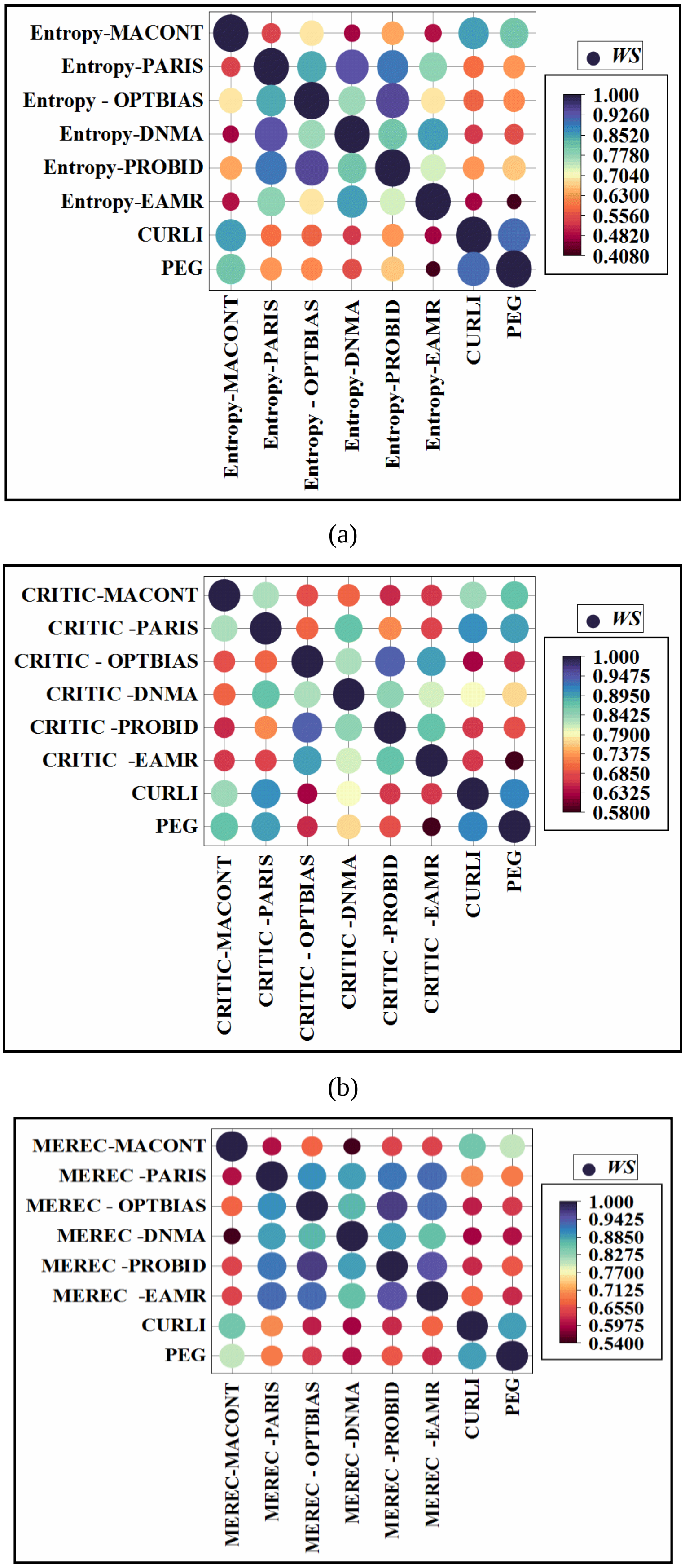
Figure 7.3 Continued

d) Based on coefficient of ranking similarity (*WS*)

Now *WS* values are computed to analyze the ranking performance of top ranked alternatives. Figure 7.4 shows the result of *WS* values of all the rankings. Under most of the weighting conditions, DNMA, PARIS, OPTBIAS and PROBID perform fairly, with occasionally crossing 0.95.

e) Based on number of operations

Figure 7.5 shows a comparative analysis between the considered MCDM methods with reference to the total number of mathematical operations required. From this figure, it can be unveiled that in order to solve this decision making problems, EAMR method needs comparatively a smaller number of operations, 168, followed by OPTBIAS, 264 and on the other hand MACONT, 368 and CURLI, 640, require a greater number of operations. EAMR technique again outperforms all of the evaluated MCDM methods.

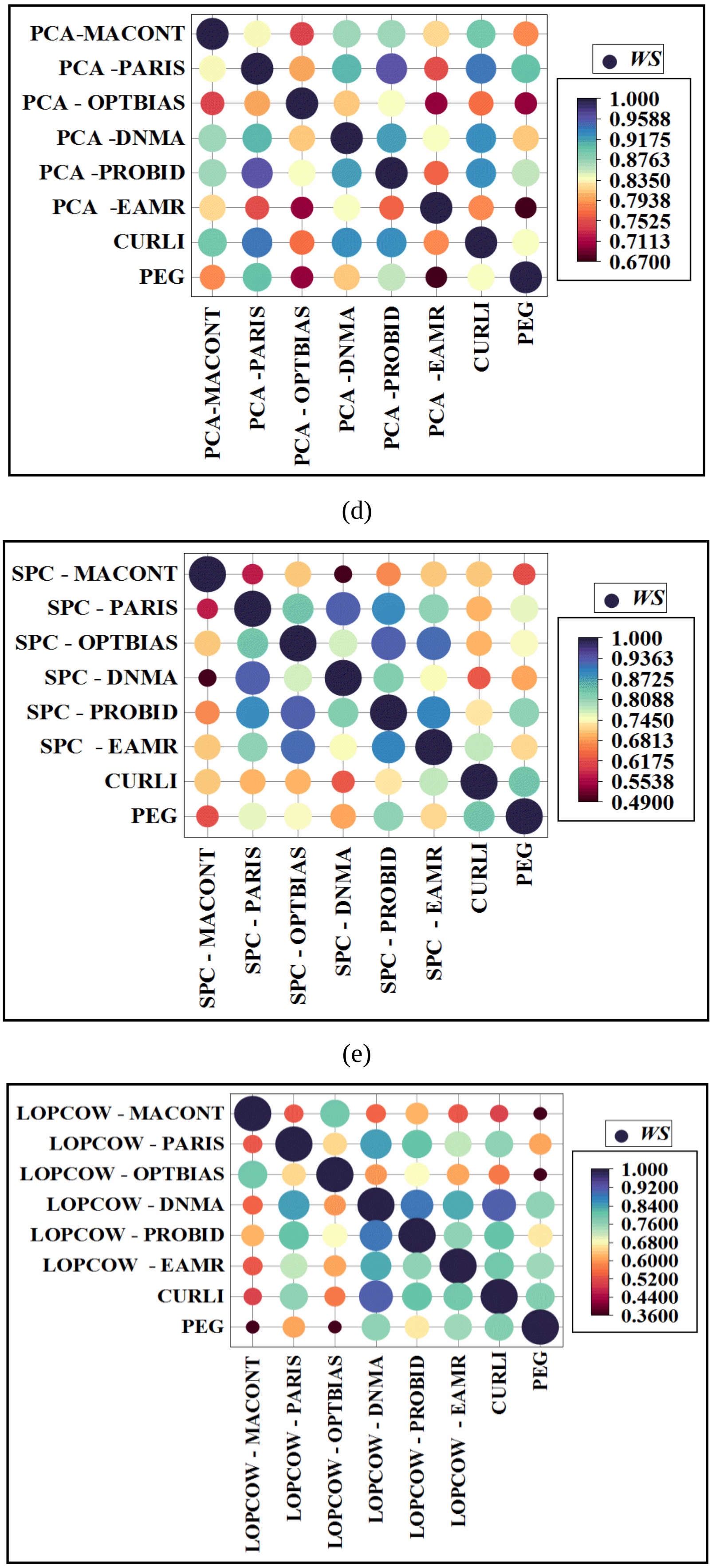


(a)

(b)

(c)

Figure 7.4 Coefficient of rank similarity (*WS*) results



(d)

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Figure 7.4 Continued

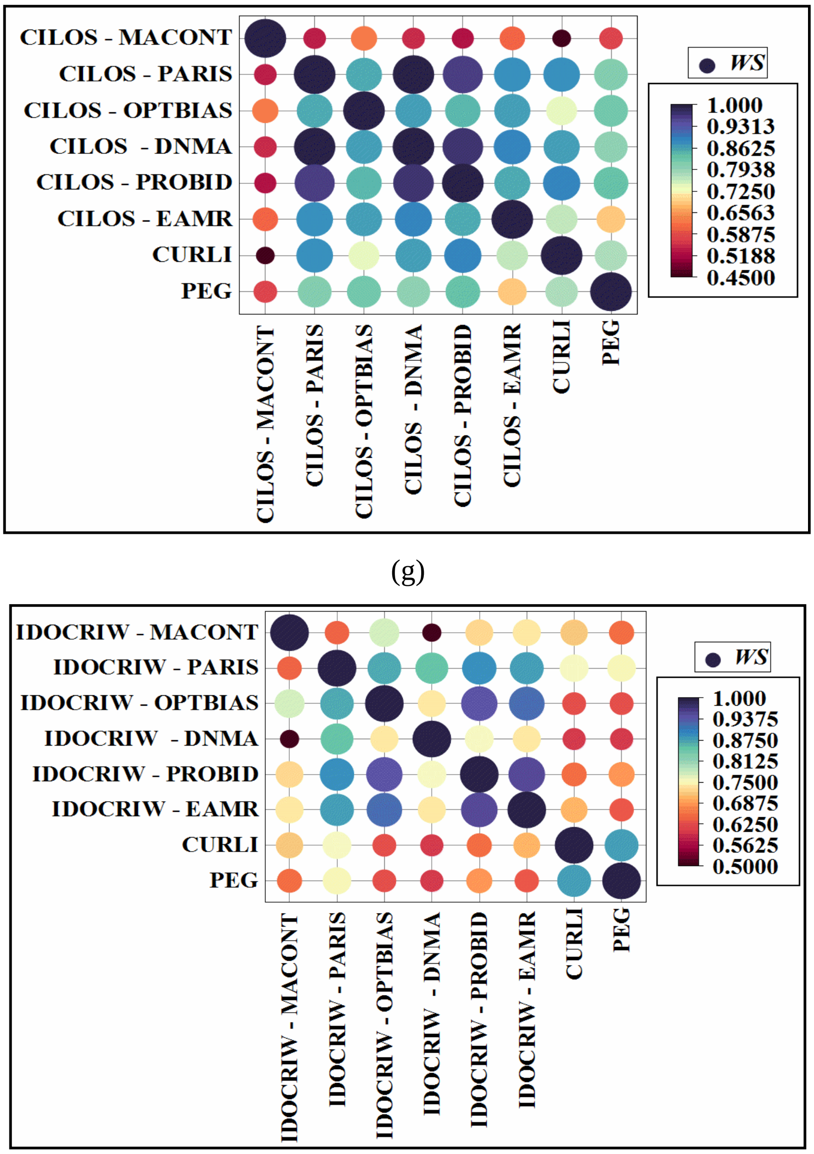

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Figure 7.4 Continued

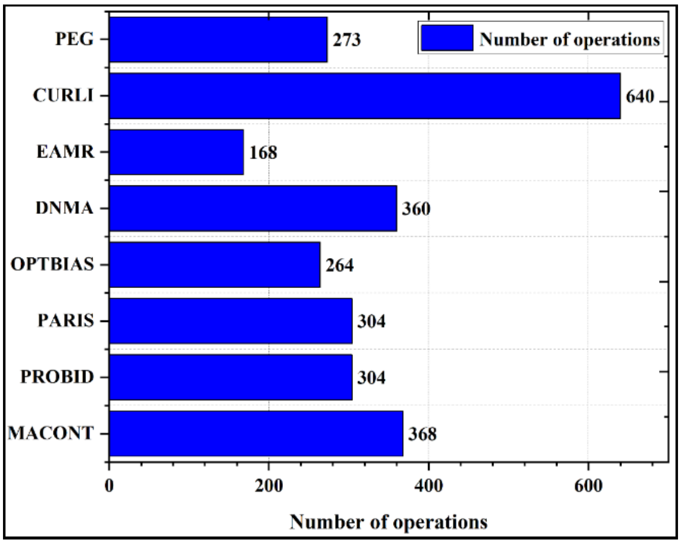


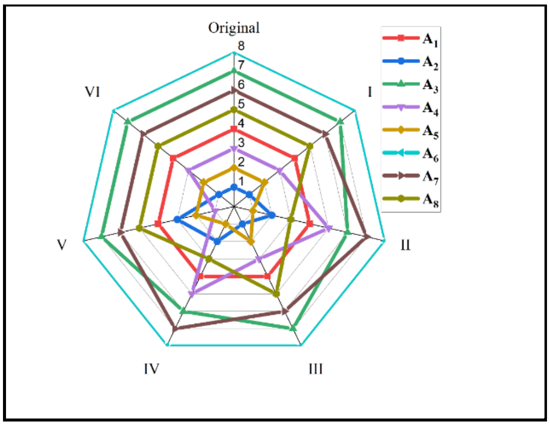
Figure 7.5 Number of operations

Sensitivity analysis

This section provides an in-depth and comprehensive sensitivity analysis, thoroughly examining the impact of different weighting scenarios on the ranking outcomes. It evaluates how variations in weighting methods influence the stability and consistency of alternative rankings, offering valuable insights into the robustness of the decision making process.

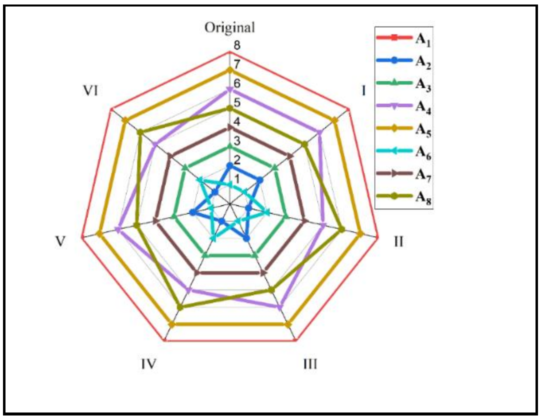
Sensitivity analysis based on gradual removal of criteria

Figure 7.6 shows the sensitivity analysis results using the SPC weighting technique under gradual criteria removal, revealing varying degrees of stability across different MCDM methods. DNMA remains completely unaffected, indicating the highest robustness, while MACONT, PARIS, OPTBIAS and PROBID exhibit minor fluctuations but maintain overall ranking consistency. EAMR demonstrates the most sensitivity, with noticeable rank shifts for alternatives such as A_2, A_3 and A_6. MACONT shows slight changes in A_2 and A_4, while PROBID sees alternating ranks for A_6 and A_2 but retains general stability. DNMA and PARIS remain mostly stable and resilient methods, while EAMR is the most sensitive, suggesting that some methods are more influenced by criteria removal than others.



MACONT

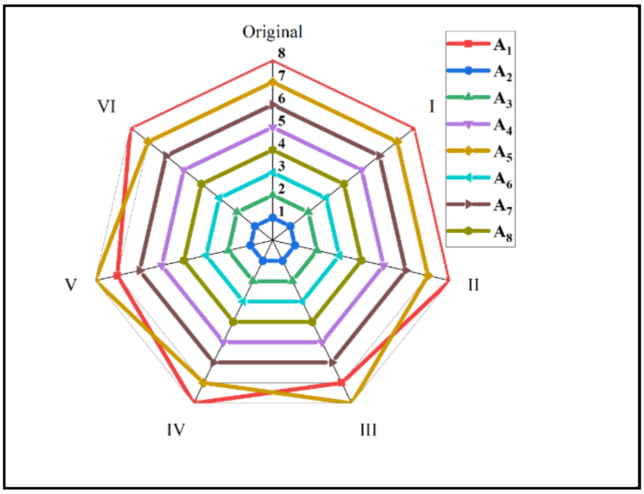
(a)



PROBID

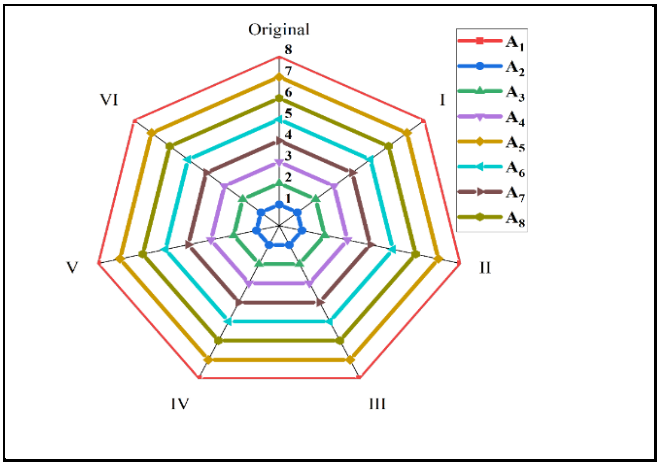
(b)

Figure 7.6 Sensitivity analyses results by gradually removal of criterion weight



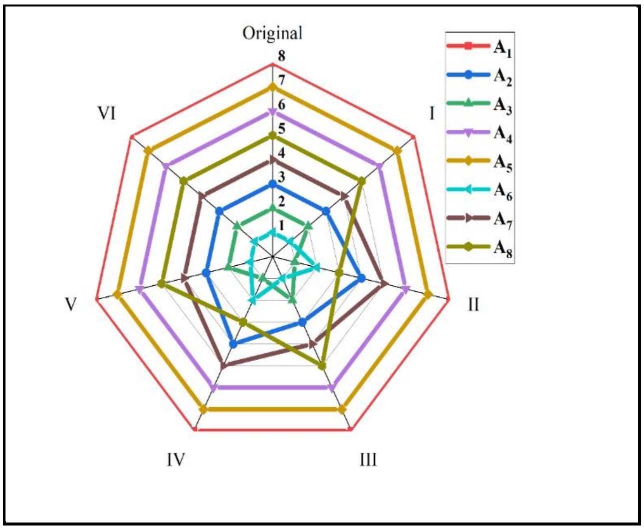
PARIS

(c)



DNMA

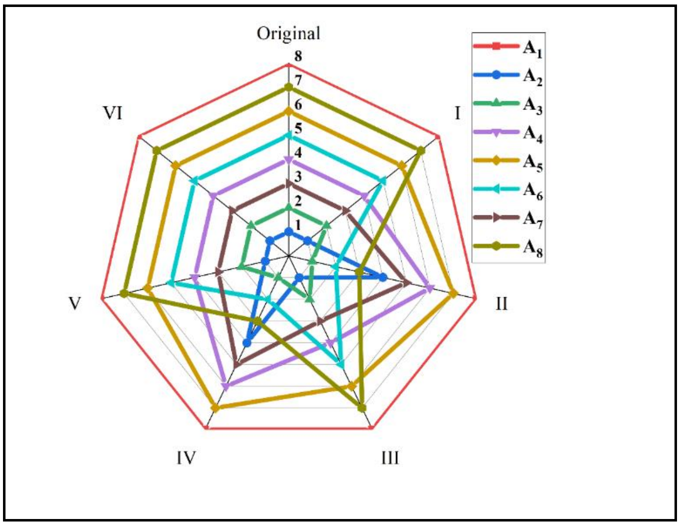
(d)



OPTBIAS

(e)

Figure 7.6 Continued



EAMR

(f)

Figure 7.6 Continued

Sensitivity analysis based on equal weighting conditions

Figure 7.7 highlights significant variations in alternative rankings, demonstrating the influence of MCDM techniques on decision making outcomes. A_2 and A_6 consistently achieve top rankings across multiple methods, indicating strong dominance irrespective of the weighting approach. A_1 shows substantial variation, ranking as high as second under MACONT and CURLI, but dropping to 8th under OPTBIAS and EAMR, suggesting sensitivity to weighting preferences. A_3, A_4 and A_5 exhibit mid-range fluctuations, with rankings shifting between third and eighth place depending on the method. A_7 and A_8 experience notable instability, particularly under OPTBIAS, PROBID and EAMR, where their rankings significantly differ. OPTBIAS appears to introduce the most ranking instability, while MACONT and PARIS maintain relatively consistent trends. The extreme shifts in certain alternatives imply that weighting techniques significantly impact the final selection, highlighting the need for careful method selection to ensure robust decision making.

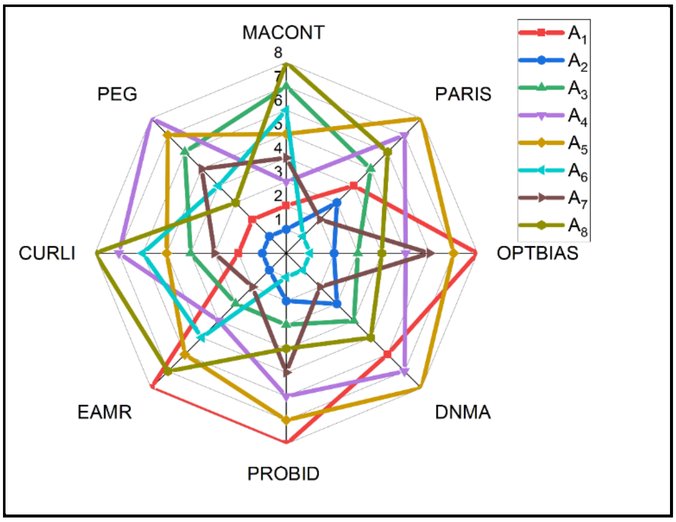
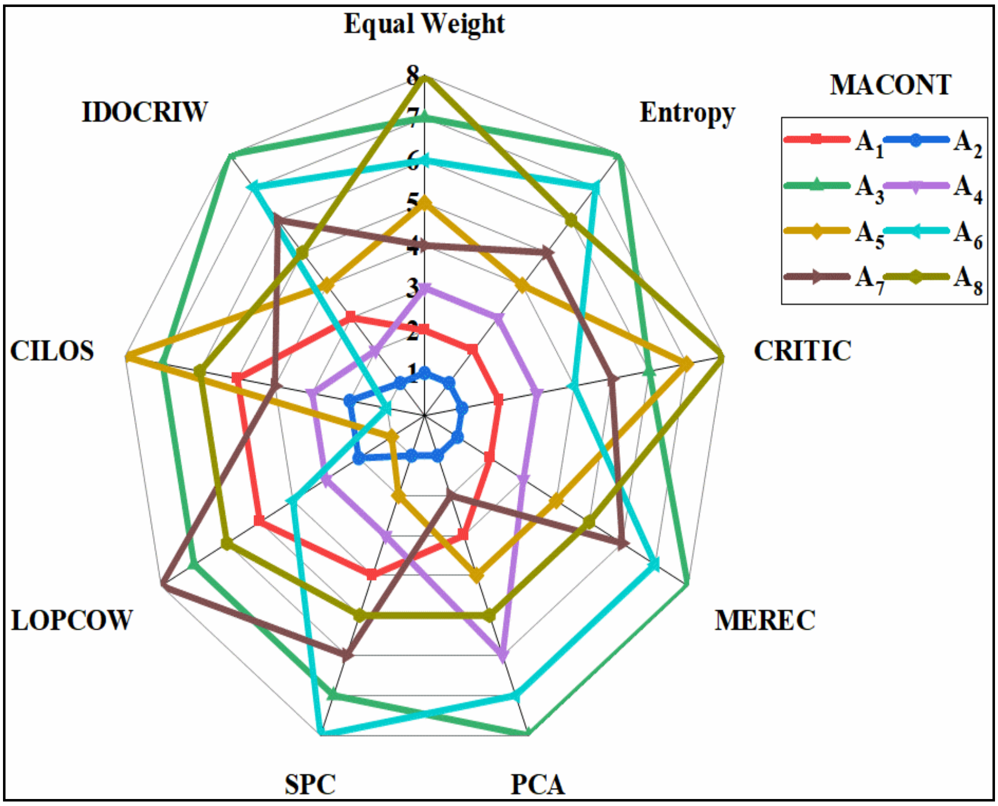


Figure 7.7 Sensitivity analyses results under equal weight condition

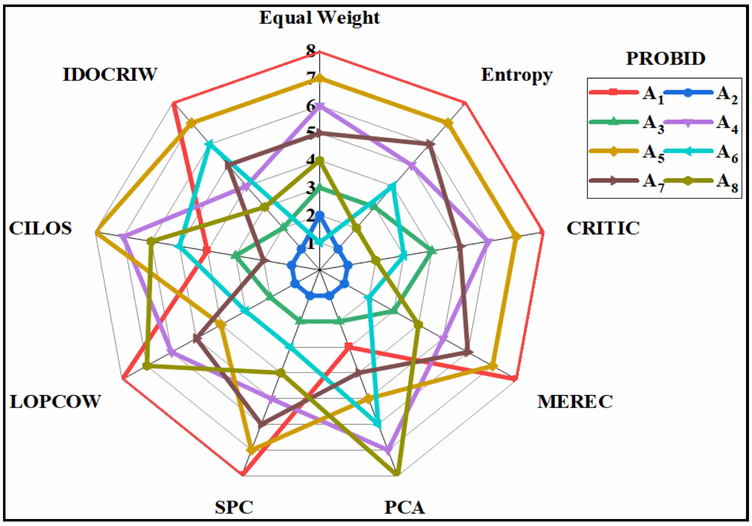
Sensitivity analysis based on all weighting conditions

Figure 7.8 reveals significant insights, where the MACONT method shows noticeable sensitivity to different weighting conditions, with alternatives A_1 and A_2 consistently ranking high, but middle-tier alternatives such as A_4, A_5 and A_7 exhibiting variability. PROBID demonstrates robust performance, consistently prioritizing A_1 across various methods, with some variability for alternatives A_8 and A_4. The PARIS method highlights A_1 and A_2 as top performers across most methods, though variability is introduced by PCA and LOPCOW. OPTBIAS consistently ranks A_1 and A_2 high under most weighting techniques, maintaining stability and reliability, while A_8 frequently ranks lowest except under PCA. DNMA method showcases strong performance for A_1 and A_2, with some variability for A_6 and A_8 across different methods. EAMR consistently ranks A_1 and A_2 at the top across various weighting conditions, while CURLI and PEG, which do not require weights, show consistent top-performing alternatives but variability in lower-ranked alternatives such as A_8 and A_9. Overall, the performance of these methods varies, with each method demonstrating strengths and weaknesses under different weighting conditions. In conclusion, the DNMA method stands out for its robust and consistent performance, consistently ranking across various weighting conditions. Its ability to maintain stable and reliable rankings across different scenarios highlights its effectiveness in decision making processes. Despite some variability introduced by specific weighting methods, DNMA remains a dependable choice, reflecting high ranking similarity and demonstrating its reliability and robustness as an MCDM method.

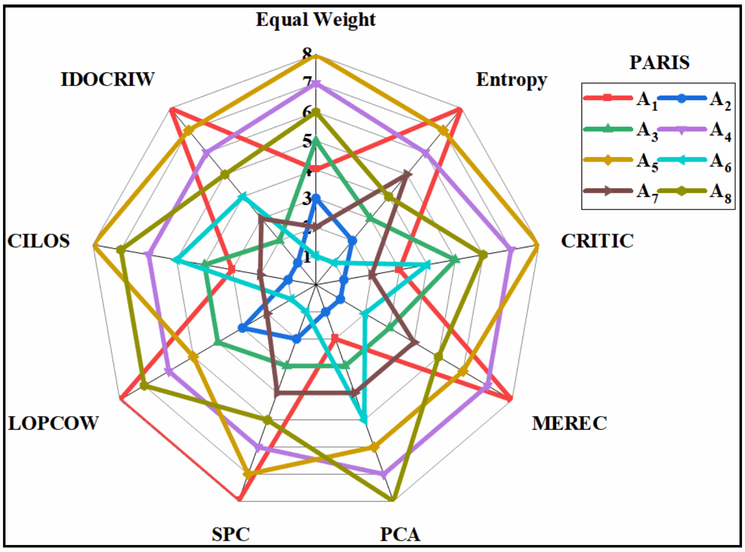


(a)

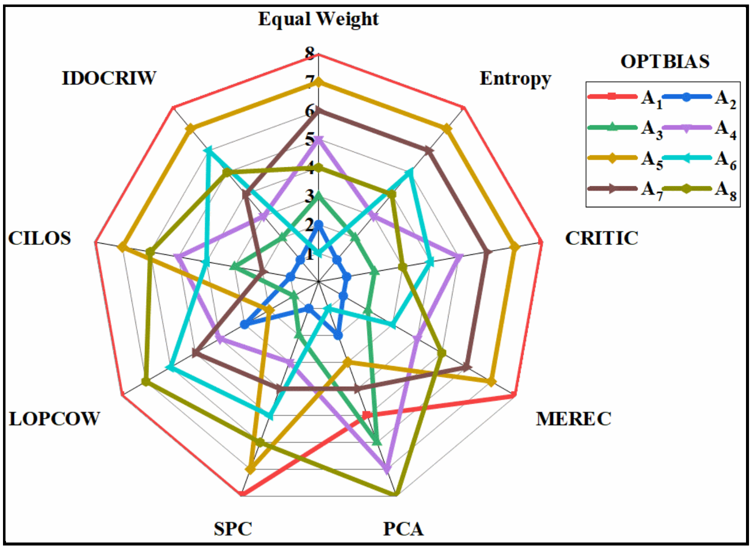
Figure 7.8 Sensitivity analyses results considering all the criteria weight



(b)

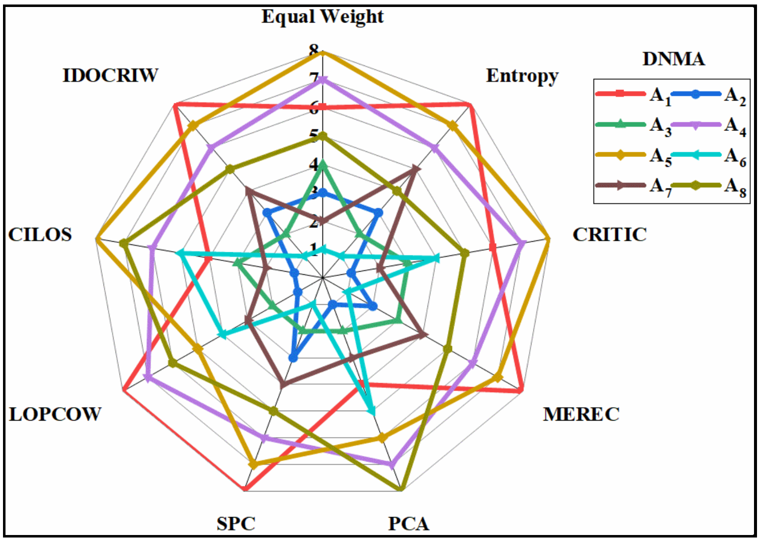


(c)

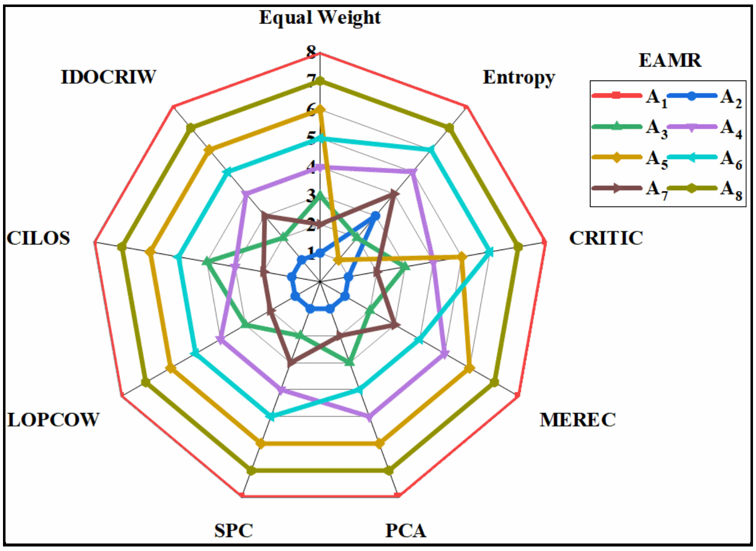


(d)

Figure 7.8 Continued



(e)



(f)

Figure 7.8 Continued

8. EDM OIL SELECTION

EDM is one of the most extensively used non-traditional material removal processes in many of the modern-day technologically advanced manufacturing industries [145]. It utilizes thermal energy to remove material from any electrically conductive workpiece regardless of its hardness and toughness by means of a series of sparks produced between the workpiece and the tool (also called as electrode) in presence of a dielectric fluid. The electrode is made to move slowly toward the workpiece until the gap between it and workpiece is small enough to ionize the dielectric to produce short duration discharges [146]. These electrical discharges create tiny craters on the workpiece surface, causing material removal through erosive action. EDM is widely employed for generation of die cavities, deep small and micro-holes, various intricate shape geometries and also precision machining of materials which are extremely difficult-to cut using conventional machining processes [147]. It started to gain attention as an efficient machining process in the early 1940s when the Lazarenko brothers discovered the decisive role of the dielectric fluid [148]. Since then, it has experienced intense upgrading and development. Despite machining conductive materials, the present-day EDM is also able to generate complex features and shape geometries in many of the semi-conductive, metal matrix and ceramic composite materials.

Generally, EDM can be classified as die-sinking EDM, wire-EDM, micro-EDM, powder-mixed EDM and dry EDM. In die-sinking EDM, the electrode and workpiece are completely submerged in a dielectric fluid [149]. Wire-EDM employs a thin metallic wire continuously travelling with the help of microprocessor-controlled guideways, thereby enabling it to generate complicated 3-D profiles on the workpiece [150, 151]. The working principle of micro-EDM is almost similar to that of die-sinking EDM; the only difference is that in micro-EDM, the diameter of the electrode is in microns [152]. In powder-mixed EDM, suitable abrasive materials in form of powder are proportionately mixed with the dielectric fluid causing faster sparking and erosive action resulting in higher material removal rate (MRR) and better surface quality of the machined components [153, 154, 155]. In dry EDM, high-pressure gas or air is supplied through a thin-walled pipe used as electrode, helping in removal of debris from the machining zone [156]. In this process, use of dielectric fluid is minimized to avoid its perilous effect during the machining operation. EDM process can also be classified based on the type of dielectric fluid utilized, i.e. hydrocarbon and EDM oil dielectric fluids, water and water-based dielectric fluids, gaseous based dielectric fluids and powder-mixed dielectric fluids.

Dielectric fluid is an insulating material acting as a poor conductor of electricity and when placed in an electric field, practically no current is allowed to flow as it does not have any loosely bound or free electron which can drift through. Dielectric fluid separates the tool and the workpiece. At the time of machining, with the spark produced, a stream of current flows with the dielectric getting ionized to form a path from the tool to the workpiece. The dielectric medium ruptures the current flow as the gap between the tool and the workpiece increases. It has already been experimented that selection of suitable dielectric fluid is extremely important with respect to enhanced machining performance and quality of the end products. The dielectric fluid in EDM process thus has the following functions [157]: (1) It serves as a medium to produce controlled electrical discharges. (2) It acts as a quenching medium to cool down and solidify the eroded gaseous particles generated from the discharges. (3) It helps in removing the solidified waste from the machining zone based on dielectric filtration system. (4) It also works as a lubrication medium to absorb and remove the heat generated by the discharges from the machining zone. Generally, hydrocarbon oil or EDM oil is used in die-sinking EDM, while deionized water is utilized in wire- and micro-EDM processes [158]. Commonly used dielectric fluids, such as EDM oil cause several problems during actual machining operation, such as air pollution, degradation of dielectric properties, carbon particles adhesion, health hazards, etc. These disadvantageous features of EDM oils all together impede stable electrical discharges between the electrode and workpiece resulting in inferior machining efficiency.

Several types of EDM oil are available in the market having varying compositions and properties. In order to perform as a good dielectric medium, an EDM oil should be low in cost, non-toxic, chemically non corrosive and has low viscosity and good wetting property, high flash and fire points to avoid fire hazards, high electric strength for proper insulation and good quenching behavior [159]. Selection of the most suitable EDM oil for a specific machining application from a pool of available alternatives can thus be regarded as a typical MCDM problem, involving evaluation of several criteria (EDM oil properties) which are often conflicting in nature, requiring trade-offs. In a recent work, Alam et al. [160] solved a sustainable dielectric fluid selection problem considering six alternatives, i.e. jatropha oil, waste vegetable oil, sunflower oil, waste palm oil blended with kerosene, bio-dielectric fluid and canola oil, based on seven properties, such as density, viscosity, thermal conductivity, specific heat, flash point, breakdown voltage and dielectric constant. The corresponding criteria weights had been first estimated using standard deviation method and sunflower oil had been singled out as the best dielectric fluid while applying proximity index value method as an MCDM tool, resulting in sustainable EDM operation. Asif et al. [161] extensively studied the effect of eco-friendly and biodegradable surfactant additives on material removal rate, surface roughness, tool wear rate and overcut during EDM operation on titanium alloy. Considerable improvements of those responses had justified addition of the surfactants, thus validating the adopted approach for one-step sustainable machining.

8.1 Review of MCDM for cutting fluid selection

The earlier researchers have also demonstrated the advantages of MCDM methods in solving cutting fluid selection problems for different machining operations. Rao and Patel [162] applied PROMETHEE for selecting suitable cutting fluid for a cylindrical grinding operation. Abhang and Hameedullah [163] combined TOPSIS and AHP in turning operation of EN31steel with tungsten carbide inserts. Prasad and Chakraborty [164] presented the application of quality function deployment based model for cutting fluid selection for drilling and honing operations. Prasad and

Chakraborty [165] employed a modified similarity-based approach in gear cutting and turning operations. Ozakin [166] presented a comparative analysis among four different MCDM methods, i.e. TOPSIS, VIKOR, MOORA and RIM while solving a cutting fluid selection problem. Based on the derived results, it was concluded that there had been a strong rank correlation between VIKOR and MOORA methods, whereas TOPSIS had not been strongly correlated with other MCDM methods. Acknowledging the immense potentiality of MCDM methods in efficiently solving cutting fluid selection problems, the past researchers explored applications of different MCDM techniques, such as TOPSIS [167, 168, 169], PSI [170], COPRAS [59], ARAS [59], range of value (ROV) [171], VIKOR [167] for the said purpose.

8.2 Illustrative example

This section presents application of various newly developed MCDM approaches for solving an EDM oil selection problem, while performing deep-hole drilling on aluminium bronze alloy. For the said purpose, ten EDM oil alternatives and six evaluation criteria are considered. These criteria are viscosity (C_1) (cSt at 40°C), dielectric strength (C_2) (kV/mm), flash point (C_3) (°C), specific gravity (C_4), aromatics (C_5) (% by weight) and cost (C_6) (USD/l). Among these criteria, C_1, C_5 and C_6 are non-beneficial in nature (requiring their lower values).

Viscosity of an EDM oil is a critical criterion influencing its flow and flushing ability during the machining operation. Low viscosity oils are ideal during deep-hole EDM operation as they efficiently promote material removal, preventing debris buildup and enhancing surface quality, while EDM oils having moderate viscosity strike a balance between flushing and electrode stability, minimizing wear and ensuring smoother finishes [172]. On the other hand, high viscosity EDM oils are less effective in chip removal, leading to higher surface roughness and increased electrode wear, making them unsuitable for deep-hole EDM applications [173]. Dielectric strength measures the EDM oil's ability to withstand electrical breakdown, a crucial factor in preventing short circuits during real-time machining operations. EDM oils with high dielectric strength are preferred for work materials, such as aluminum bronze alloy due to their higher conductivity, minimizing risk of short circuits. Conversely, lower dielectric strength would increase the risk of short circuits, adversely affecting machining stability and overall performance [174]. The flash point of an EDM oil indicates the temperature at which it ignites, an important safety consideration during high temperature EDM operations. EDM oils with high flash point provide a wider safety margin, particularly important during deep-hole EDM with increased heat generation [159]. On the other hand, EDM oils with lower flash point require strict safety precautions and increased awareness of potential fire hazards. Specific gravity is the measure of how denser an EDM oil is compared to water, impacting performance of EDM operation. Higher specific gravity EDM oil may have several benefits, such as improved flushing and debris removal, better thermal conductivity and enhanced stability during machining operations [175]. The level of aromatics in an EDM oil indicates the proportion of various aromatic compounds within its overall weight. This can vary based on the specific oil type. Opting for an EDM oil with less aromatics is a wise decision. It not only promotes a safer workplace and reduces environmental impact, but also ensures smoother machining operation dissipating the heat more effectively [176]. Lastly, cost of an EDM oil is considered as an important criterion for selection as it is directly proportional to the total machining cost.

Based on the identified criteria, ten feasible EDM oils, i.e. Spark SPO-A (A_1), DIEL 7500 (A_2), Lubricut EDM SX2 (A_3), Lubrall EDM 90 (A_4), RBM oil (A_5), EDM-244 (A_6), IPOL SEO 450 (A_7), Fine Spark 110 (A_8), Exxsol D80 (A_9) and Extro EDM Plus 222 (A_{10}) are shortlisted from a pool of synthetic EDM oils available in the market. They possess specific characteristics and benefits and are well-known for their widespread industrial applications. Spark SPO-A has comparatively low cost and viscosity, making it a good alternative for better flushing while producing smoother surface finish. With higher dielectric strength, flash point and specific gravity, Diel 7500 as a dielectric fluid assist in reducing short circuits, enhances safety and improves flushing. Lubricut EDM SX2 is a better alternative as dielectric fluid compared to others in terms of its aromatic's presence. In addition to being one of the cheapest EDM oils, Lubrall EDM 90 also offers low aromatic presence, allowing safer working environment. Similarly, RBM oil also falls under the low-cost category of EDM oils along with higher dielectric strength. EDM-244 is known for its low aromatics with comparatively high specific gravity. IPOL SEO 450 offers higher dielectric strength at low cost making it more suitable for machining tough materials with minimum electrode wear and better surface quality. With low aromatics and cost, Fine Spark 110 EDM oil provides better environment to work upon. Exxsol D80 has low viscosity, higher dielectric strength and specific gravity, allowing it to withstand any chance of electrical breakdown, thus preventing short circuits during machining. Extro EDM Plus 222 is one of the EDM oils that offers lower viscosity at comparatively low cost, thus making it more suitable for deep-hole drilling with better flushing ability.

Ten viable EDM oil options are assessed based on six criteria in the initial decision matrix of Table 8.1, which is based on the websites and catalogues of several EDM oil manufacturers. IDOCRIW, which combines the entropy and CILOS approaches, is first used to determine the objective weights of the criterion under consideration. Table 8.2 provides the associated criteria weights, which were determined using the entropy, CILOS, and IDOCRIW methods using Eq. (2.20). It is evident from Table 8.2 that the IDOCRIW technique gives aromatics (C_5) the highest weight (0.4366). Specific gravity (C_4) is the least important requirement, and cost (C_6) is the next important one.

DNMA method

Both linear and vector normalisation techniques are now used to normalise the DNMA method in Table 8.1, based on Eqs. (3.59) and (3.60), respectively. These normalized values are provided in Table 8.3. The adjusted weight coefficients for the six evaluation criteria under consideration are thus calculated to be 0.1859, 0.0113, 0.0701, 0.0030, 0.3941, and 0.3356, respectively, using Eqs. (3.61)–(3.63). Based on these weight adjusted coefficients and normalized values of the decision matrix and applying Eqs. (3.64)-(3.66), the corresponding utility values of all the candidate EDM oils are computed using three different aggregation operators, i.e. CCM, UCM and ICM, as shown in Table 8.4. In Table 8.4, based on the computed utility values, the alternative EDM oils are subsequently ranked in descending, ascending and descending orders for CCM, UCM and ICM aggregators, respectively. Finally, the comprehensive utility values for each of the alternative EDM oils are calculated using Eq. (3.67), considering values of different tuning parameters as φ = 0.5, $\overline{\omega}_1$= 0.6, $\overline{\omega}_2$= 0.1 and $\overline{\omega}_3$= 0.3. Ten EDM oils are subsequently ranked in decreasing order of their S_i values. It is clearly noticed from Figure 8.1 that Spark SPO-A EDM oil emerges as the best dielectric fluid having the maximum comprehensive utility score, followed by Fine Spark 110. Exxsol D80 is the worst choice for the said deep-hole drilling operation. Moderately low viscosity and cost and lowest aromatics; and moderately high dielectric strength and specific gravity and highest flashing point are responsible for its superiority over the competing EDM oil alternatives under consideration. The DNMA method thus ensures a balanced evaluation through its diverse aggregation mechanisms. It also accommodates both optimistic and pessimistic viewpoints using its parameterized structure.

Table 8.1 Decision matrix for synthetic EDM oil selection

EDM oil	C_1	C_2	C_3	C_4	C_5	C_6
A_1	2	45	140	0.77	0.01	2
A_2	2	45	110	0.776	0.1	2.4
A_3	2.4	46	105	0.75	0.01	4.57
A_4	3	40	120	0.81	0.01	0.96
A_5	4	46	93	0.764	0.24	1.4
A_6	2.45	45	110	0.77	0.01	14.89
A_7	2.3	46	110	0.758	0.1	1.63
A_8	2.3	46	105	0.8	0.01	1.42
A_9	1.4	46	77	0.809	0.5	8.18
A_{10}	1.9	45	93	0.764	0.24	2.29

Table 8.2 Entropy, CILOS and IDOCRIW weights

Weight	C_1	C_2	C_3	C_4	C_5	C_6
Entropy	0.0321	0.0007	0.0098	0.0003	0.5975	0.3596
CILOS	0.3364	0.2656	0.2300	0.0648	0.0446	0.0587
IDOCRIW	0.1773	0.0029	0.0369	0.0003	0.4366	0.3459

Table 8.3 Linear and vector normalized values

EDM oil	Linear normalization						Vector normalization					
	C_1	C_2	C_3	C_4	C_5	C_6	C_1	C_2	C_3	C_4	C_5	C_6
A_1	0.7692	0.8333	1.0000	0.3333	1.0000	0.9253	0.9243	0.9926	1.0000	0.9829	1.0000	0.9430
A_2	0.7692	0.8333	0.5238	0.4333	0.8163	0.8966	0.9243	0.9926	0.9136	0.9855	0.8551	0.9211
A_3	0.6154	1.0000	0.4444	0.0000	1.0000	0.7408	0.8739	1.0000	0.8992	0.9743	1.0000	0.8022
A_4	0.3846	0.0000	0.6825	1.0000	1.0000	1.0000	0.7982	0.9556	0.9424	1.0000	1.0000	1.0000
A_5	0.0000	1.0000	0.2540	0.2333	0.5306	0.9684	0.6721	1.0000	0.8647	0.9803	0.6297	0.9759
A_6	0.5962	0.8333	0.5238	0.3333	1.0000	0.0000	0.8676	0.9926	0.9136	0.9829	1.0000	0.2366
A_7	0.6538	1.0000	0.5238	0.1333	0.8163	0.9519	0.8865	1.0000	0.9136	0.9777	0.8551	0.9633
A_8	0.6538	1.0000	0.4444	0.8333	1.0000	0.9670	0.8865	1.0000	0.8992	0.9957	1.0000	0.9748

A_9	1.0000	1.0000	0.0000	0.9833	0.0000	0.4817	1.0000	1.0000	0.8186	0.9996	0.2111	0.6043
A_{10}	0.8077	0.8333	0.2540	0.2333	0.5306	0.9045	0.9369	0.9926	0.8647	0.9803	0.6297	0.9271

Table 8.4 Ranking of EDM oils using IDOCRIW-DNMA method

EDM oil	CCM		UCM		ICM		Utility value (S_i)	Rank
	$u_1(a_i)$	Rank	$u_2(a_i)$	Rank	$u_3(a_i)$	Rank		
A_1	0.9282	1	0.0429	1	0.9661	1	0.8895	1
A_2	0.8131	4	0.0724	3	0.8955	6	0.6743	4
A_3	0.7996	6	0.0870	5	0.8989	5	0.6188	6
A_4	0.8521	3	0.1144	6	0.9545	3	0.7391	3
A_5	0.5639	8	0.1859	8	0.7599	8	0.4004	8
A_6	0.5521	9	0.3356	9	0.5966	9	0.3163	9
A_7	0.8111	5	0.0724	3	0.9021	4	0.6724	5
A_8	0.8851	2	0.0644	2	0.9623	2	0.8228	2
A_9	0.3618	10	0.3941	10	0.4511	10	0.1720	10
A_{10}	0.6907	7	0.1850	7	0.7944	7	0.4928	7

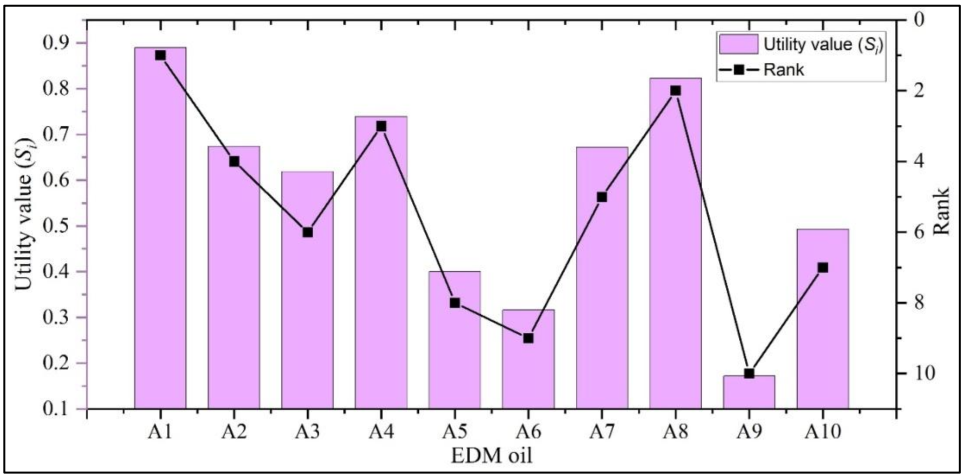


Figure 8.1 Ranking of EDM oils

MACONT method

The EDM oil selection problem is now solved using MACONT method with IDOCRIW weights. In Table 8.1, Eq. (3.2), (3.3) and (3.4) are first applied to obtain the normalized values. To obtain comprehensive decision matrix values Eq. (3.5) is applied. To calculate the subordinate comprehensive values, Eqs. (3.6) and (3.7) are used, considering the $\delta = 0.5$ and $\vartheta = 0.5$ respectively. Finally, the comprehensive scores are evaluated using Eq. (3.8). The ranking results are provided in Table 8.5. It is revealed that A_1 is the best EDM oil followed by A_8 as they secure the first and second positions, respectively. The MACONT method efficiently integrates subjective and objective assessments through its dual parameters. Its capability to handle inter-criteria relationships enhances decision quality.

PARIS method

Now, the EDM oil selection problem is solved using PARIS method. The three different weighted normalized matrices are calculated. To rank the alternatives, the rest of the equations are applied and results are displayed in Table 8.6. It is revealed that A_1 is the best EDM oil, followed by

A_8, as they secure the first and second positions, respectively. The PARIS methods emphasis on parallel ranking structures ensures consistency across evaluation dimensions.

Table 8.5 Ranking results of the EDM selection problem using MACONT method

Alternative	ρ_i	Q_i	$S_1 (A_i)$	$S_2 (A_i)$	$S (A_i)$	Rank
A_1	0.1516	8.6501	0.6469	0.0521	0.5153	1
A_2	0.0754	0.4581	0.1295	0.0438	0.226	4
A_3	-0.0202	1.4542	0.0442	-0.0099	-0.0145	6
A_4	0.1144	0.9798	0.2107	0.045	0.2711	3
A_5	-0.111	0.9697	-0.1083	-0.0449	-0.2196	8
A_6	-0.1754	0.1443	-0.2405	-0.0519	-0.3114	9
A_7	0.0748	1.7421	0.1929	0.032	0.2145	5
A_8	0.183	4.1751	0.4674	0.0519	0.4251	2
A_9	-0.2232	0.2723	-0.3017	-0.049	-0.3313	10
A_{10}	-0.0696	0.5309	-0.0718	-0.0289	-0.1424	7

Table 8.6 Ranking based on R_i values, using PARIS method

Alternative	Ri (WAY_1)	Rank	Ri (WAY_2)	Rank	Ri (WAY_3)	Rank
A_1	0.2616	1	0.0961	1	0	1
A_2	0.3374	4	0.2888	4	0.1523	4
A_3	0.3533	6	0.6452	6	0.1573	6
A_4	0.2682	3	0.2052	3	0.0796	3
A_5	0.5213	8	0.6786	8	0.4999	8
A_6	0.5994	9	0.7441	9	0.5209	9
A_7	0.3433	5	0.5649	5	0.1536	5
A_8	0.2621	2	0.1086	2	0.0367	2
A_9	0.8717	10	0.8383	10	0.8278	10
A_{10}	0.4797	7	0.6494	7	0.3293	7

EAMR method

The EAMR method is applied to this EDM oil selection problem. Table 8.7 displays the evaluation scores and ranking results using IDOCRIW weights. It is unveiled that A_1 is the best alternative. From this table, it is also observed that A_8 is the second best, whereas A_9 is the worst choice. The EAMR method effectively balances attribute weights while ensuring fairness in rank distribution.

CURLI method

This selection problem is solved using the CURLI approach. The processing matrix, which is produced by adding up the values in the scoring matrix, is shown in Table 8.8. Additionally, this matrix is rearranged so that the negative and zero values are located in the upper portion of the major diagonal. Table 8.9 displays the final ranks. A_1 secures the top position, followed by A_8.

PEG method

The PEG method is now used to solve this problem. Table 8.10 displays the final MSE values. Table 8.10 shows that A_1 is the alternative with the highest ranking.

Table 8.7 Ranking results based on EAMR method

Alternative	G_i^+	G_i^-	$RV(G_i^+)$	$RV(G_i^-)$	S_i	Rank
A_1	0.0375	0.5315	0.0997	0.074	1.3471	1
A_2	0.0383	0.6311	0.102	0.0879	1.1605	4
A_3	0.035	0.739	0.0931	0.1029	0.9054	6
A_4	0.0397	0.6069	0.1055	0.0845	1.2488	3
A_5	0.0359	0.818	0.0955	0.1139	0.8385	8
A_6	0.0401	0.9599	0.1066	0.1336	0.798	9
A_7	0.0391	0.6464	0.104	0.09	1.1557	5
A_8	0.0384	0.5674	0.1021	0.079	1.2919	2
A_9	0.0369	0.9043	0.0981	0.1259	0.779	10
A_{10}	0.0351	0.7785	0.0934	0.1084	0.8621	7

Table 8.8 Processing scoring matrix after changing the positions of rows and columns

Alternative	P_1	P_8	P_2	P_7	P_3	P_{10}	P_4	P_6	P_5	P_9
A_1	0	1	-4	-4	-4	-1	1	1	-2	1
A_8	-1	-1	-2	-2	-2	1	-2	1	-4	1
A_2	5	3	1	-1	0	4	5	3	2	5
A_7	3	2	2	1	2	5	3	2	0	4
A_3	3	2	0	-1	-1	2	3	1	0	3
A_{10}	0	-1	-4	-3	-3	1	0	-1	-3	2
A_4	-2	0	-5	-3	-5	-1	-1	0	-3	-1
A_6	0	-2	-1	-2	-1	1	-1	1	-3	2
A_5	2	2	0	0	0	3	1	2	-1	3
A_9	0	-1	-3	-3	-3	-2	1	0	-2	1

Table 8.9 Ranking results using CURLI method

Alternative	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}
Rank	1	3	5	7	9	8	4	2	10	6

Table 8.10 Ranking results using PEG method

Alternative	x	y	x^*	y^*	MSE	Rank
A_1	0.1159	0.1147	0.3749	0.3740	39.6250	1
A_2	0.1091	0.1314	0.3700	0.3858	35.1084	4
A_3	0.1364	0.1142	0.3893	0.3737	29.0226	6
A_4	0.0000	0.1371	0.2929	0.3898	35.1287	3
A_5	0.1159	0.1298	0.3749	0.3847	21.1978	8
A_6	0.1773	0.0000	0.4183	0.2929	20.7596	9
A_7	0.1364	0.0833	0.3893	0.3518	34.9552	5
A_8	0.1057	0.1323	0.3676	0.3864	35.2788	2
A_9	0.1432	0.0684	0.3942	0.3412	10.3667	10
A_{10}	0.0682	0.1333	0.3411	0.3872	29.0095	7

PROBID method

The PROBID method is now applied to this decision making problem. Table 8.11 provides the positive ideal ($E_{i(pos\text{-}ideal)}$), negative ideal ($E_{i(neg\text{-}ideal)}$), positive-ideal or negative-ideal ratio (RA_i) and performance score (PS_i) of each of the alternatives. Clearly, A_1 occupies the top position in the ranking list with maximum performance score, followed by A_8. Table 8.11 reveals that alternatives A_4 and A_2 also show strong performance, securing third and fourth ranks respectively. This method effectively highlights the dominance of alternatives based on their proximity to ideal and negative-ideal solutions.

Table 8.11 Ranking results using PROBID method

Alternative	$E_{pos-ideal}$	$E_{neg-ideal}$	*RA*	*PS*	Rank
A_1	0.0336	0.6213	0.0541	1.0902	1
A_2	0.147	0.5741	0.256	1.0187	4
A_3	0.1544	0.4846	0.3186	0.9429	6
A_4	0.0372	0.6109	0.0608	1.0846	3
A_5	0.388	0.4513	0.8599	0.6775	8
A_6	0.3726	0.4216	0.8837	0.6504	9
A_7	0.1497	0.503	0.2976	0.966	5
A_8	0.0693	0.6311	0.1098	1.087	2
A_9	0.8419	0.4355	1.9333	0.4888	10
A_{10}	0.5909	0.6449	0.9163	0.7655	7

OPTBIAS method

Employing the OPTBIAS method, the decision matrix is normalized with the vector normalization approach. The bi-positive ideal, bi-negative ideal, and average solutions are calculated using Eqs. (3.43)-(3.45). Table 8.12 shows the Euclidean distances of alternatives from the positive ideal, negative ideal, and average solutions. It also includes values of *B* (ratio of the Euclidean distances of *RN* and *RP*) and overall performance scores (*PS*) of all alternatives, computed using Eqs. (3.46) and (3.47). A_1 ranks first, followed by A_8 and A_4 in second and third positions, respectively.

Table 8.12 Ranking results based on performance score, *PS*

Alternative	*RP*	*RN*	*RA*	*B*	*PS*	Rank
A_1	0.0388	0.5863	0.0931	15.0955	153.2194	1
A_2	0.1392	0.5330	0.0802	3.8294	3.5880	4
A_3	0.1394	0.4640	0.0350	3.3284	3.0345	6
A_4	0.0682	0.5958	0.0989	8.7338	18.3851	3
A_5	0.3285	0.3745	0.0889	1.1401	1.4668	8
A_6	0.5266	0.5674	0.2219	1.0774	1.4432	9
A_7	0.1346	0.4827	0.0474	3.5850	3.3059	5
A_8	0.0426	0.5755	0.0883	13.5158	90.4983	2
A_9	0.7412	0.3579	0.2777	0.4828	1.1885	10
A_{10}	0.3441	0.4076	0.1026	1.1846	1.4893	7

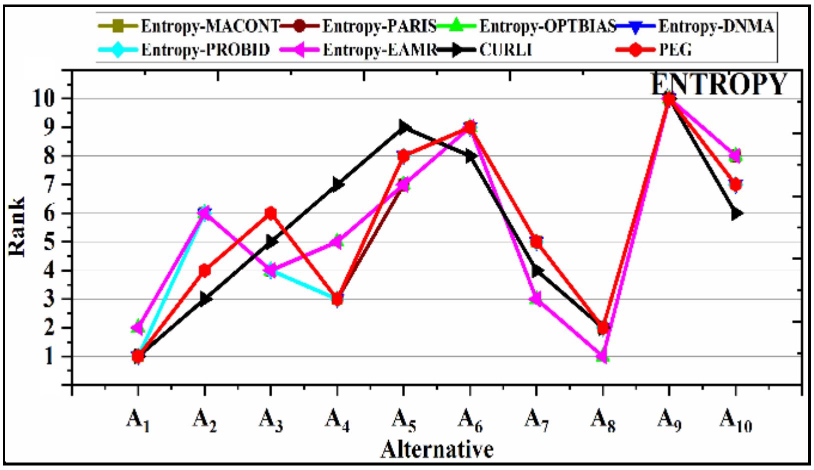
Comparative analyses of MCDM methods

a) Based on rankings

Figure 8.2 presents the ranking results under various criteria weight set as presented in Table 8.13. The detailed observations under different weighting conditions highlight consistent patterns and noteworthy trends. Entropy based methods generally place A_1 at the top, but OPTBIAS and EAMR slightly deviate, ranking A_2 first. The CRITIC based methods show A_2 as the top alternative, with notable consistency, while A_9 maintains low ranks. MEREC based methods highlight A_2 as a consistent top rank performer but introduce variability with A_8 ranking. PCA based methods display uniform rankings, with slight deviations for A_2 and A_7. SPC based methods consistently rank A_2 at the top with some variability for A_5. LOPCOW method show stable rankings for most alternatives, with CURLI and PEG diverging slightly. CILOS based methods maintain consistency, with minor deviations for A_1 and A_6. IDOCRIW based methods show complete consistency, with A_1 consistently at the top. CURLI and PEG methods often diverge from other methods, indicating different prioritization criteria. DNMA secures top rank for A_1 across various weighting scenarios, demonstrating robust and reliable performance. Its ability to maintain consistent rankings while effectively distinguishing between top and lower-performing alternatives highlight its effectiveness in decision making processes, making it the most dependable choice.

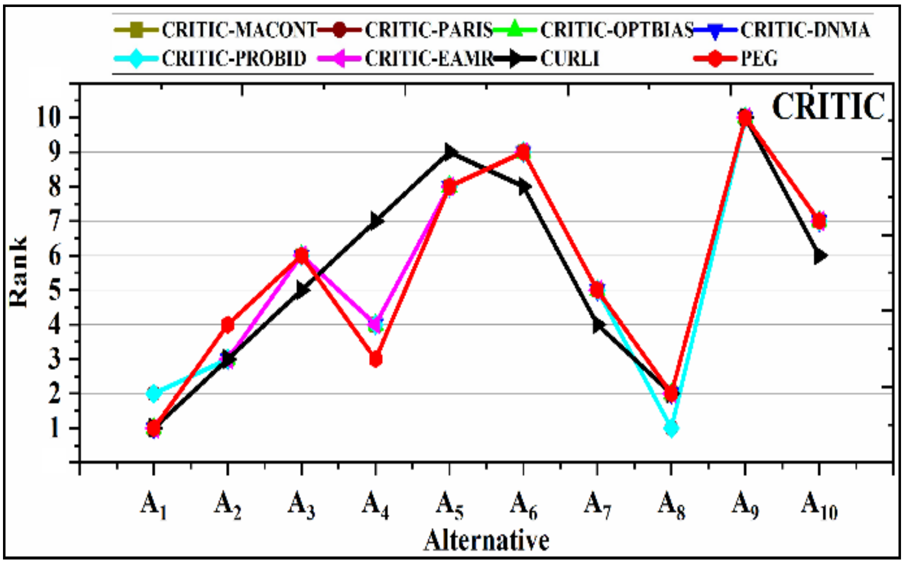
Table 8.13 Different criteria weight sets for sensitivity analysis

Weighting method	C_1	C_2	C_3	C_4	C_5	C_6
Entropy	0.0321	0.0007	0.0098	0.0003	0.5975	0.3596
CRITIC	0.1440	0.1910	0.1264	0.2093	0.1648	0.1645
MEREC	0.2708	0.0090	0.2609	0.0027	0.3193	0.1373
PCA	0.2569	0.2814	0.0991	0.1308	0.1147	0.1171
SPC	0.0230	0.0046	0.0089	0.0019	0.7562	0.2055
LOPCOW	0.1947	0.2265	0.1346	0.0741	0.1714	0.1988
CILOS	0.3364	0.2656	0.2300	0.0648	0.0446	0.0587
IDOCRIW	0.1773	0.0029	0.0369	0.0003	0.4366	0.3459

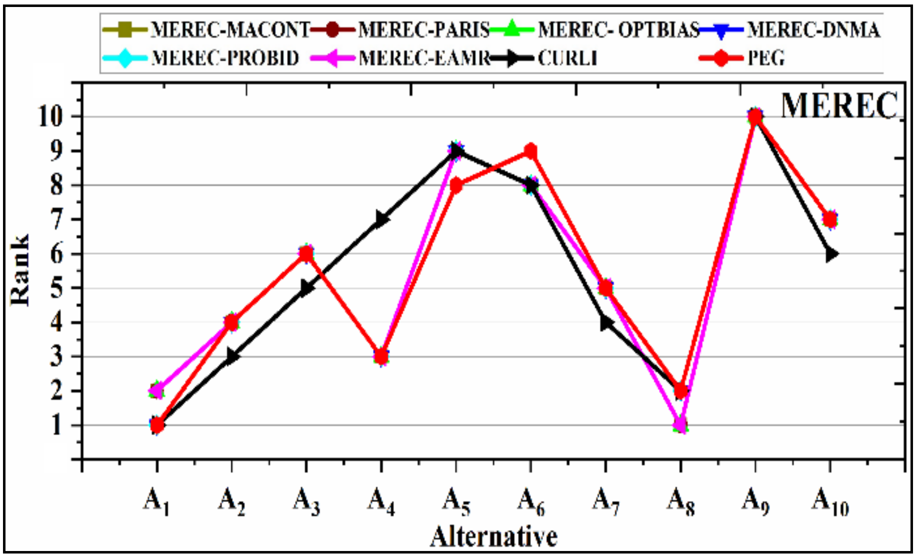


(a)

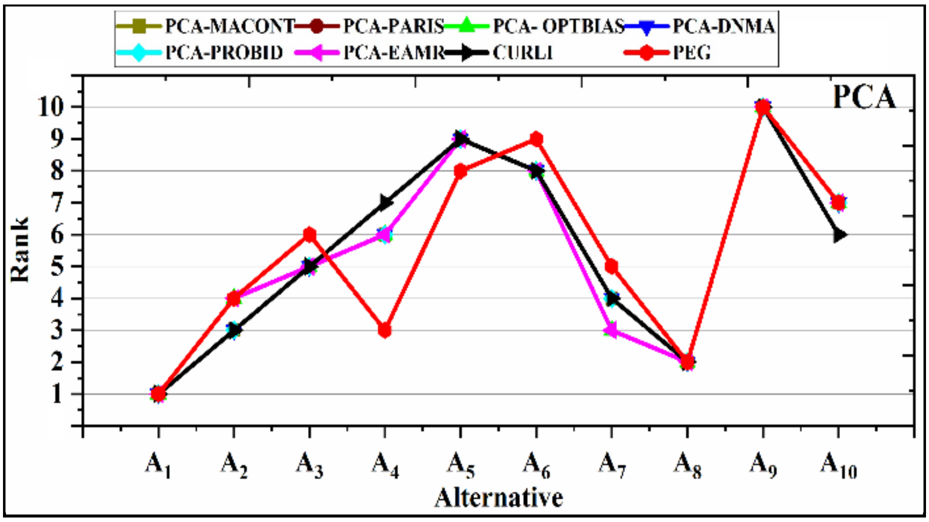
Figure 8.2 Weight wise ranking result



(b)

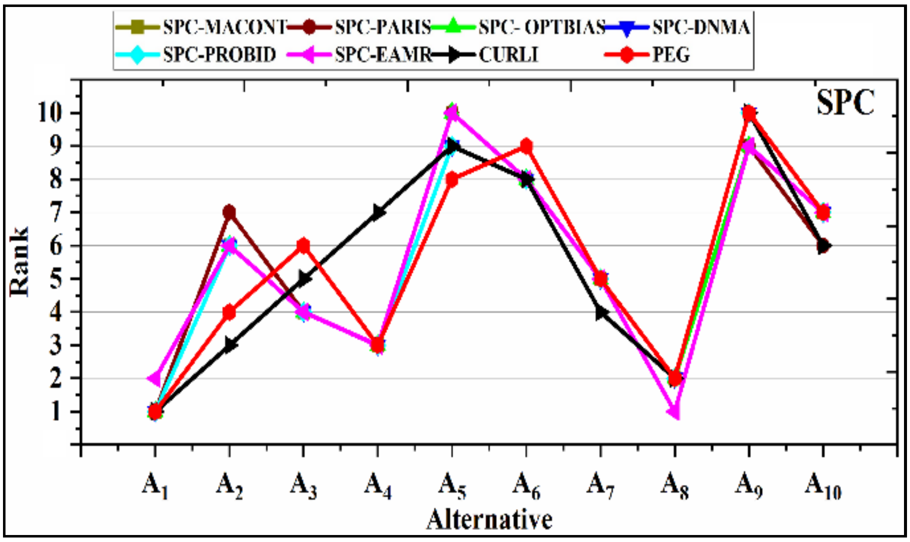


(c)

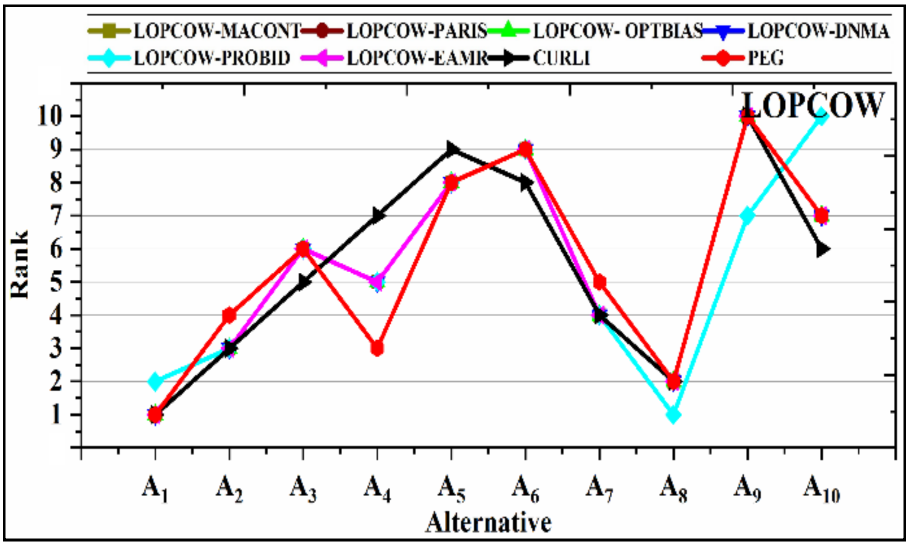


(d)

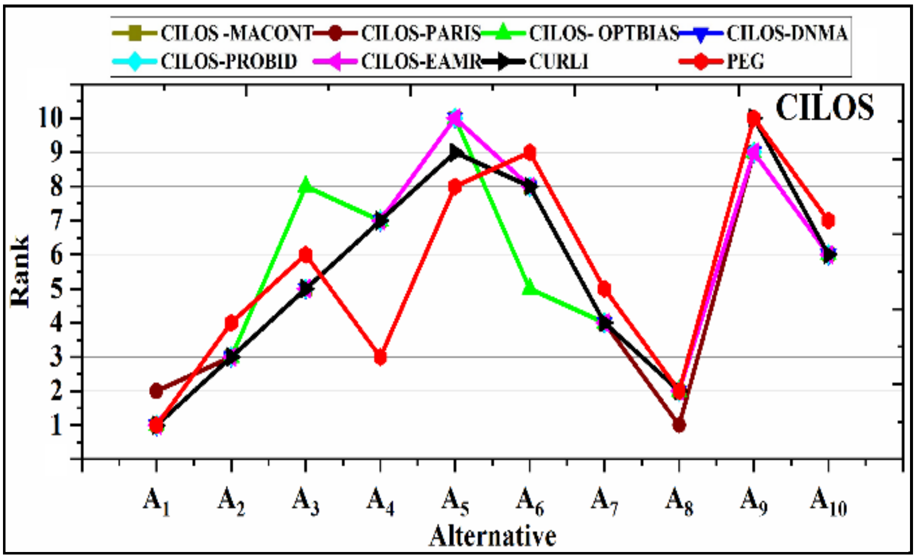
Figure 8.2 Continued



(e)

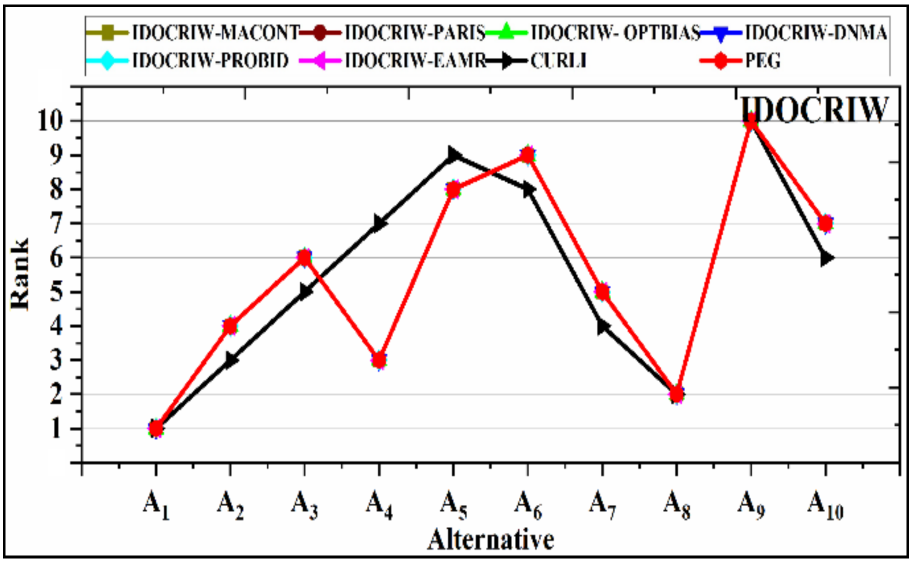


(f)



(g)

Figure 8.2 Continued

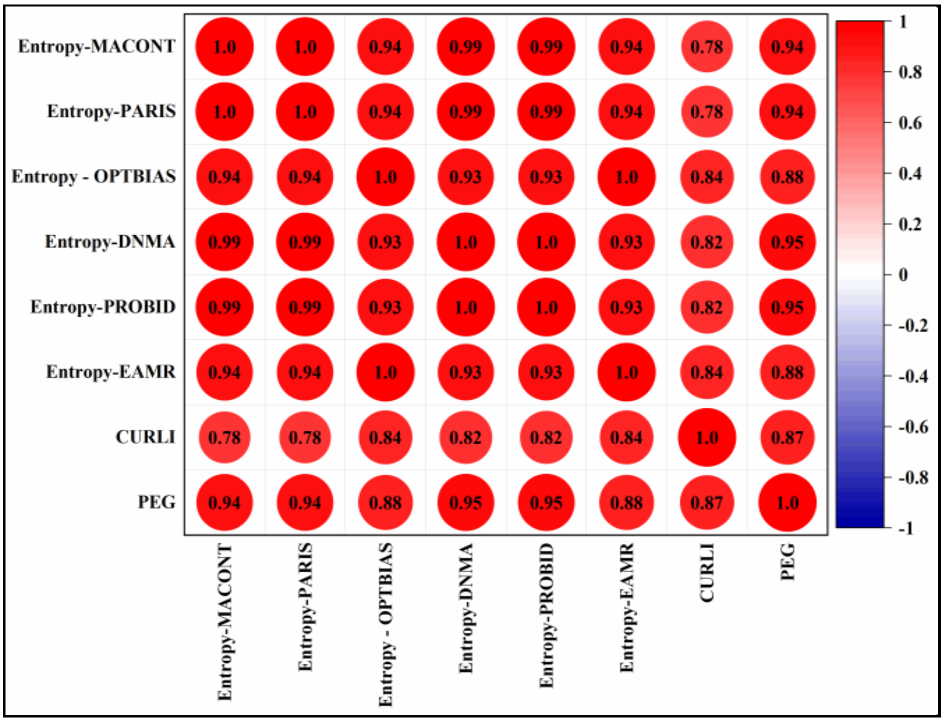


(h)

Figure 8.2 Continued

b) Based on Spearman co-relation coefficients

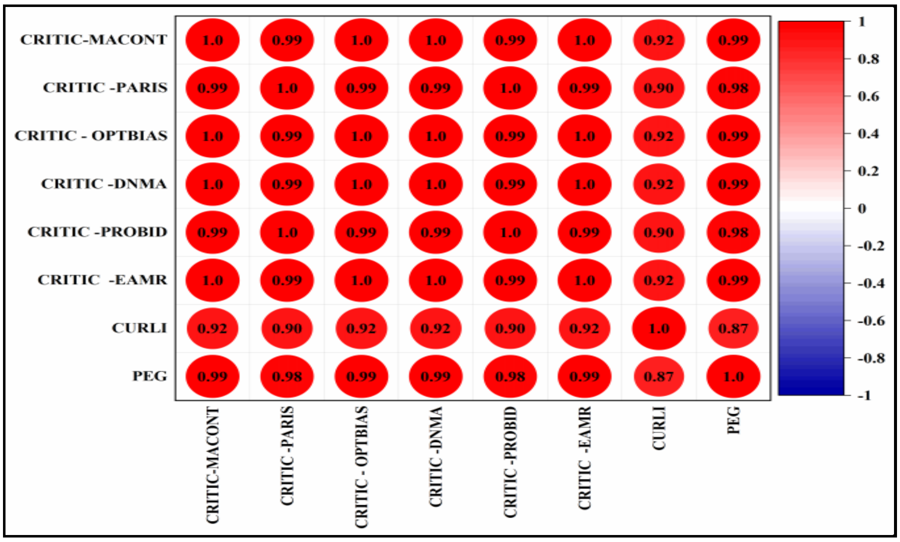
Figure 8.3 shows the Spearman correlation between the different methods. Clearly, all the methods result in higher correlation coefficient, thus indicating similarity in ranking, despite change in weight and methods. This study concludes that under all the weighting conditions, there are very high correlations among all the methods. This suggests that the different MCDM methods, regardless of the weighting technique applied, provide consistent and reliable rankings for this EDM oil selection problem.



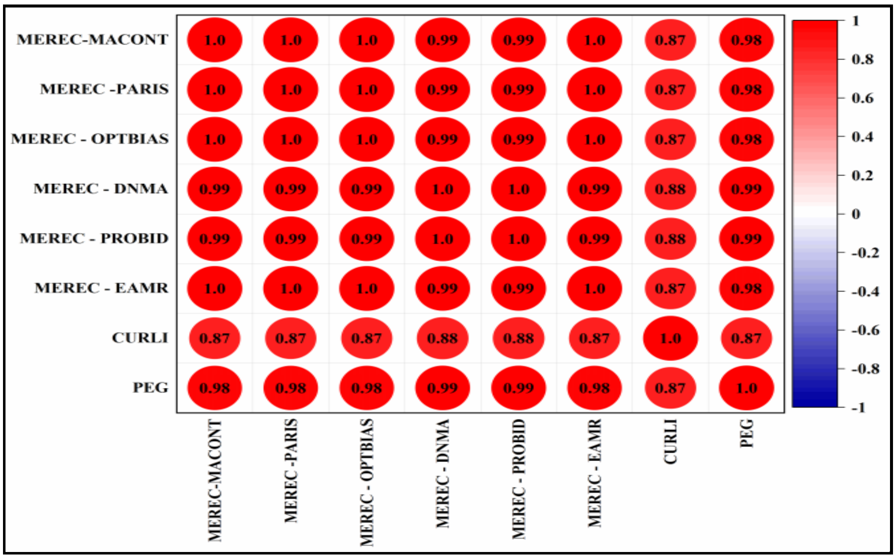
	Entropy-MACONT	Entropy-PARIS	Entropy - OPTBIAS	Entropy-DNMA	Entropy-PROBID	Entropy-EAMR	CURLI	PEG
Entropy-MACONT	1.0	1.0	0.94	0.99	0.99	0.94	0.78	0.94
Entropy-PARIS	1.0	1.0	0.94	0.99	0.99	0.94	0.78	0.94
Entropy - OPTBIAS	0.94	0.94	1.0	0.93	0.93	1.0	0.84	0.88
Entropy-DNMA	0.99	0.99	0.93	1.0	1.0	0.93	0.82	0.95
Entropy-PROBID	0.99	0.99	0.93	1.0	1.0	0.93	0.82	0.95
Entropy-EAMR	0.94	0.94	1.0	0.93	0.93	1.0	0.84	0.88
CURLI	0.78	0.78	0.84	0.82	0.82	0.84	1.0	0.87
PEG	0.94	0.94	0.88	0.95	0.95	0.88	0.87	1.0

(a)

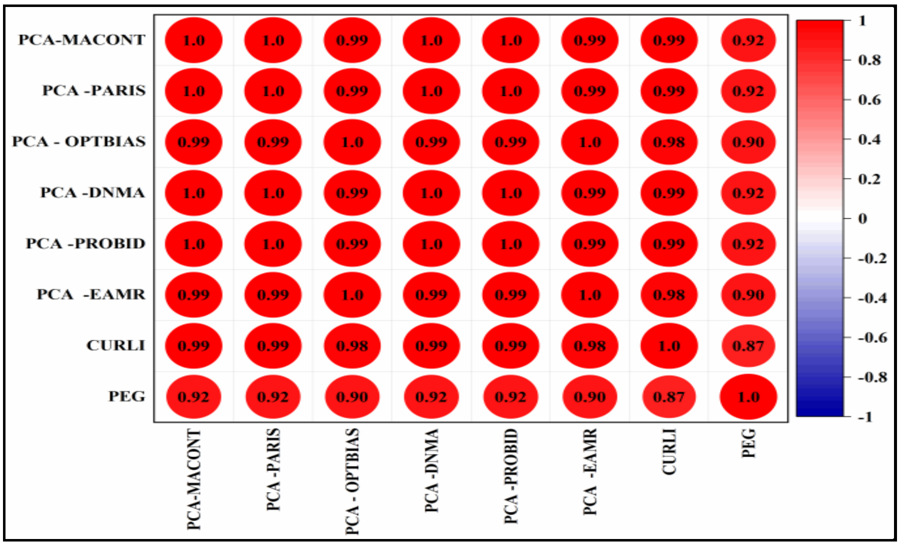
Figure 8.3 Spearman correlation coefficient result



(b)

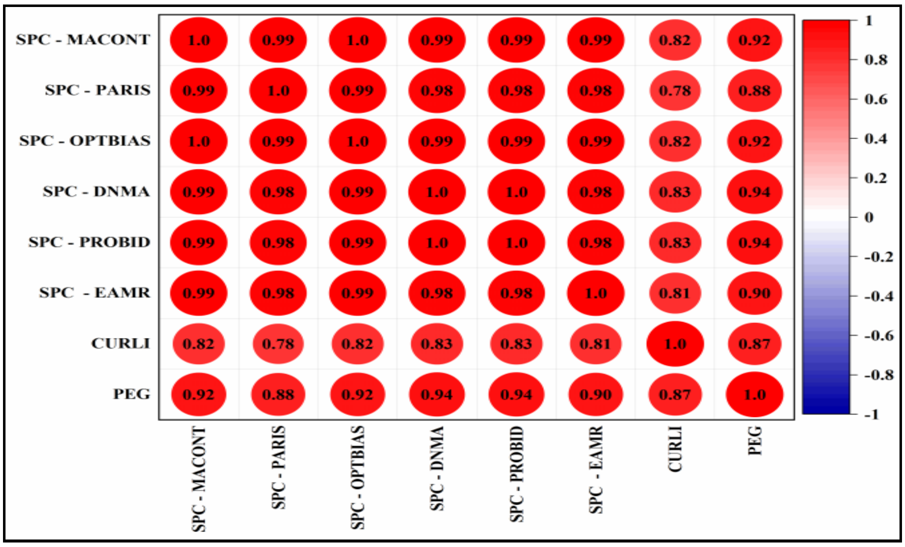


(c)

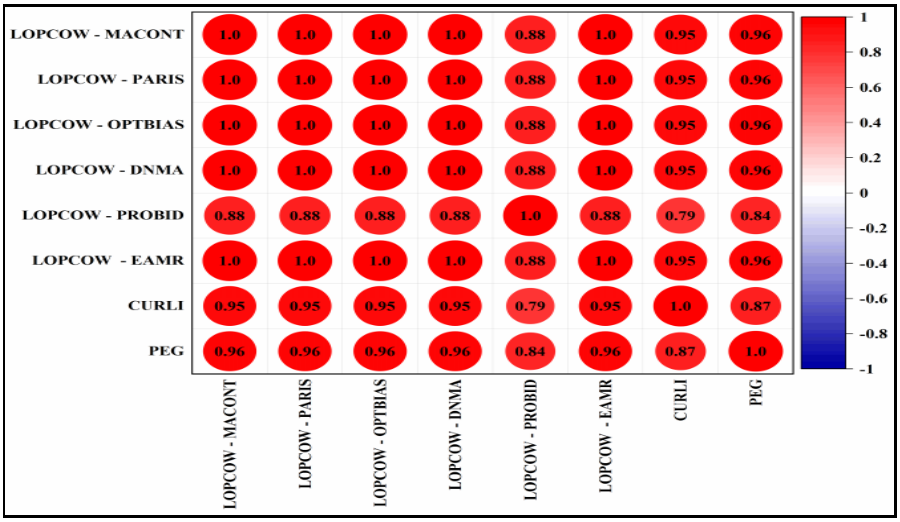


(d)

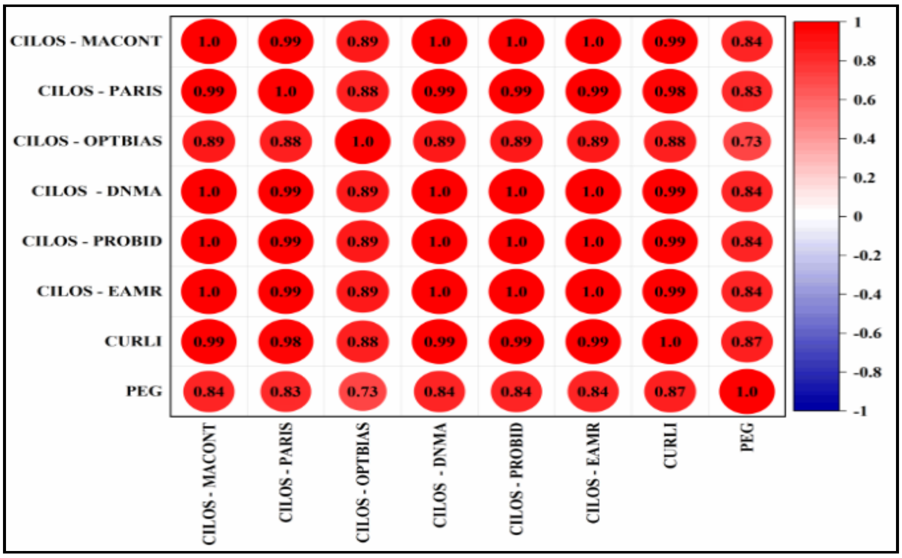
Figure 8.3 Continued



(e)

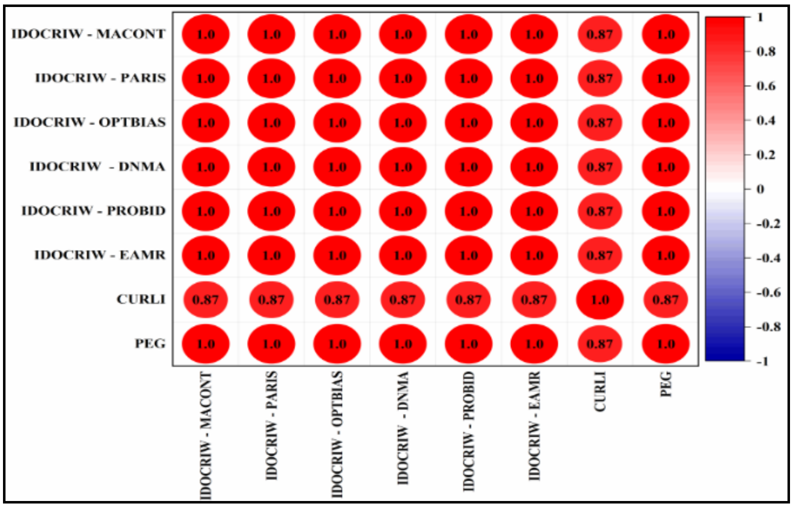


(f)



(g)

Figure 8.3 Continued

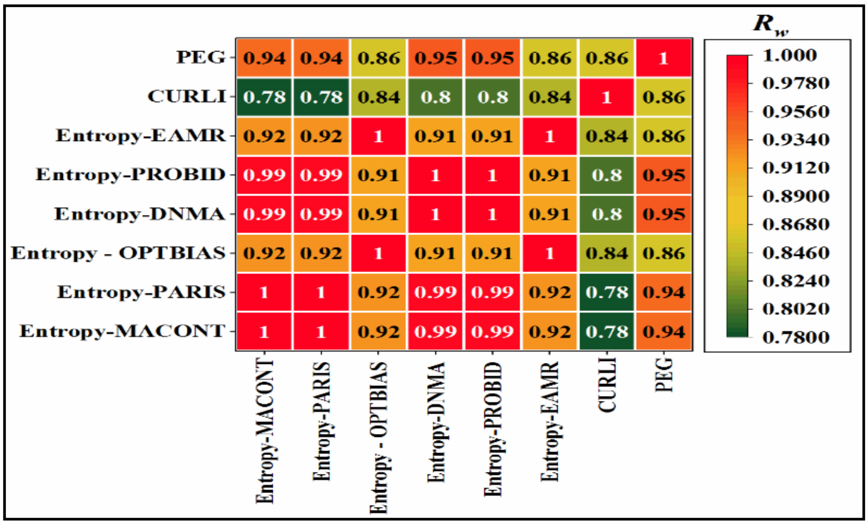


(h)

Figure 8.3 Continued

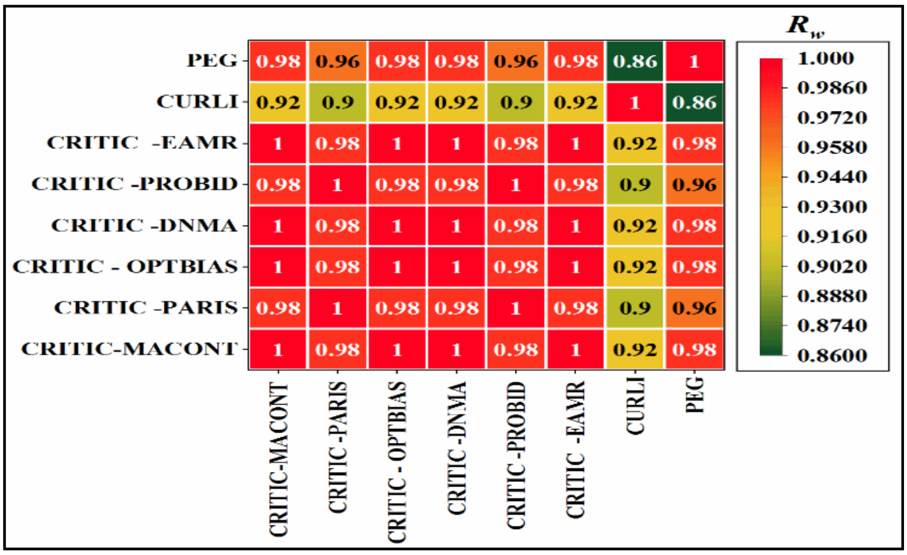
c) Based on weighted Spearman (R_w) rank co-relation coefficient

Figure 8.4 reveals that for entropy combined conditions, PROBID-DNMA and EAMR-OPTBIAS show very high R_w values of 1. CRITIC weighting reveals high correlations for all MCDM methods. MEREC weighting indicates that all methods, except CURLI, achieve very high values. PCA weighting also shows very high correlations between different methods. SPC weighting highlights that all methods achieve very good weighted coefficient values except CURLI. LOPCOW weighting sees almost perfect 1 in most cases. CILOS weighting shows that, except for OPTBIAS and PEG, all other methods perform extremely well. Finally, IDOCRIW weighting indicates perfect 1 in all cases except for CURLI. Clearly, CURLI does not perform well compared to the other MCDM methods. DNMA and PARIS consistently outperform others, showcasing exceptional adaptability and accuracy. On the other hand, CURLI emerges as the least reliable method, with suboptimal performance under multiple conditions.



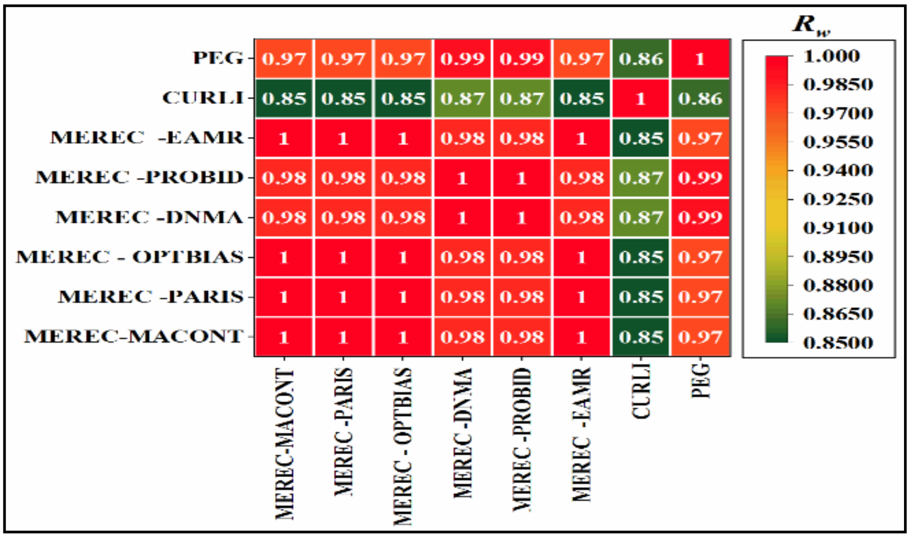
(a)

Figure 8.4 Spearman correlation coefficient result



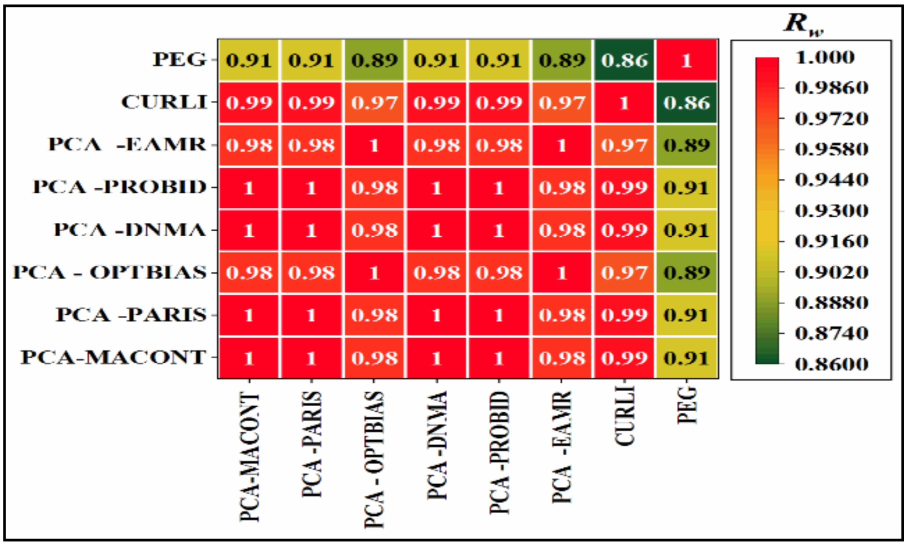
	CRITIC-MACONT	CRITIC -PARIS	CRITIC - OPTBIAS	CRITIC -DNMA	CRITIC -PROBID	CRITIC -EAMR	CURLI	PEG
PEG	0.98	0.96	0.98	0.98	0.96	0.98	0.86	1
CURLI	0.92	0.9	0.92	0.92	0.9	0.92	1	0.86
CRITIC -EAMR	1	0.98	1	1	0.98	1	0.92	0.98
CRITIC -PROBID	0.98	1	0.98	0.98	1	0.98	0.9	0.96
CRITIC -DNMA	1	0.98	1	1	0.98	1	0.92	0.98
CRITIC - OPTBIAS	1	0.98	1	1	0.98	1	0.92	0.98
CRITIC -PARIS	0.98	1	0.98	0.98	1	0.98	0.9	0.96
CRITIC-MACONT	1	0.98	1	1	0.98	1	0.92	0.98

(b)



	MEREC-MACONT	MEREC -PARIS	MEREC - OPTBIAS	MEREC -DNMA	MEREC -PROBID	MEREC -EAMR	CURLI	PEG
PEG	0.97	0.97	0.97	0.99	0.99	0.97	0.86	1
CURLI	0.85	0.85	0.85	0.87	0.87	0.85	1	0.86
MEREC -EAMR	1	1	1	0.98	0.98	1	0.85	0.97
MEREC -PROBID	0.98	0.98	0.98	1	1	0.98	0.87	0.99
MEREC -DNMA	0.98	0.98	0.98	1	1	0.98	0.87	0.99
MEREC - OPTBIAS	1	1	1	0.98	0.98	1	0.85	0.97
MEREC -PARIS	1	1	1	0.98	0.98	1	0.85	0.97
MEREC-MACONT	1	1	1	0.98	0.98	1	0.85	0.97

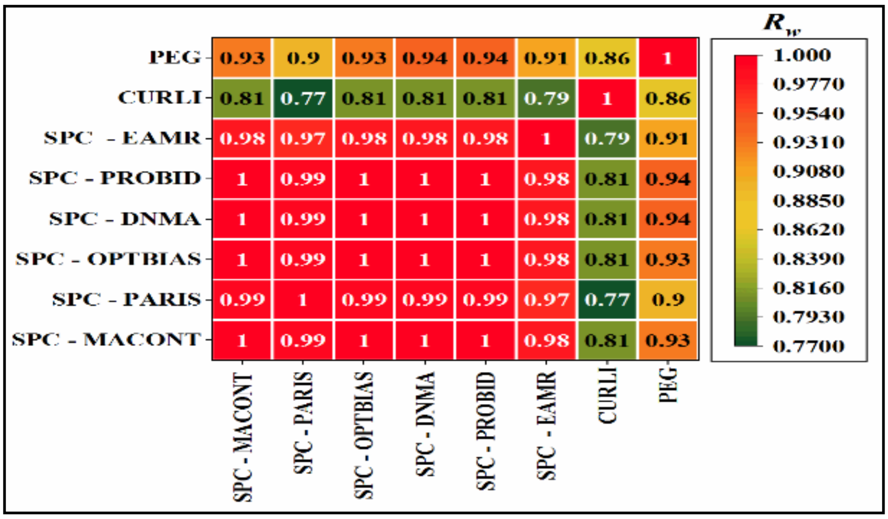
(c)



	PCA-MACONT	PCA -PARIS	PCA - OPTBIAS	PCA -DNMA	PCA -PROBID	PCA -EAMR	CURLI	PEG
PEG	0.91	0.91	0.89	0.91	0.91	0.89	0.86	1
CURLI	0.99	0.99	0.97	0.99	0.99	0.97	1	0.86
PCA -EAMR	0.98	0.98	1	0.98	0.98	1	0.97	0.89
PCA -PROBID	1	1	0.98	1	1	0.98	0.99	0.91
PCA -DNMA	1	1	0.98	1	1	0.98	0.99	0.91
PCA - OPTBIAS	0.98	0.98	1	0.98	0.98	1	0.97	0.89
PCA -PARIS	1	1	0.98	1	1	0.98	0.99	0.91
PCA-MACONT	1	1	0.98	1	1	0.98	0.99	0.91

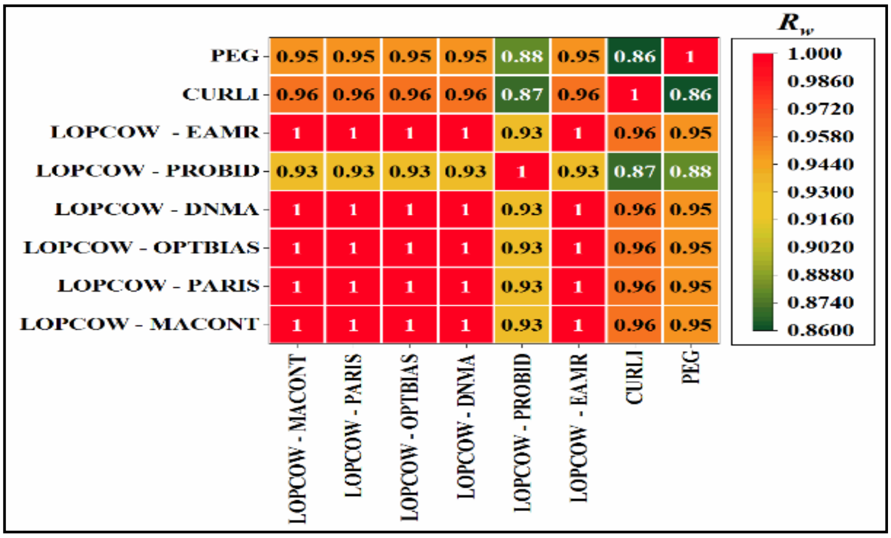
(d)

Figure 8.3 Continued



	SPC - MACONT	SPC - PARIS	SPC - OPTBIAS	SPC - DNMA	SPC - PROBID	SPC - EAMR	CURLI	PEG
PEG	0.93	0.9	0.93	0.94	0.94	0.91	0.86	1
CURLI	0.81	0.77	0.81	0.81	0.81	0.79	1	0.86
SPC - EAMR	0.98	0.97	0.98	0.98	0.98	1	0.79	0.91
SPC - PROBID	1	0.99	1	1	1	0.98	0.81	0.94
SPC - DNMA	1	0.99	1	1	1	0.98	0.81	0.94
SPC - OPTBIAS	1	0.99	1	1	1	0.98	0.81	0.93
SPC - PARIS	0.99	1	0.99	0.99	0.99	0.97	0.77	0.9
SPC - MACONT	1	0.99	1	1	1	0.98	0.81	0.93

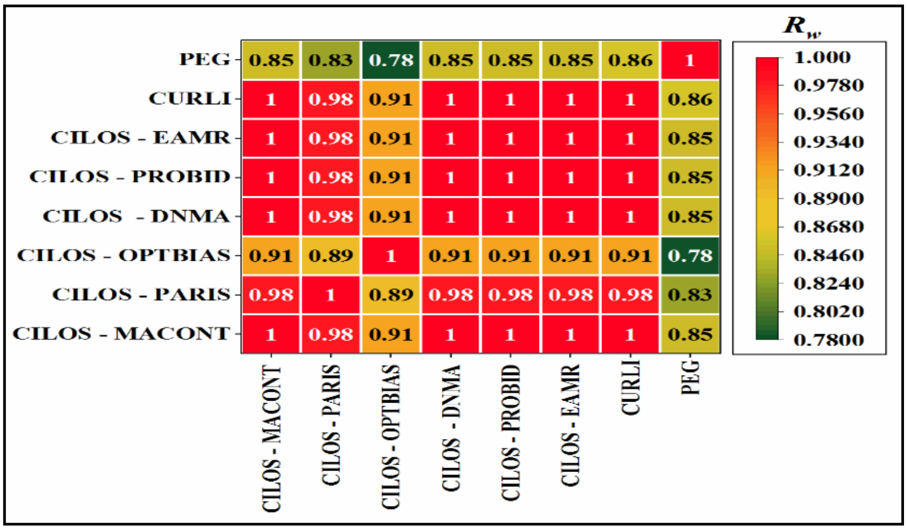
(e)



	LOPCOW - MACONT	LOPCOW - PARIS	LOPCOW - OPTBIAS	LOPCOW - DNMA	LOPCOW - PROBID	LOPCOW - EAMR	CURLI	PEG
PEG	0.95	0.95	0.95	0.95	0.88	0.95	0.86	1
CURLI	0.96	0.96	0.96	0.96	0.87	0.96	1	0.86
LOPCOW - EAMR	1	1	1	1	0.93	1	0.96	0.95
LOPCOW - PROBID	0.93	0.93	0.93	0.93	1	0.93	0.87	0.88
LOPCOW - DNMA	1	1	1	1	0.93	1	0.96	0.95
LOPCOW - OPTBIAS	1	1	1	1	0.93	1	0.96	0.95
LOPCOW - PARIS	1	1	1	1	0.93	1	0.96	0.95
LOPCOW - MACONT	1	1	1	1	0.93	1	0.96	0.95

(f)

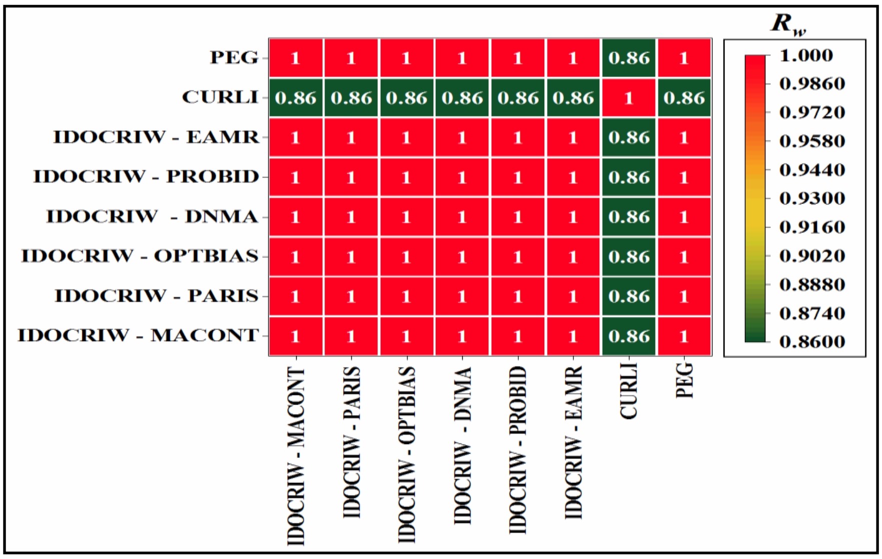
Figure 8.3 Continued



	CILOS - MACONT	CILOS - PARIS	CILOS - OPTBIAS	CILOS - DNMA	CILOS - PROBID	CILOS - EAMR	CURLI	PEG
PEG	0.85	0.83	0.78	0.85	0.85	0.85	0.86	1
CURLI	1	0.98	0.91	1	1	1	1	0.86
CILOS - EAMR	1	0.98	0.91	1	1	1	1	0.85
CILOS - PROBID	1	0.98	0.91	1	1	1	1	0.85
CILOS - DNMA	1	0.98	0.91	1	1	1	1	0.85
CILOS - OPTBIAS	0.91	0.89	1	0.91	0.91	0.91	0.91	0.78
CILOS - PARIS	0.98	1	0.89	0.98	0.98	0.98	0.98	0.83
CILOS - MACONT	1	0.98	0.91	1	1	1	1	0.85

(g)

Figure 8.3 Continued

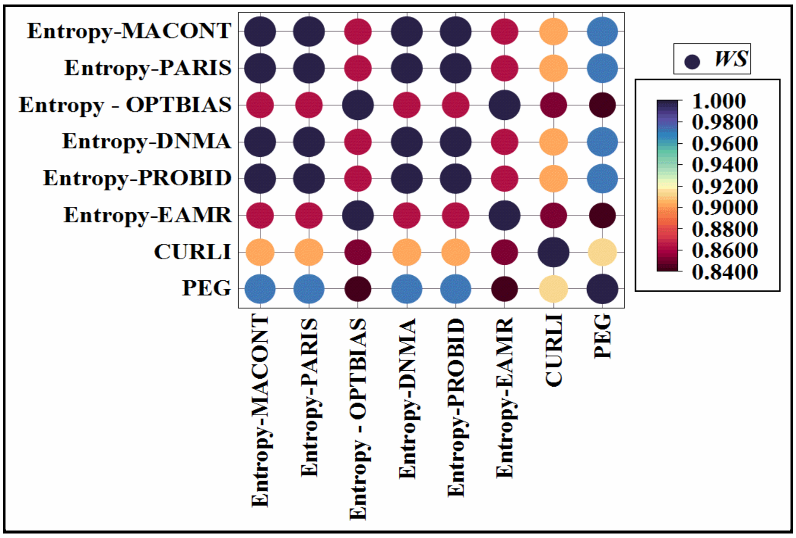


(h)

Figure 8.3 Continued

d) Based on coefficient of ranking similarity (*WS*)

Figure 8.5 shows the result of *WS* values of all the rankings. Under all the weighting conditions, contrasting results are observed. PCA stands out with the highest *WS* values above 0.94, suggesting excellent ranking consistency, followed by IDOCRIW with *WS* values above 0.91. CRITIC, LOPCOW and CILOS methods also demonstrate strong reliability with *WS* values consistently above 0.87. Entropy based methods show *WS* values above 0.84, indicating good ranking similarity, though slightly lower than CRITIC and CILOS. MEREC and SPC methods, both with *WS* values above 0.81, suggest moderate ranking similarity with some variability. DNMA performs exceptionally well across different weighting techniques. PARIS also displays good performance in few cases. However, CURLI and PEG struggle in many cases, reflecting lower reliability and greater variability in their rankings.



(a)

Figure 8.4 Coefficient of rank similarity (*WS*) results

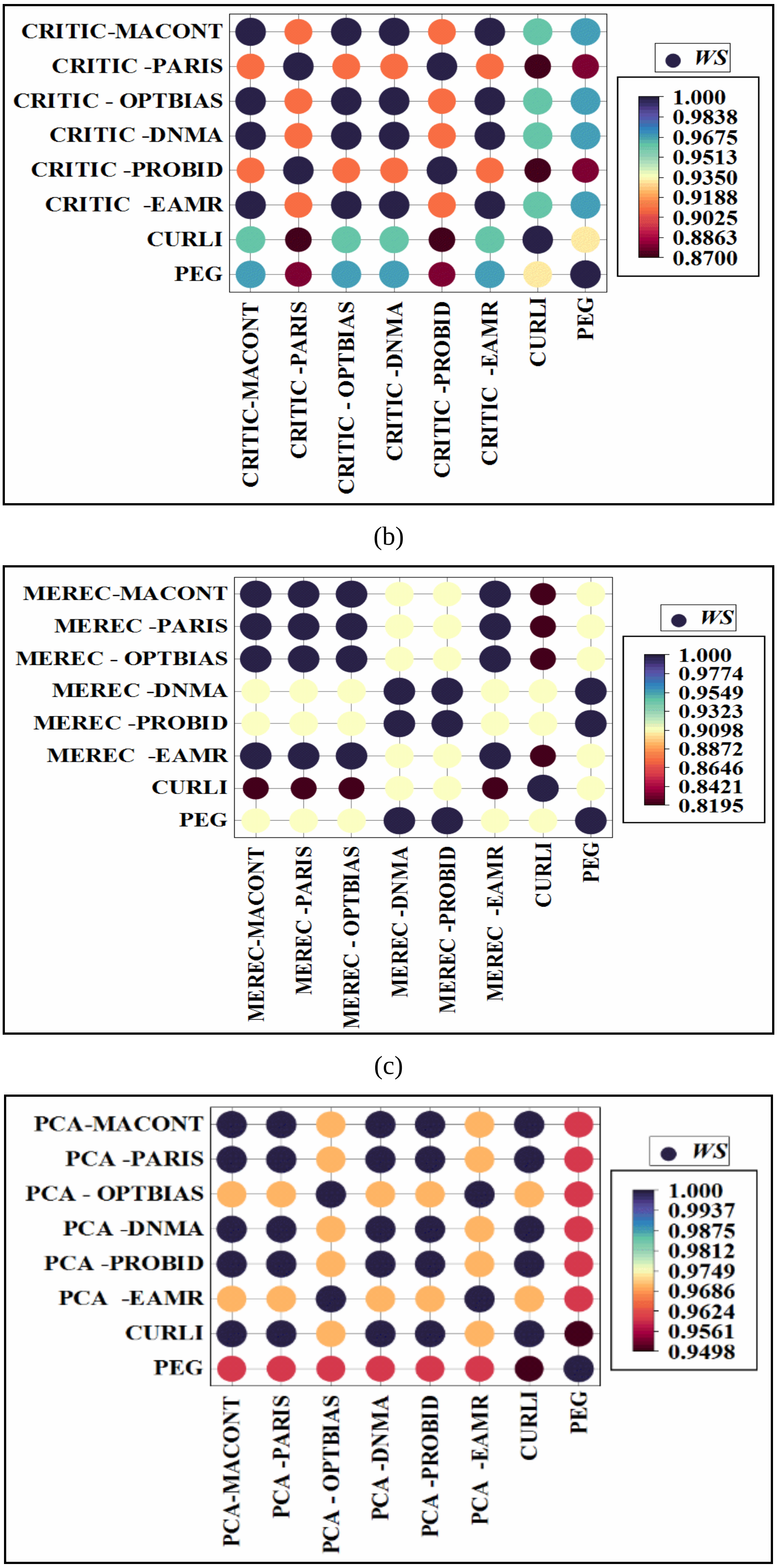
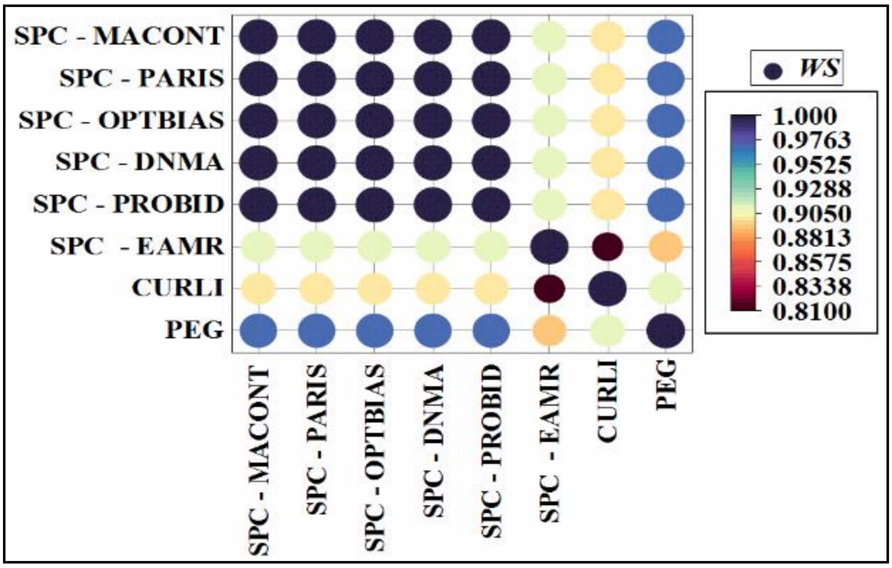
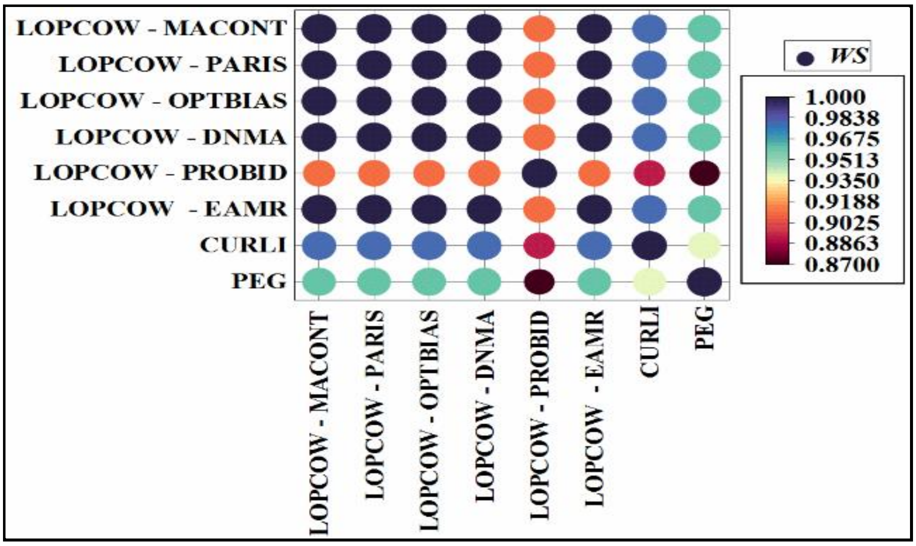


Figure 8.4 Continued



(e)



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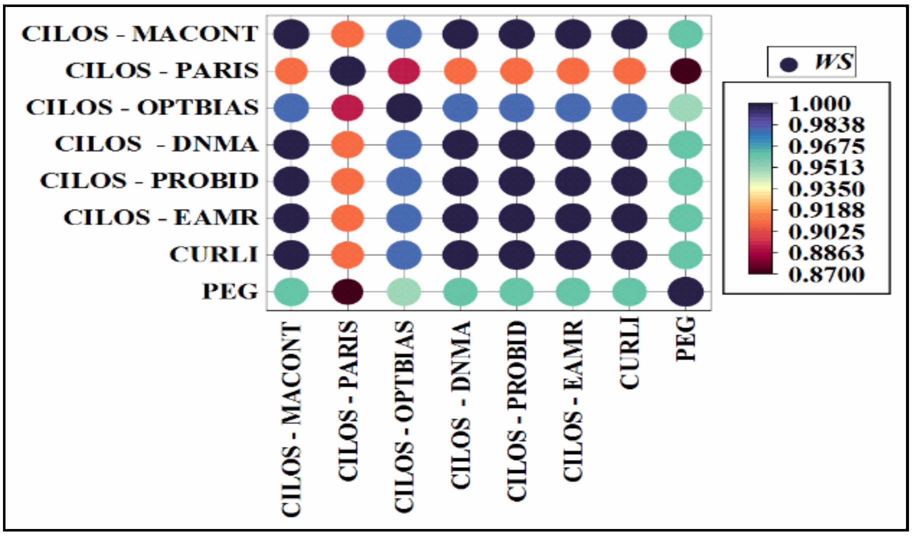
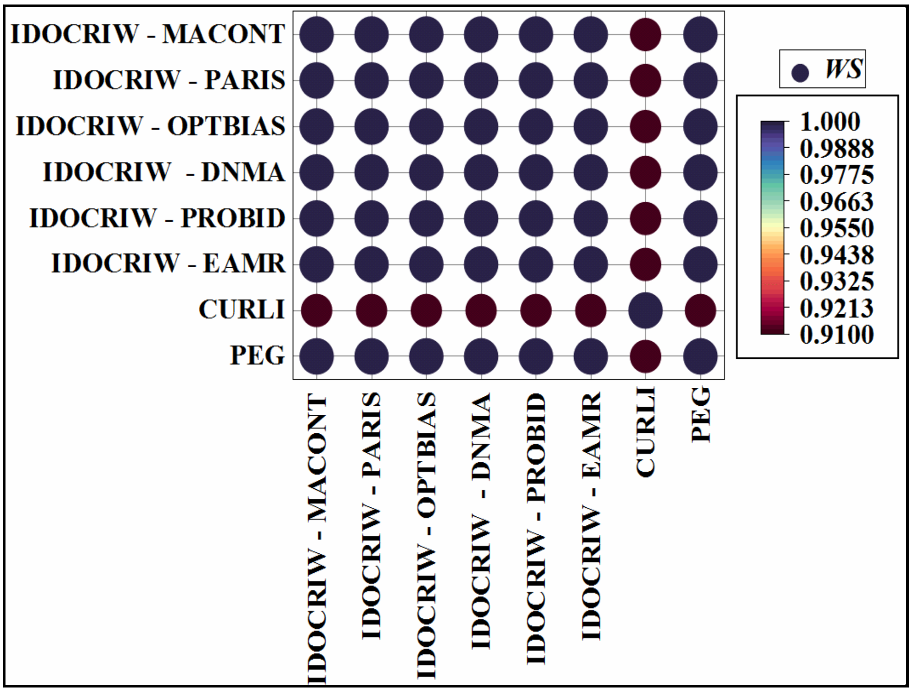


(g)

Figure 8.4 Continued



(h)

Figure 8.4 Continued

e) Based on number of operations

Figure 8.6 shows a comparative analysis between the considered MCDM methods with reference to the total number of mathematical operations required. From this figure, it is observed that in order to solve this decision making problems, EAMR method requires comparatively fewer operations, 170, followed by PEG, 257 and on the other hand MACONT, 356 and CURLI, which require 800 operations. Thus, EAMR technique clearly outperforms all the other methods in this study.

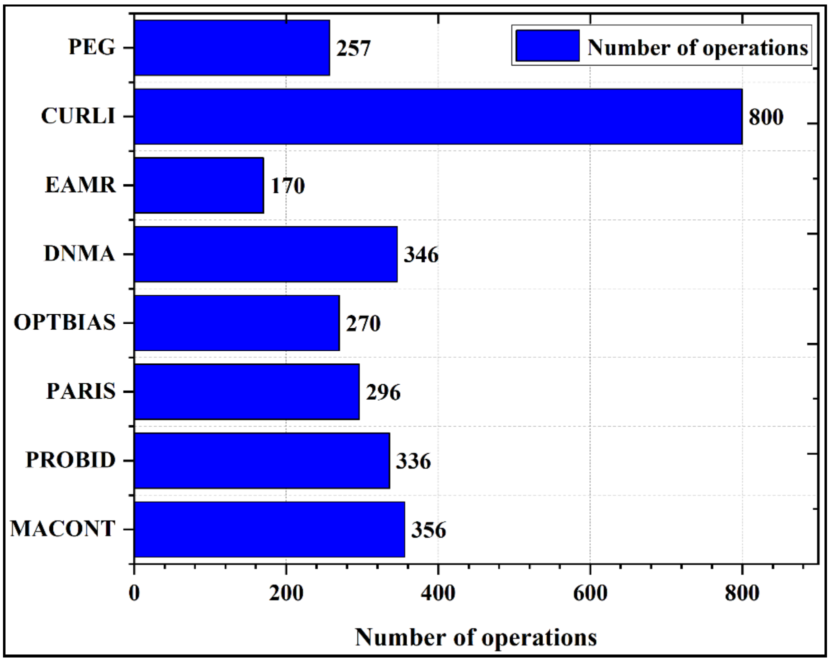


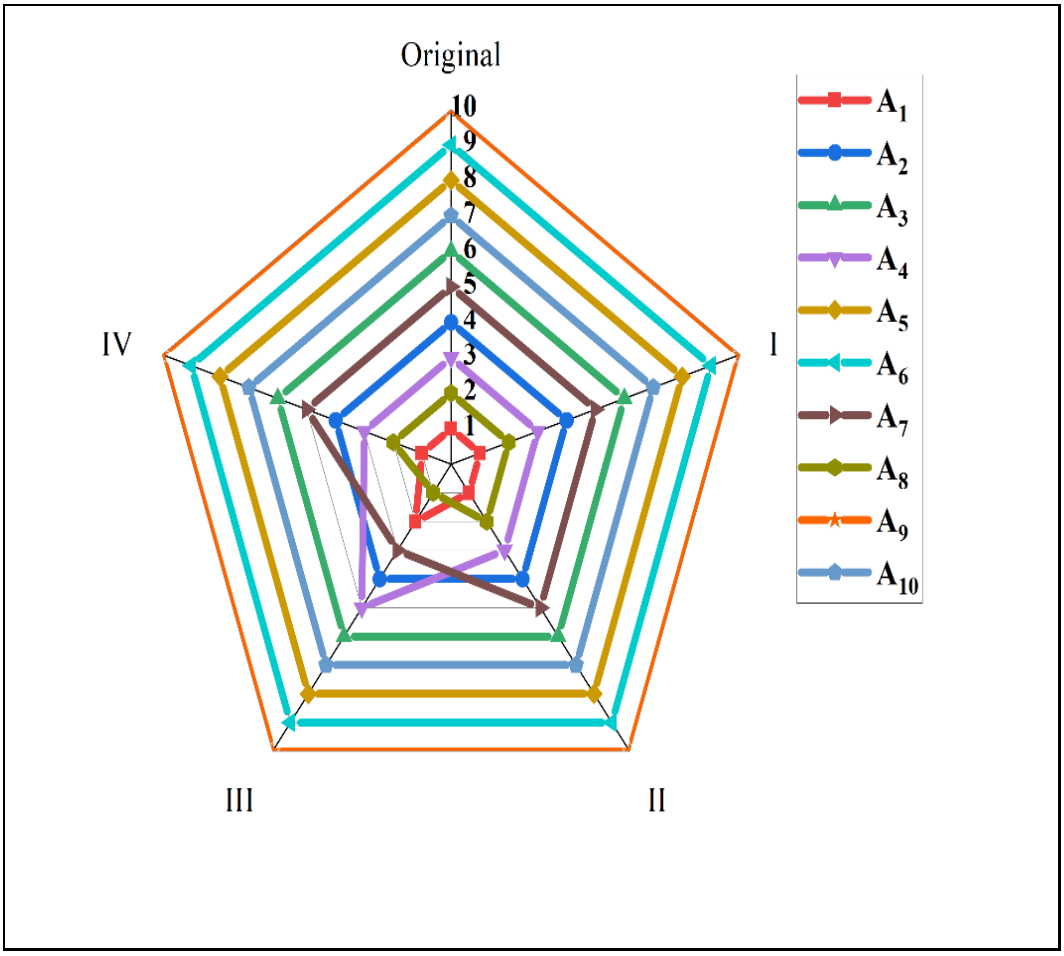
Figure 8.6 Number of computations

Sensitivity analysis

Effects of various weighting scenarios on ranking results are analyzed. It explores how changes in weighting methods impact the stability and reliability of alternative rankings, providing critical insights into the robustness of the decision making framework.

Sensitivity analysis based on gradual removal of criteria

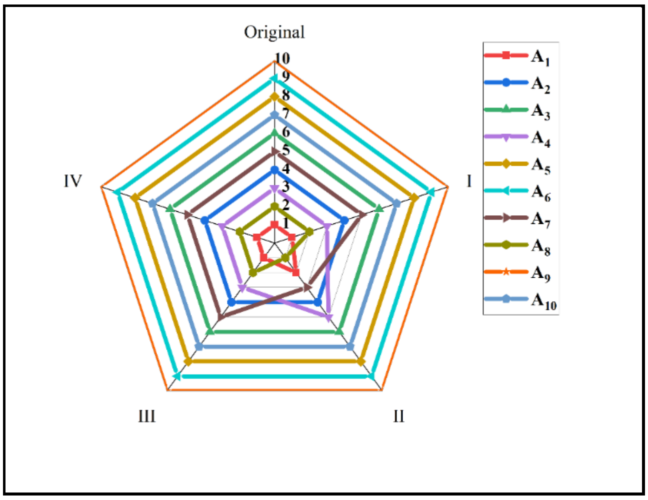
The sensitivity analysis of EDM OIL selection using the IDOCRIW weighting technique reveals varying levels of ranking stability. In Figure 8.7, PARIS emerges as the most robust method, showing no ranking changes across all scenarios, while DNMA also exhibits strong stability with only minor fluctuations in scenario IV. MACONT, PROBID, OPTBIAS and EAMR display moderate sensitivity, particularly affecting A_1 and A_4 rankings in certain scenarios. MACONT and OPTBIAS witness shifts in A_1 (rank one to two) and A_4 (rank three to five) in scenario III, while PROBID and EAMR show minor variations in A_1 and A_4 under different conditions. These results suggest that DNMA and PARIS are the least sensitive to changes in weighting conditions, making them the most reliable choice for decision making.



MACONT

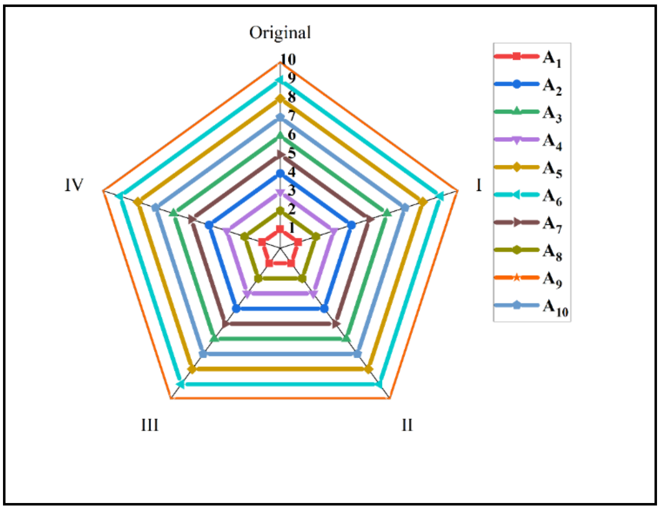
(a)

Figure 8.7 Sensitivity analyses results by gradually removal of criterion weight



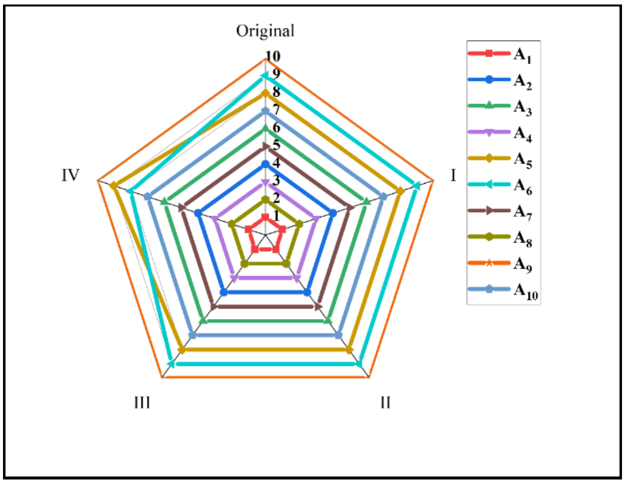
PROBID

(b)



PARIS

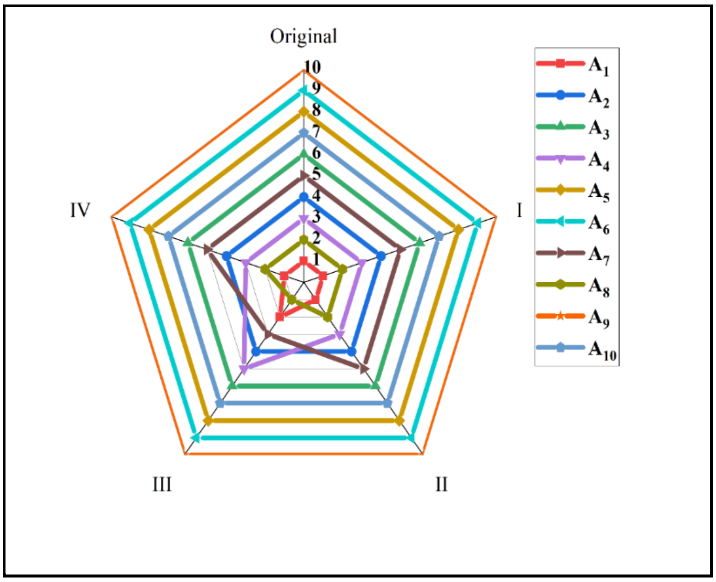
(c)



DNMA

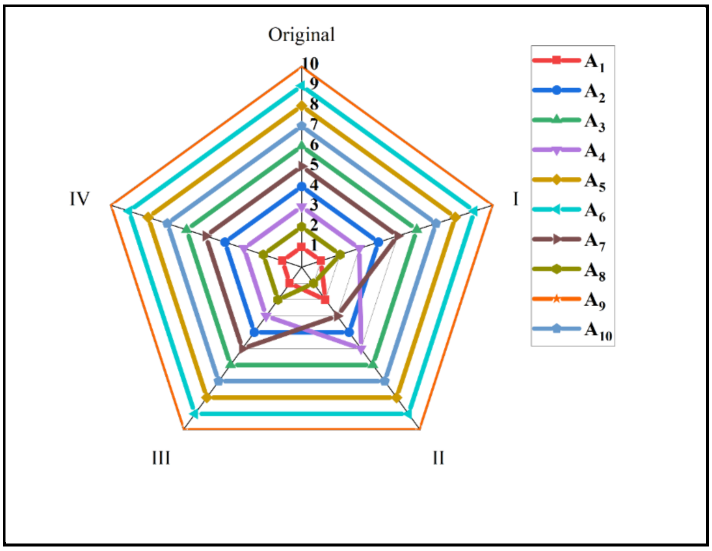
(d)

Figure 8.7 Continued



OPTBIAS

(e)



EAMR

(f)

Figure 8.7 Continued

Sensitivity analysis based on equal weighting conditions

Figure 8.8 highlights significant ranking stability, with most alternatives maintaining their positions across different weighting scenarios. Alternative A_1 consistently holds the top rank, demonstrating its robustness irrespective of the weighting technique applied. Similarly, A_9 remains the lowest-ranked alternative across all methods, indicating a strong consensus on its ranking. Minor fluctuations are observed in alternatives such as A_3, A_4 and A_7, where slight variations appear in CURLI and PEG rankings, suggesting these methods introduce marginal sensitivity to the ranking process. The PEG method, in particular, deviates slightly by ranking A_2 lower (rank four) compared to the other methods (rank three) and shifting A_4 to rank three instead of four. Despite these small changes, the overall ranking trend remains largely stable, reinforcing the reliability of the decision making framework.

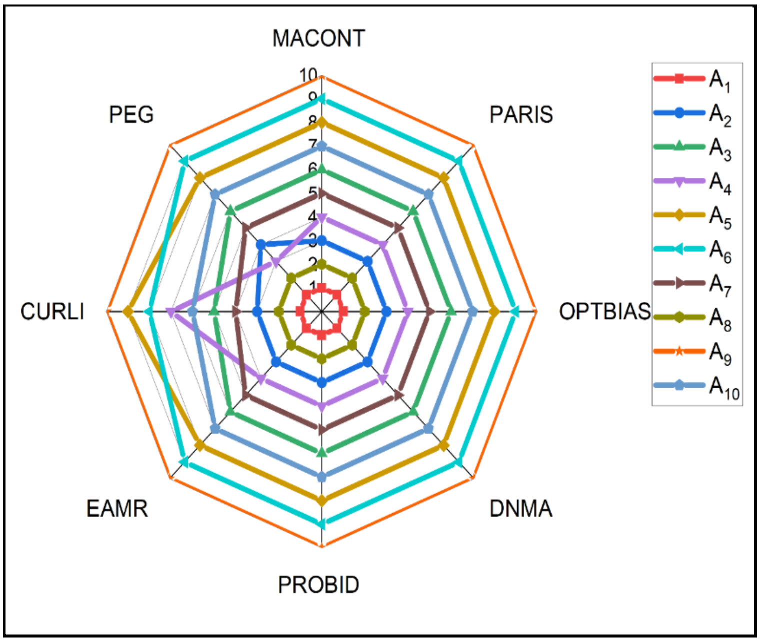
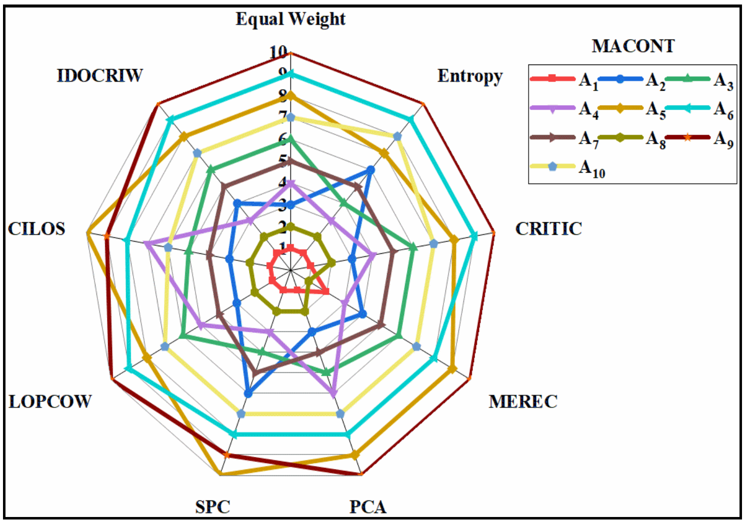


Figure 8.8 Sensitivity analyses results under equal weight condition

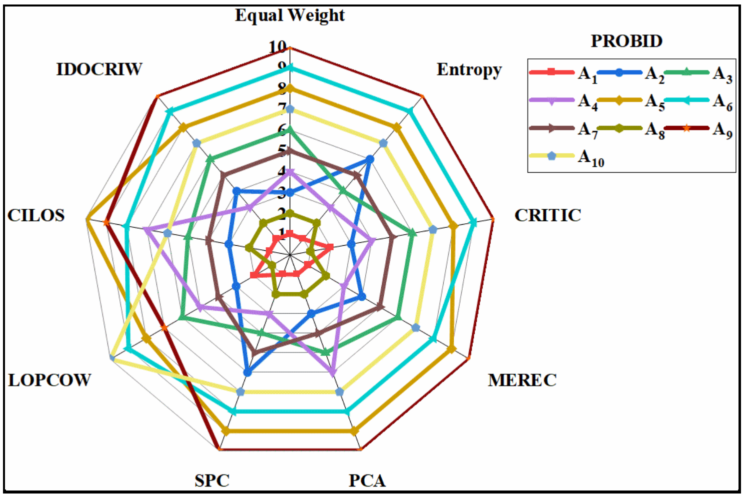
Sensitivity analysis based on all weighting conditions

Figure 8.9 reveals that, MACONT shows notable variation in rankings, with A_1 consistently at the top, while A_9 remains at the bottom in all methods. The performance of middle-tier alternatives such as A_3 and A_4 fluctuates notably under methods such as MEREC, PCA and SPC, indicating their sensitivity to the weighting schemes. A_2 and A_{10} also experience shifts, especially under entropy and MEREC. PROBID shows stable performance for A_1 across all methods, but the rankings of middle-tier alternatives such as A_4 and A_5 fluctuate more significantly depending on the weighting method. A_4 ranks lower under CRITIC and LOPCOW, while it maintains a higher position in other methods. A_6, A_7 and A_8 demonstrate varying positions, especially A_8, which shifts notably under MEREC and CILOS. A_9 and A_{10} consistently rank at the bottom. PARIS demonstrates stable performance for A_1, consistently ranked at the top, with A_2 performing well across most methods. However, A_4 and A_5 shift positions depending on the weighting condition, especially with A_4 dropping in entropy and CILOS. A_7, A_8 and A_9 show more variation, with A_7 ranked lower under certain methods and A_9 and A_{10} consistently underperforming. OPTBIAS exhibits stable performance for A_1, with A_2, A_3 and A_5 also consistently ranking in the top positions. A_7, A_8 and A_9 experience moderate fluctuations, especially under CILOS and entropy, but A_9 remains near the bottom in many methods, while A_{10} is consistently ranked last. DNMA shows consistent ranking for A_1 at the top across all methods, with A_2, A_3 and A_5 remaining stable. A_4 and A_7 show moderate fluctuations, with A_9 consistently at the bottom and A_{10} consistently last. EAMR shows consistent top ranks for A_1, with A_2, A_3 and A_5 maintaining relatively stable positions. However, A_4, A_7 and A_9 experience fluctuations, particularly in methods such as entropy and MEREC. CURLI and PEG, which do not require weighting, demonstrate stable rankings for A_1 at the top, followed by minor shifts for other alternatives, though A_{10} consistently ranks at the bottom.

In conclusion, MACONT provides reliable rankings for the best and worst alternatives, but the middle-tier rankings are highly sensitive to weighting schemes, suggesting that more nuanced approaches could provide deeper insights, especially for A_3 and A_4. PROBID is stable for top-ranked alternatives but shows variability for mid-tier alternatives, indicating that a more detailed analysis of these alternatives might improve performance. PARIS shows stability for the top performers, but its performance for middle and lower-ranked alternatives is more variable, suggesting that the method might benefit from more precise weighting strategies. DNMA is consistent for A_1 and A_8 but its performance for middle-tier alternatives shows moderate fluctuations. However, it is effective for identifying top performers and offers more stability than methods such as EAMR, which provides more nuanced rankings for middle-tier alternatives, while CURLI and PEG maintain consistent rankings without the depth of analysis that weighted methods provide.

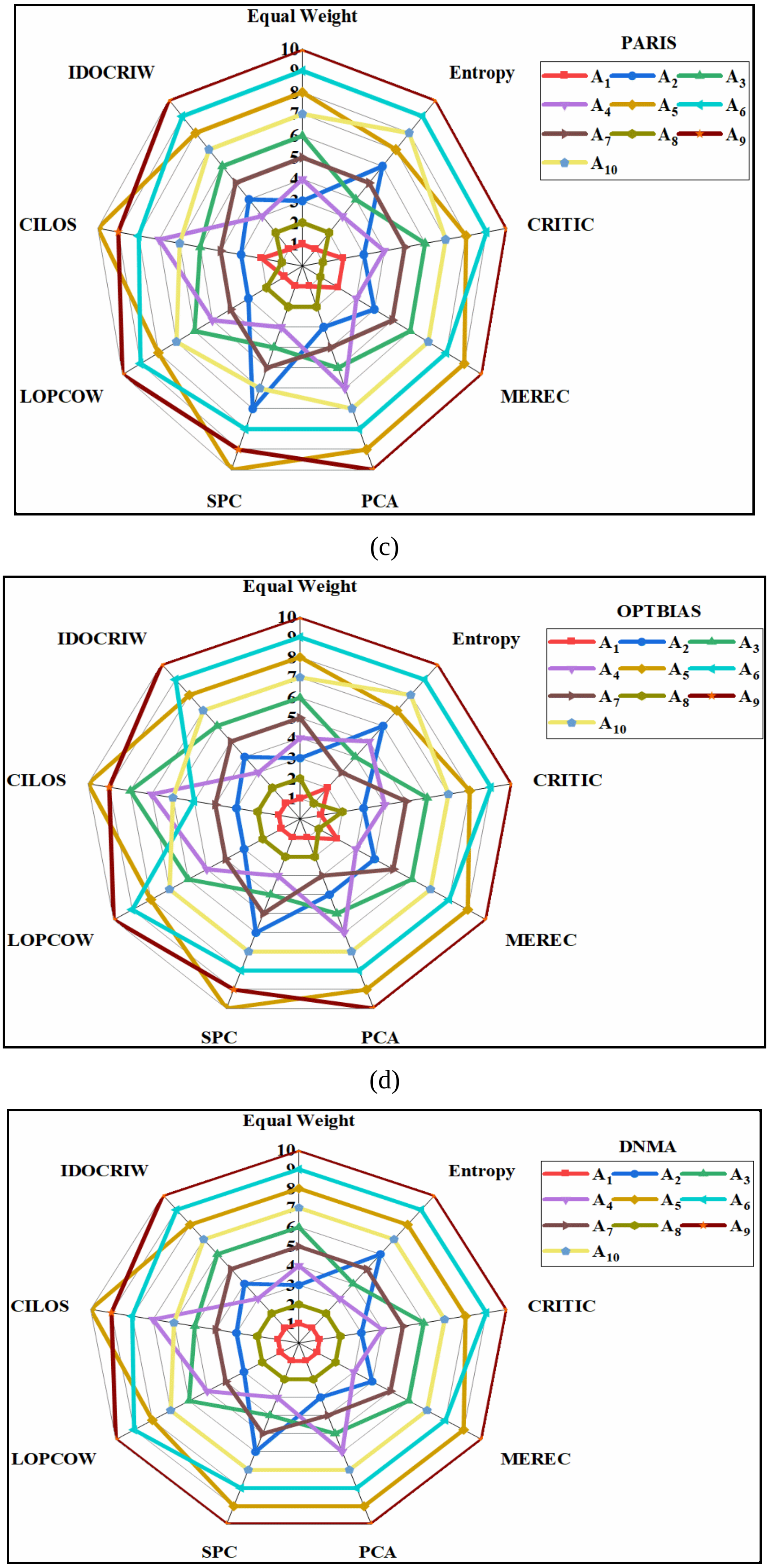


(a)



(b)

Figure 8.9 Sensitivity analyses results considering all the criteria weight

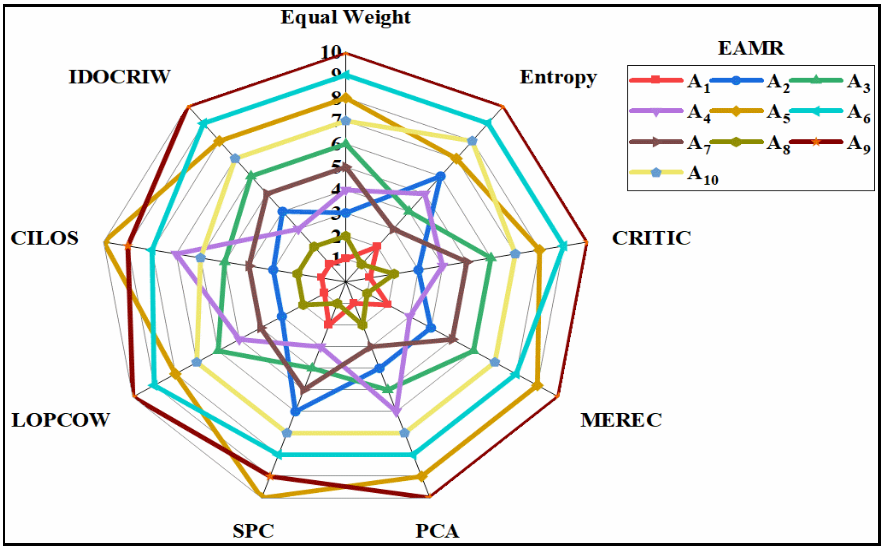


(c)

(d)

(e)

Figure 8.9 Continued



(f)

Figure 8.9 Continued

9. IDENTIFICATION OF THE SUPERIOR WEIGHTING AND MCDM METHOD

This chapter aims to identify the superior weighting technique and MCDM method by applying an ensemble aggregate ranking approach to evaluate performance across various selection problems. Since different MCDM methods generate varying rankings due to differences in mathematical formulations, weighting mechanisms and normalization procedures, aggregating these rankings ensures consistency and reliability. This comprehensive evaluation facilitates objective comparison and strengthens the decision making framework.

9.1 Ensemble ranking methodology

The ensemble ranking method systematically integrates multiple rankings by assigning optimal weights to each MCDM method, proposed by Mohammadi and Rezaei in 2020 [177], which is based on HQ theory. These weights, derived through a minimizer function inspired by HQ theory, naturally satisfy the fundamental constraints of MCDM weighting. Methods that closely align with others receive higher weights, while those that significantly deviate are assigned lower ones. To assess the quality of the final ranking, the framework incorporates two key indicators: CI and TL. CI with a maximum value of 1, measures the agreement among different MCDM methods and decreases as rankings diverge. TL, also ranging up to 1, evaluates the reliability of the final ranking, remaining high if some rankings align but dropping significantly when all rankings differ, indicating lower reliability. Higher values for both indicators strengthen the robustness of the ensemble ranking. By systematically determining the weight of each of the ranking contribution, this approach reduces bias, enhances mathematical rigor and improves the practical applicability of MCDM outcomes in complex decision making scenarios. The methodology for determining the ensemble ranking involves minimizing a HQ function to optimize ranking aggregation. This is formulated as:

$$\min_{R^*} \frac{1}{2} \sum_{m=1}^{M} g(\|R^m - R^*\|_2 \tag{9.1}$$

where m represents the m^{th} MCDM method, M is the total number of MCDM methods considered, R^m denotes the ranking produced by the m^{th} method and R^* is the final ensemble ranking. The notation $\| \bullet \|_2$ refers to the Euclidean norm, while g(•) represents the HQ function applied in the optimization process.

For this methodology, the Welsch estimator serves as the HQ function, expressed as:

$$1 - \exp\left(-\frac{s_j^2}{\sigma^2}\right) \tag{9.2}$$

This function has a corresponding minimizer, given by:

$$\exp\left(-\frac{s_j^2}{\sigma^2}\right) \tag{9.3}$$

where s_j represents the j^{th} element in a given vector and σ is a parameter that is iteratively refined through recursive optimization.

CI measures the agreement among all MCDM ranking methods with the final ranking. It quantifies the similarity of each ranking to the combined (aggregated) ranking using the Eq. (9.4).

$$C(R^*) = \frac{1}{KM}\sum_{k=1}^{K}\sum_{m=1}^{M} q_{km}\,, \qquad q_{km} = \frac{N_\sigma\left(R_k^* - R_k^m\right)}{N_\sigma(0)}, \tag{9.4}$$

where the function $N_\sigma(.)$ represents a Gaussian (normal) distribution with a mean of zero and a standard deviation of σ. The term $N_\sigma(0)$ is used to normalize the similarity calculation, ensuring that q_{km} falls between 0 and 1. If all ranking methods completely agree, then: $q_{km} = \frac{N_\sigma(0)}{N_\sigma(0)} = 1,\ \forall\ k,\ m,\ \sigma$ which gives a CI of 1 (full agreement). When rankings differ, the CI decreases, meaning there is less agreement among methods. If one ranking method is very different from the others, it lowers the CI. However, because the HQ functions treat this ranking as an outlier, it has less influence on the final ranking, but it still significantly affects the CI.

TL indicates the reliability of the final combined ranking. If a ranking method differs significantly from the majority, it receives a lower weight in Algorithm 1, reducing its influence on the final ranking. A lower-weighted ranking method also has less impact on the TL. TL follows the Eq. (9.5) and (9.6) that accounts for the weights and agreement between rankings:

$$T(R^*) = \frac{1}{k}\sum_{k=1}^{K}\sum_{m=1}^{M} w_m \cdot q_{km} \tag{9.5}$$

here,
$$w_m = \frac{\alpha_m}{\sum_{j=1}^{M}\alpha_j}\,, \alpha_m = \delta(\|R^m - R^*\|_2^2) \tag{9.6}$$

where w_m represents weight assigned to the m^{th} MCDM method, α_m indicates half-quadratic auxiliary variable for the m^{th} MCDM method, $\sum_{j=1}^{M}\alpha_j$ represents the sum of all auxiliary variables across all MCDM methods, ensuring the weights sum to 1.

9.2 Identification of the superior weighting method

This section evaluates the effectiveness of eight different weighting methods across five distinct decision making problems, using the rankings generated by the ensemble methodology outlined in Section 9.1 as the basis for assessment. To determine the most effective weighting method, a Pareto-based analysis is applied, leveraging ensemble ranking weights to identify methods that consistently contribute to stable and reliable decision outcomes. The aggregated rankings, along with their corresponding CI and TL values, provide a structured framework for selecting the optimal weighting method. Following the presentation of ranking results, a comparative analysis is conducted using Pareto analysis and other measures. The objective is to recognize the weighting method that establishes consistency and reliability, ensuring robustness in decision making applications.

Aggregated ranking results

This subsection summarizes the ranking results obtained through the ensemble methodology, by using the Eqs. (9.1) - (9.6). The rankings are generated for five distinct decision problems, each evaluated using eight different MCDM methods subject to eight weighting methods. Each table provides aggregated ranking results for a single MCDM method, incorporating rankings derived from eight different weighting techniques. The key components of these tables include aggregated ranking, which represent the combined ranking of alternatives, where lower values indicate higher preference. The final aggregate rank assigns an overall ranking to each alternative based on these scores.

Additionally, the contribution of different weighting methods are displayed, indicating their influence on the final ranking, with higher weights signifying greater impact. Two key indicators CI, which measures agreement among MCDM methods under different weighting schemes and the TL, which evaluates the reliability of the final ranking. A higher CI suggests stronger consensus, while a higher TL indicates greater stability and consistency in the ranking results. These tables provide a structured comparison of how different weighting methods affect the final rankings, offering insights into their relative effectiveness across five decision problems.

3D printer nozzle material selection

The aggregate rankings presented in Tables 9.1 to 9.7 offer valuable insights into how different MCDM methods assess the same set of alternatives under varying weighting schemes. A clear pattern emerges as alternative A_4 consistently achieves the highest rank across all methods, reflecting its strong and stable performance regardless of the technique or weighting method used. In contrast, alternative A_1 frequently ranks at the bottom, highlighting its consistently poor evaluation. Alternatives such as A_5, A_6 and A_7 display more fluctuation in their ranks, suggesting that their outcomes are more sensitive to the choice of method and weight distribution. Most of the methods report high CI (> 0.66) and TL (> 0.94), indicating dependable aggregation results. Weighting approaches such as IDOCRIW, LOPCOW, CRITIC and entropy play a significant role in shaping these rankings. IDOCRIW notably influences MACONT and DNMA, while LOPCOW has a strong impact in the OPTBIAS method. The CURLI and PEG methods, unlike the others, are not based on any external weighting scheme; instead, they rely on their internal ranking computations, with the ensemble approach assigning equal weight to each. Despite the limited weighting variation in CURLI and PEG, their outcomes support the general trend observed in other methods. Taken together, the findings consistently point to A_4 as the most favourable choice, while A_1 stands out as the least preferred across the board.

Table 9.1 MACONT aggregate ranking (CI:0.668, TL:0.965)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	8.000	8	Entropy (0.004) CRITIC (0.132) MEREC (0.002) PCA (0.000) SPC (0.000) LOPCOW (0.000) CILOS (0.001) IDOCRIW (0.861)
A_2	6.860	7	
A_3	6.134	6	
A_4	1.000	1	
A_5	4.860	5	
A_6	2.877	3	
A_7	4.130	4	
A_8	2.139	2	

Table 9.2 PROBID aggregate ranking (CI:0.776, TL:0.954)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	7.991	8	Entropy (0.345) CRITIC (0.003) MEREC (0.000) PCA (0.068)
A_2	5.942	6	
A_3	6.202	7	
A_4	1.206	1	

A_5	1.905	2	SPC (0.000)
A_6	4.456	4	LOPCOW (0.004)
A_7	5.226	5	CILOS (0.202)
A_8	3.072	3	IDOCRIW (0.377)

Table 9.3 PARIS aggregate ranking (CI:0.779, TL:0.963)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	7.997	8	Entropy (0.452)
A_2	3.453	3	CRITIC (0.432)
A_3	6.27	6	MEREC (0.001)
A_4	1	1	PCA (0.043)
A_5	2.018	2	SPC (0.000)
A_6	6.44	7	LOPCOW (0.002)
A_7	4.421	5	CILOS (0.002)
A_8	4.402	4	IDOCRIW (0.069)

Table 9.4 OPTBIAS aggregate ranking (CI:0.762, TL:0.945)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	5.883	6	Entropy (0.005)
A_2	4.077	4	CRITIC (0.186)
A_3	5.084	5	MEREC (0.257)
A_4	1.257	1	PCA (0.003)
A_5	7.026	7	SPC (0.003)
A_6	1.790	2	LOPCOW (0.543)
A_7	7.506	8	CILOS (0.001)
A_8	3.378	3	IDOCRIW (0.003)

Table 9.5 DNMA aggregate ranking (CI:0.699, TL:0.951)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	7.999	8	Entropy (0.454)
A_2	4.108	4	CRITIC (0.006)
A_3	5.984	6	MEREC (0.000)
A_4	1.002	1	PCA (0.002)
A_5	2.003	2	SPC (0.001)
A_6	6.989	7	LOPCOW (0.001)
A_7	4.445	5	CILOS (0.000)
A_8	3.469	3	IDOCRIW (0.536)

Table 9.6 EAMR aggregate ranking (CI:0.728, TL:0.941)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	6.941	7	Entropy (0.000)
A_2	3.697	4	CRITIC (0.555)
A_3	3.352	3	MEREC (0.004)
A_4	1.089	1	PCA (0.348)
A_5	6.055	6	SPC (0.055)
A_6	8.000	8	LOPCOW (0.000)
A_7	1.911	2	CILOS (0.004)
A_8	4.955	5	IDOCRIW (0.034)

Table 9.7 CURLI and PEG aggregate ranking (CI:0.568, TL:0.568)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	8.000	8	CURLI (0.500) PEG (0.500)
A_2	3.500	3	
A_3	5.500	5	
A_4	1.000	1	
A_5	2.000	2	
A_6	7.000	7	
A_7	5.500	5	
A_8	3.500	3	

Piston material selection

The evaluation of alternatives for piston material selection, as reflected in Tables 9.8 through 9.14, highlights a consistent preference pattern among the methods used. Alternative A_7 emerges as the clear frontrunner, ranking first across all methods and weighting schemes, which points to its strong suitability regardless of methodological differences. A_6 also performs consistently well, frequently securing the second rank, particularly in the more diverse and weight-sensitive methods such as DNMA, OPTBIAS and PARIS. On the opposite end, A_8 regularly occupies the bottom rank, suggesting it is the least viable alternative in this decision context. Alternatives such as A_1 and A_5 show moderate to high variation, with A_1 ranking as high as third in DNMA and as low as seventh under CURLI and PEG, indicating that its evaluation is highly dependent on the chosen weighting configuration. Interestingly, methods such as MACONT and DNMA show strong influence from CILOS and CRITIC, while OPTBIAS heavily weights CILOS and CRITIC again, in contrast to earlier problem where IDOCRIW and LOPCOW dominated. The ensemble method combining CURLI and PEG continues to assign equal weights to both, yet still reinforces the dominance of A_7 and the lower placement of A_8. The reliability of the results is supported by consistently high CI and TL values across most methods, particularly in CURLI and PEG (CI: 0.929, TL: 0.929).

Furthermore, the alignment of top and bottom alternatives across techniques adds to the confidence in the final selection outcome. The ensemble-based analysis validates A_7 as the optimal piston material, offering both methodological agreement and high decision confidence.

Table 9.8 MACONT aggregate ranking (CI:0.750, TL:0.960)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	4.363	4	Entropy (0.000) CRITIC (0.000) MEREC (0.097) PCA (0.035) SPC (0.002) LOPCOW (0.386) CILOS (0.478) IDOCRIW (0.001)
A_2	5.790	6	
A_3	2.958	3	
A_4	4.587	5	
A_5	6.919	7	
A_6	2.253	2	
A_7	1.137	1	
A_8	7.994	8	

Table 9.9 PROBID aggregate ranking (CI:0.683, TL:0.997)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	4.994	5	Entropy (0.000)
A_2	7.007	7	CRITIC (0.000)
A_3	3.991	4	MEREC (0.000)
A_4	6.001	6	PCA (0.990)
A_5	3.022	3	SPC (0.007)
A_6	2.000	2	LOPCOW (0.003)
A_7	1.000	1	CILOS (0.000)
A_8	7.985	8	IDOCRIW (0.000)

Table 9.10 PARIS aggregate ranking (CI: 0.761, TL: 0.951)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	4.026	4	Entropy (0.000)
A_2	5.963	6	CRITIC (0.001)
A_3	3.354	3	MEREC (0.037)
A_4	4.630	5	PCA (0.425)
A_5	7.219	7	SPC (0.219)
A_6	2.027	2	LOPCOW (0.307)
A_7	1.000	1	CILOS (0.013)
A_8	7.781	8	IDOCRIW (0.000)

Table 9.11 OPTBIAS aggregate ranking (CI: 0.748, TL: 0.973)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	3.168	3	Entropy (0.000)
A_2	6.167	6	CRITIC (0.392)
A_3	4.814	5	MEREC (0.049)
A_4	4.168	4	PCA (0.000)
A_5	6.734	7	SPC (0.000)
A_6	2.000	2	LOPCOW (0.167)
A_7	1.000	1	CILOS (0.392)
A_8	7.949	8	IDOCRIW (0.000)

Table 9.12 DNMA aggregate ranking (CI: 0.701, TL: 0.983)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	3.002	3	Entropy (0.000)
A_2	5.993	6	CRITIC (0.450)
A_3	4.914	5	MEREC (0.008)
A_4	4.091	4	PCA (0.000)
A_5	7.007	7	SPC (0.089)
A_6	2.000	2	LOPCOW (0.002)
A_7	1.000	1	CILOS (0.450)
A_8	7.992	8	IDOCRIW (0.000)

Table 9.13 EAMR aggregate ranking (CI: 0.566, TL: 1.000)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	5.000	5	Entropy (0.000)
A_2	6.000	6	CRITIC (0.000)

A_3	2.000	2	MEREC (0.000) PCA (0.000) SPC (0.000) LOPCOW (1.000) CILOS (0.000) IDOCRIW (0.000)
A_4	4.000	4	
A_5	7.000	7	
A_6	3.000	3	
A_7	1.000	1	
A_8	8.000	8	

Table 9.14 CURLI and PEG aggregate ranking (CI: 0.929, TL: 0.929)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	6.500	7	CURLI (0.500) PEG (0.500)
A_2	5.000	5	
A_3	6.000	6	
A_4	6.500	7	
A_5	4.500	3	
A_6	2.000	2	
A_7	1.000	1	
A_8	4.500	3	

Cobot selection

Tables 9.15 through 9.21, exhibit a strikingly consistent preference pattern across multiple methods, decisively highlighting alternative A_6 as the most robust and universally favourable alternative. A_6 secures the top rank in every method irrespective of the varied weight distributions, thereby affirming its superior adaptability and technical suitability across methodological frameworks. A_{11} also emerges as a dependable alternative, ranking second in DNMA, EAMR and PARIS, indicating a solid and repeatable performance profile. Alternative A_1 consistently holds positions within the top four across MACONT, PROBID, PARIS, OPTBIAS and DNMA driven by significant weight contributions from CRITIC (up to 0.265) and LOPCOW (as high as 0.251), suggesting a generally favourable though slightly weight-sensitive positioning. Similarly, A_9 performs well, maintaining top-five positions across MACONT, PROBID, PARIS and DNMA, although its rank falls to seventh in EAMR and twelfth in the CURLI and PEG ensemble, revealing a susceptibility to ranking volatility under certain configurations. At the opposite end, A_8 consistently ranks last across all seven methods, with uniform placement at 13th, indicating clear and repeated inferiority. A_5 and A_{13} are similarly confined to the lower ranks, suggesting limited practical feasibility. In contrast, A_2 and A_{10} present more nuanced behaviour, where A_2 achieves a peak ranking of third in CURLI and PEG despite being placed as low as eleventh elsewhere, while A_{10} reaches second place in the ensemble but fluctuates across DNMA and EAMR, implying a balanced rather than dominant performance. The influence of weighting schemes shifts subtly in this case, while earlier problems emphasized IDOCRIW and LOPCOW, the present analysis shows CRITIC and CILOS asserting stronger dominance, particularly in MACONT, OPTBIAS and DNMA. LOPCOW, however, maintains heavy dominance in EAMR with an exceptional weight of 0.994. Notably, the ensemble method, CURLI and PEG, applies equal weighting (0.500 each), which still aligns with the consensus by placing A_6 first and A_8 last, reaffirming the overall consistency and credibility of findings. The consistently high CI and TL values, peaking at 0.994 in the ensemble method, further validate the stability and reliability of the aggregated outcomes. Taken together, these observations confirm A_6 as the best cobot, with A_{11} and A_1 following closely and A_8 persistently the least favourable, demonstrating a strong convergence across diverse analytical models and weight constructs.

Table 9.15 MACONT aggregate ranking (CI: 0.909, TL: 0.963)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	4.388	3	Entropy (0.003) CRITIC (0.203) MEREC (0.224) PCA (0.099) SPC (0.194) LOPCOW (0.185) CILOS (0.089) IDOCRIW (0.002)
A_2	9.090	9	
A_3	4.642	5	
A_4	7.011	8	
A_5	11.794	12	
A_6	1.000	1	
A_7	4.458	4	
A_8	13.000	13	
A_9	3.842	2	
A_{10}	10.980	11	
A_{11}	4.666	6	
A_{12}	6.447	7	
A_{13}	9.683	10	

Table 9.16 PROBID aggregate ranking (CI: 0.909, TL: 0.970)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	3.623	4	Entropy (0.001) CRITIC (0.161) MEREC (0.207) PCA (0.150) SPC (0.174) LOPCOW (0.197) CILOS (0.110) IDOCRIW (0.001)
A_2	9.950	11	
A_3	3.074	2	
A_4	9.826	10	
A_5	11.441	12	
A_6	1.000	1	
A_7	7.580	7	
A_8	13.000	13	
A_9	4.513	5	
A_{10}	8.505	8	
A_{11}	3.232	3	
A_{12}	5.755	6	
A_{13}	9.502	9	

Table 9.17 PARIS aggregate ranking (CI: 0.893, TL: 0.967)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	3.113	3	Entropy (0.000) CRITIC (0.265) MEREC (0.220) PCA (0.159) SPC (0.088) LOPCOW (0.219) CILOS (0.048) IDOCRIW (0.000)
A_2	8.090	8	
A_3	6.204	6	
A_4	7.346	7	
A_5	12.000	12	
A_6	1.000	1	
A_7	10.648	11	
A_8	13.000	13	
A_9	3.719	4	
A_{10}	8.376	9	

A_{11}	2.265	2	
A_{12}	5.420	5	
A_{13}	9.819	10	

Table 9.18 OPTBIAS aggregate ranking (CI: 0.906, TL: 0.971)

Alternative	R^*	Aggregate rank	Method (weight)
A_{1}	3.536	4	Entropy (0.001) CRITIC (0.182) MEREC (0.214) PCA (0.133) SPC (0.191) LOPCOW (0.210) CILOS (0.067) IDOCRIW (0.001)
A_{2}	10.650	11	
A_{3}	3.192	3	
A_{4}	10.109	10	
A_{5}	11.396	12	
A_{6}	1.450	1	
A_{7}	7.147	7	
A_{8}	13.000	13	
A_{9}	4.602	5	
A_{10}	8.107	8	
A_{11}	2.863	2	
A_{12}	5.713	6	
A_{13}	9.236	9	

Table 9.19 DNMA aggregate ranking (CI: 0.879, TL: 0.978)

Alternative	R^*	Aggregate rank	Method (weight)
A_{1}	3.163	3	Entropy (0.000) CRITIC (0.251) MEREC (0.229) PCA (0.163) SPC (0.027) LOPCOW (0.251) CILOS (0.079) IDOCRIW (0.000)
A_{2}	7.692	8	
A_{3}	5.242	5	
A_{4}	7.441	7	
A_{5}	12.000	12	
A_{6}	1.000	1	
A_{7}	9.998	10	
A_{8}	13.000	13	
A_{9}	3.837	4	
A_{10}	8.948	9	
A_{11}	2.000	2	
A_{12}	5.758	6	
A_{13}	10.921	11	

Table 9.20 EAMR aggregate ranking (CI: 0.757, TL: 0.999)

Alternative	R^*	Aggregate rank	Method (weight)
A_{1}	4.000	4	Entropy (0.002) CRITIC (0.000) MEREC (0.002) PCA (0.000) SPC (0.002) LOPCOW (0.994) CILOS (0.000) IDOCRIW (0.002)
A_{2}	3.000	3	
A_{3}	10.000	10	
A_{4}	9.000	9	
A_{5}	12.000	12	
A_{6}	1.000	1	
A_{7}	11.000	11	
A_{8}	13.000	13	
A_{9}	7.006	7	
A_{10}	7.994	8	
A_{11}	2.000	2	
A_{12}	5.000	5	
A_{13}	6.000	6	

Table 9.21 CURLI and PEG aggregate ranking (CI: 0.994, TL: 0.994)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	9.000	10	CURLI (0.500) PEG (0.500)
A_2	5.500	3	
A_3	7.500	7	
A_4	9.000	10	
A_5	7.500	7	
A_6	1.000	1	
A_7	6.000	5	
A_8	11.500	13	
A_9	10.000	12	
A_{10}	4.500	2	
A_{11}	8.000	9	
A_{12}	5.500	3	
A_{13}	6.000	5	

Drone selection

Tables 9.22 to 9.28 highlight alternative A_2 as the unanimous top performer, consistently ranking first across all methods. A_3 also performs well, staying within the top three across most methods. A_6 shows strength in PARIS and DNMA but drops to mid-rank in OPTBIAS. A_1 ranks last in most of the methods, yet surprisingly jumps to second place in the aggregate ranking of CURLI and PEG, indicating inconsistency and sensitivity to aggregation. Weighting methods such as SPC and IDOCRIW dominate influence in EAMR and OPTBIAS, while CRITIC, PCA and CILOS remain negligible. The findings validate A_2 as the most reliable and robust drone alternative.

Table 9.22 MACONT aggregate ranking (CI: 0.740, TL: 0.963)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	2.371	2	Entropy (0.289) CRITIC (0.000) MEREC (0.373) PCA (0.000) SPC (0.032) LOPCOW (0.000) CILOS (0.000) IDOCRIW (0.306)
A_2	1.000	1	
A_3	7.968	8	
A_4	2.694	3	
A_5	3.936	4	
A_6	7.032	7	
A_7	5.710	6	
A_8	5.289	5	

Table 9.23 PROBID aggregate ranking (CI: 0.736, TL: 0.944)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	8.000	8	Entropy (0.144) CRITIC (0.078) MEREC (0.369) PCA (0.000) SPC (0.401) LOPCOW (0.000) CILOS (0.000) IDOCRIW (0.009)
A_2	1.000	1	
A_3	2.669	2	
A_4	5.070	5	
A_5	6.999	7	
A_6	2.801	3	
A_7	5.913	6	
A_8	3.548	4	

Table 9.24 PARIS aggregate ranking (CI: 0.750, TL: 0.956)

Alternative	*R**	Aggregate rank	Method (weight)
A_1	8.000	8	Entropy (0.303)
A_2	1.701	2	CRITIC (0.000)
A_3	2.968	3	MEREC (0.267)
A_4	6.267	6	PCA (0.000)
A_5	6.713	7	SPC (0.378)
A_6	1.395	1	LOPCOW (0.010)
A_7	4.240	4	CILOS (0.000)
A_8	4.718	5	IDOCRIW (0.043)

Table 9.25 OPTBIAS aggregate ranking (CI: 0.729, TL: 0.955)

Alternative	*R**	Aggregate rank	Method (weight)
A_1	8.000	8	Entropy (0.110)
A_2	1.000	1	CRITIC (0.006)
A_3	2.011	2	MEREC (0.024)
A_4	3.058	3	PCA (0.000)
A_5	7.000	7	SPC (0.416)
A_6	5.367	6	LOPCOW (0.000)
A_7	4.260	4	CILOS (0.011)
A_8	5.304	5	IDOCRIW (0.433)

Table 9.26 DNMA aggregate ranking (CI: 0.704, TL: 0.972)

Alternative	*R**	Aggregate rank	Method (weight)
A_1	8.000	8	Entropy (0.188)
A_2	2.811	3	CRITIC (0.000)
A_3	2.188	2	MEREC (0.188)
A_4	6.000	6	PCA (0.000)
A_5	7.000	7	SPC (0.312)
A_6	1.000	1	LOPCOW (0.000)
A_7	4.188	4	CILOS (0.000)
A_8	4.812	5	IDOCRIW (0.312)

Table 9.27 EAMR aggregate ranking (CI: 0.698, TL: 1.000)

Alternative	*R**	Aggregate rank	Method (weight)
A_1	8.000	8	Entropy (0.000)
A_2	1.000	1	CRITIC (0.000)
A_3	2.001	2	MEREC (0.001)
A_4	4.001	4	PCA (0.000)
A_5	6.000	6	SPC (0.499)
A_6	4.999	5	LOPCOW (0.001)
A_7	2.999	3	CILOS (0.000)
A_8	7.000	7	IDOCRIW (0.499)

Table 9.28 CURLI and PEG aggregate ranking (CI: 0.917, TL: 0.917)

Alternative	*R**	Aggregate rank	Method (weight)
A_1	2.000	2	CURLI (0.500)
A_2	1.000	1	PEG (0.500)

A_3	5.000	4	
A_4	7.500	8	
A_5	6.000	7	
A_6	5.000	4	
A_7	4.000	3	
A_8	5.500	6	

EDM oil selection

Tables 9.29 to 9.35 collectively confirm alternative A_1 as the most consistent and dominant choice, ranking first across all MCDM methods. A_8 secures second position in every method, reflecting its stable performance across different weighting schemes. A_2 and A_4 frequently interchange between third and fourth positions, indicating close competition. A_3 and A_{10} drift in mid-rank zones, while A_5, A_6 and A_9 consistently underperform, appearing in the bottom three across all models. Weight dominance varies, with CRITIC heavily influencing MACONT and DNMA while IDOCRIW contributes significantly in PARIS. LOPCOW holds major weight in EAMR, unlike SPC, PCA and CILOS, which remain functionally negligible throughout. The strong agreement across methods underlines the robustness of A_1 as the optimal EDM oil choice. CI values ranged from 0.603 to 0.690 and TL remains high throughout, peaking at 0.994, indicating stable and credible results. Notably, CRITIC holds dominant weight in MACONT and DNMA, IDOCRIW led in PARIS and LOPCOW contributed significantly in EAMR. Entropy, PCA, SPC and CILOS have minimal or zero influence across most tables.

Table 9.29 MACONT aggregate ranking (CI: 0.651, TL: 0.986)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	1.000	1	Entropy (0.000) CRITIC (0.918) MEREC (0.000) PCA (0.000) SPC (0.000) LOPCOW (0.041) CILOS (0.000) IDOCRIW (0.041)
A_2	3.041	3	
A_3	6.000	6	
A_4	4.000	4	
A_5	8.000	8	
A_6	9.000	9	
A_7	4.959	5	
A_8	2.000	2	
A_9	10.000	10	
A_{10}	7.000	7	

Table 9.30 PROBID aggregate ranking (CI: 0.690, TL: 0.967)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	1.003	1	Entropy (0.000) CRITIC (0.003) MEREC (0.761) PCA (0.000) SPC (0.000) LOPCOW (0.000) CILOS (0.000) IDOCRIW (0.236)
A_2	3.998	4	
A_3	6.000	6	
A_4	3.003	3	
A_5	8.761	9	
A_6	8.239	8	
A_7	5.000	5	
A_8	1.997	2	
A_9	10.000	10	

A_{10}	7.000	7	

Table 9.31 PARIS aggregate ranking (CI: 0.654, TL: 0.993)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	1.025	1	Entropy (0.000)
A_2	3.986	4	CRITIC (0.013)
A_3	6.000	6	MEREC (0.013)
A_4	3.015	3	PCA (0.000)
A_5	8.013	8	SPC (0.000)
A_6	8.987	9	LOPCOW (0.001)
A_7	4.999	5	CILOS (0.000)
A_8	1.975	2	IDOCRIW (0.973)
A_9	10.000	10	
A_{10}	7.000	7	

Table 9.32 OPTBIAS aggregate ranking (CI: 0.675, TL: 0.962)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	1.005	1	Entropy (0.000)
A_2	3.168	3	CRITIC (0.690)
A_3	6.000	6	MEREC (0.005)
A_4	3.974	4	PCA (0.000)
A_5	8.005	8	SPC (0.000)
A_6	8.995	9	LOPCOW (0.142)
A_7	4.858	5	CILOS (0.000)
A_8	1.995	2	IDOCRIW (0.163)
A_9	10.000	10	
A_{10}	7.000	7	

Table 9.33 DNMA aggregate ranking (CI: 0.685, TL: 0.994)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	1.000	1	Entropy (0.000)
A_2	3.018	3	CRITIC (0.964)
A_3	6.000	6	MEREC (0.000)
A_4	4.000	4	PCA (0.000)
A_5	8.000	8	SPC (0.000)
A_6	9.000	9	LOPCOW (0.018)
A_7	4.982	5	CILOS (0.000)
A_8	2.000	2	IDOCRIW (0.018)
A_9	10.000	10	
A_{10}	7.000	7	

Table 9.34 EAMR aggregate ranking (CI: 0.603, TL: 0.981)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	1.000	1	Entropy (0.000)
A_2	3.001	3	CRITIC (0.118)
A_3	6.000	6	MEREC (0.000)
A_4	4.881	5	PCA (0.000)
A_5	8.000	8	SPC (0.000)
A_6	9.000	9	LOPCOW (0.881)

A_7	4.118	4	CILOS (0.000) IDOCRIW (0.001)
A_8	2.000	2	
A_9	10.000	10	
A_{10}	1.000	1	

Table 9.35 CURLI and PEG aggregate ranking (CI: 0.896, TL: 0.896)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	1.000	1	CURLI (0.500) PEG (0.500)
A_2	3.500	3	
A_3	5.500	6	
A_4	5.000	5	
A_5	8.500	8	
A_6	8.500	8	
A_7	4.500	4	
A_8	2.000	2	
A_9	10.000	10	
A_{10}	6.500	7	

Comparative analysis of weighting methods based on ensemble aggregate weights

This subsection provides a comparative evaluation of weighting methods based on ensemble aggregate weights across various decision problems. Table 9.36 is divided into two sections, i.e. the upper section presents the ensemble aggregate weights assigned by each method across selection problems, illustrating the distributed weights among methods, while the lower section highlights key performance metrics that analyze the characteristics of these methods. The key metrics include the frequency of scoring maximum weight, which indicates how often a method is assigned the highest weight among competing methods for a given selection problem. This metric reflects the role of each method in influencing these decision making problems. Similarly, the frequency of scoring second maximum weight shows the ability of the method to receive the second-highest weight, highlighting its role as a consistent secondary contributor, even if not the primary influencer. The frequency of scoring zero weight captures instances where a method is assigned no weight during the aggregate weighting process. This could indicate potential redundancy or irrelevance in specific problem contexts. The cumulative weight refers to the total weight assigned to a method across all selection problems. This provides a direct measure of overall involvement in the weighting procedure. Finally, the contribution percentage normalizes the cumulative weight by dividing cumulative weight by the total cumulative weight across all methods. This percentage offers a proportional measure of influence of each method within the ensemble. Together, these metrics offer a comprehensive and structured view of how different weighting methods perform across decision making environments. Additionally, the distribution of weights across methods can offer insights into the relative significance of each weighting approach in different problem contexts. This analysis enables a better understanding about the various methods, indicating the way these methods contribute to the decision making. By examining these metrics, decision makers can assess the performance and superiority of these methods for better decision making outcomes.

Table 9.36 Comparison of weighting methods using ensemble aggregate weights and performance metrics

Decision problems	Entropy	CRITIC	MEREC	PCA	SPC	LOPCOW	CILOS	IDOCRIW
3D Printer nozzle material selection	0.004	0.132	0.002	0.000	0.000	0.000	0.001	0.861
	0.345	0.003	0.000	0.068	0.000	0.004	0.202	0.377
	0.452	0.432	0.001	0.043	0.000	0.002	0.002	0.069
	0.005	0.186	0.257	0.003	0.003	0.543	0.001	0.003
	0.454	0.006	0.000	0.002	0.001	0.001	0.000	0.536
	0.000	0.555	0.004	0.348	0.055	0.000	0.004	0.034
Piston material selection	0.000	0.000	0.097	0.035	0.002	0.386	0.478	0.001
	0.000	0.000	0.000	0.990	0.007	0.003	0.000	0.000
	0.000	0.001	0.037	0.425	0.219	0.307	0.013	0.000
	0.000	0.392	0.049	0.000	0.000	0.167	0.392	0.000
	0.000	0.450	0.008	0.000	0.089	0.002	0.450	0.000
	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000
Cobot selection	0.003	0.203	0.224	0.099	0.194	0.185	0.089	0.002
	0.001	0.161	0.207	0.150	0.174	0.197	0.110	0.001
	0.000	0.265	0.220	0.159	0.088	0.219	0.048	0.000
	0.001	0.182	0.214	0.133	0.191	0.210	0.067	0.001
	0.000	0.251	0.229	0.163	0.027	0.251	0.079	0.000
	0.002	0.000	0.002	0.000	0.002	0.994	0.000	0.002
Drone selection	0.289	0.000	0.373	0.000	0.032	0.000	0.000	0.306
	0.144	0.078	0.369	0.000	0.401	0.000	0.000	0.009
	0.303	0.000	0.267	0.000	0.378	0.010	0.000	0.043
	0.110	0.006	0.024	0.000	0.416	0.000	0.011	0.433
	0.188	0.000	0.188	0.000	0.312	0.000	0.000	0.312
	0.000	0.000	0.001	0.000	0.499	0.001	0.000	0.499
EDM oil selection	0.000	0.918	0.000	0.000	0.000	0.041	0.000	0.041
	0.000	0.003	0.761	0.000	0.000	0.000	0.000	0.236
	0.000	0.013	0.013	0.000	0.000	0.001	0.000	0.973
	0.000	0.690	0.005	0.000	0.000	0.142	0.000	0.163
	0.000	0.964	0.000	0.000	0.000	0.018	0.000	0.018
	0.000	0.118	0.000	0.000	0.000	0.881	0.000	0.001
Frequency of scoring maximum weight	1	8	5	2	4	5	3	7
Frequency of scoring second maximum weight	5	5	7	1	5	7	0	6
Frequency of scoring zero weight	16	7	7	17	11	7	15	7
Cumulative weight	2.301	6.009	3.552	2.618	3.09	5.565	1.947	4.921
Contribution (%)	7.67	20.02	11.84	8.73	10.30	18.55	6.49	16.40

Figure 9.1 highlights that CRITIC is the most dominant weighting method, as it assigned the highest weight most frequently (8 times), making it the most influential in ranking determination. Figure

9.2 confirms the superiority of CRITIC with the highest cumulative weight contribution (20.02%), reinforcing its strong impact on decision outcomes. LOPCOW (18.55%) and IDOCRIW (16.40%) follow as the second and third most impactful methods, while entropy (7.67%) had the least influence. PCA, with the highest occurrence of zero weights (17 times), proved to be the least reliable in consistently distributing weights.

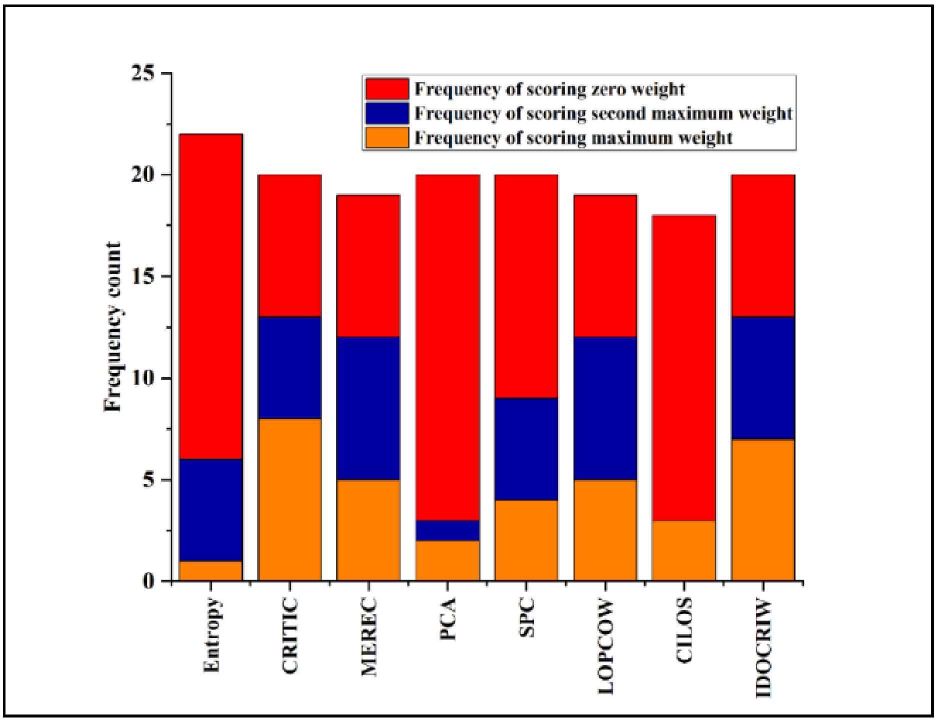


Figure 9.1 Dominant weighting method

Pareto analysis for identification of the superior weighting methods

To further refine the evaluation of weighting methods and extract meaningful insights from the performance metrics presented in Table 9.36, a Pareto analysis is conducted to systematically prioritize the most influential techniques. While the previous section assessed weighting methods based on ensemble aggregate weights and performance indicators such as frequency of scoring maximum and zero weights, cumulative weight and contribution percentage, the need for a structured prioritization method arises. The Pareto principle, commonly known as the 80/20 rule, helps identify methods that contribute the most to decision outcomes, distinguishing dominant techniques from those with relatively minor influence. By organizing and analyzing cumulative contributions, this approach provides a clearer understanding of which weighting methods consistently exhibit superior performance and which ones demonstrate inconsistencies, aiding in selecting the most reliable technique for robust decision making. The significance of Pareto analysis in this context lies in its ability to offer a quantitative justification for focusing on a subset of weighting methods that have the greatest impact on ranking determination. Instead of relying on absolute values alone, this method prioritizes techniques based on their relative importance, ensuring that only the most effective ones are emphasized. This distinction is especially crucial when handling multiple weighting approaches, as it helps eliminate less reliable methods, ultimately enhancing the robustness of decision making models.

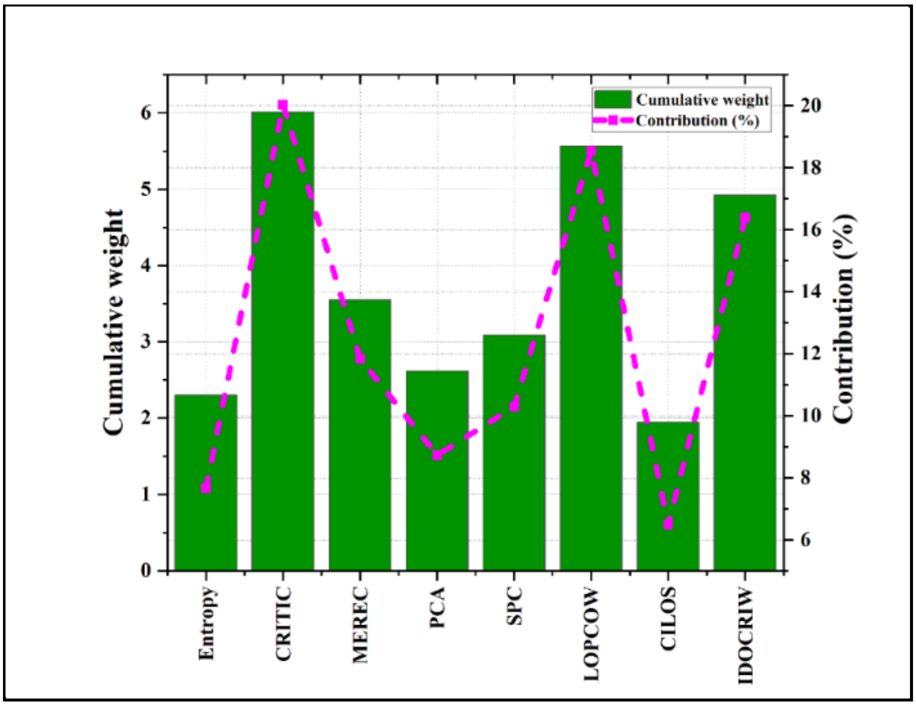


Figure 9.2 Weight contribution of different weighting method

Figure 9.3 illustrates the frequency with which each weighting method assigns the highest relative weight across decision problems. The chart follows the Pareto principle to identify the most dominant methods. CRITIC emerges as the most influential method, securing the maximum weight most frequently (8 times), followed by IDOCRIW (7 times). LOPCOW and MEREC each record 5 occurrences, indicating their significant but slightly lower influence. Entropy, PCA and CILOS exhibit the least dominance, with fewer occurrences of maximum weight assignments. The cumulative Pareto curve reveals that the top four methods contribute to over 70% of the total occurrences, reinforcing their strong influence in ranking determination. Figure 9.4 evaluates how often each method ranked as the second most influential in weight assignment. LOPCOW and MEREC both lead with 7 occurrences, followed by IDOCRIW. A consistent presence in the second-highest weight category indicates reliability and stability in decision making contributions. The Pareto curve shows that a few methods dominate this metric, covering a significant proportion of the total second-rank occurrences. This supports the observation that these methods maintain influence even when not securing the highest weight. Figure 9.5 highlights the frequency with which each method is assigned zero weight, indicating cases where a method contributes nothing to the decision making process. PCA exhibits the highest number of zero-weight occurrences (17 times), suggesting inconsistency in its applicability across problems. Entropy and CILOS also show a high frequency of zero weight, pointing to their selective influence. Conversely, CRITIC, LOPCOW and IDOCRIW demonstrate fewer occurrences of zero weight, reinforcing their stability as weighting techniques. The Pareto curve emphasizes that a small subset of methods account for the majority of zero-weight assignments, highlighting their reduced reliability in certain cases. Figure 9.6 presents the total weight accumulated by each weighting method across all decision problems, serving as an indicator of overall significance in ranking determination. CRITIC holds the highest cumulative weight (6.009), followed by LOPCOW (5.565) and IDOCRIW (4.921), indicating their strong influence in weight distribution. Entropy (2.301) has the lowest cumulative weight, confirming its limited impact. The Pareto curve highlights that the top three methods collectively contribute to more than 55% of the total weight distribution, emphasizing their dominance. The Pareto curve further underscores that a few dominant methods account for the majority of the contribution, aligning with the 80/20 principle and highlighting the necessity of prioritizing high-impact weighting techniques. The Pareto analysis identifies CRITIC, LOPCOW and IDOCRIW as the most influential weighting methods, consistently dominating key metrics such as maximum assigned weight, cumulative weight and contribution. These methods exhibit stability with minimal zero-weight occurrences, reinforcing their reliability. In contrast, Entropy, PCA and CILOS show inconsistent impact. Among all, CRITIC emerges as superior, leading in cumulative weight (20.02%), securing the highest weights most frequently (8 times) and maintaining stability, making it the most effective technique for ranking determination.

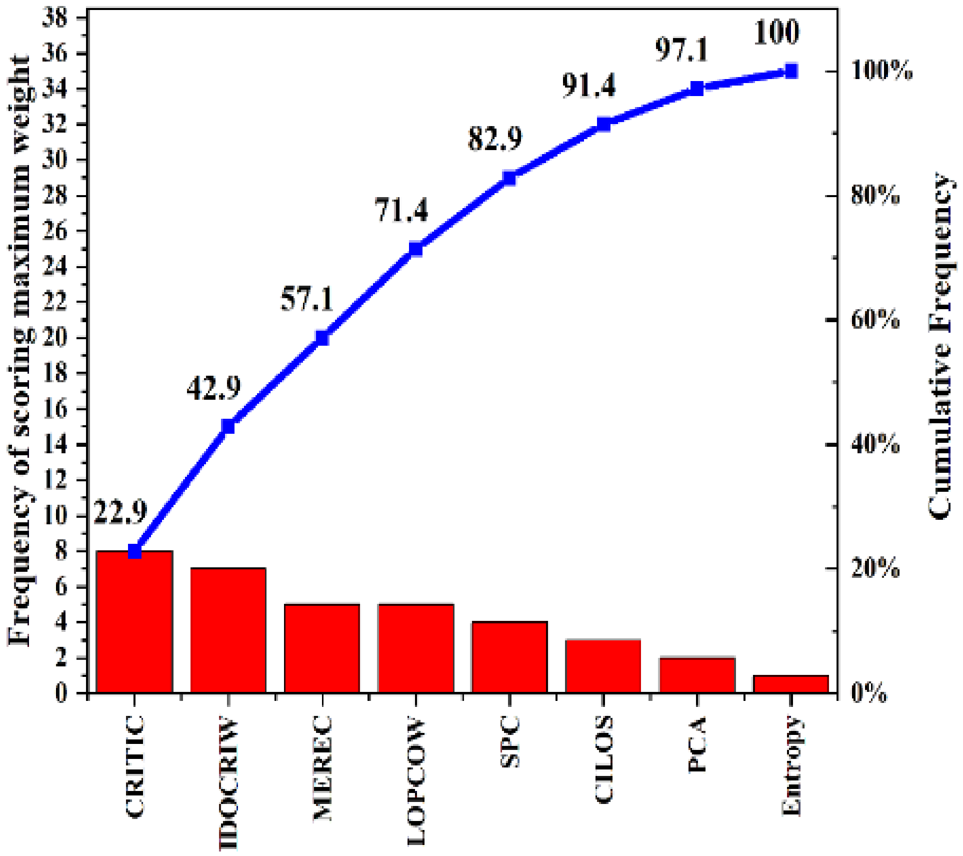


Figure 9.3 Pareto chart for number of times weighting method scored maximum

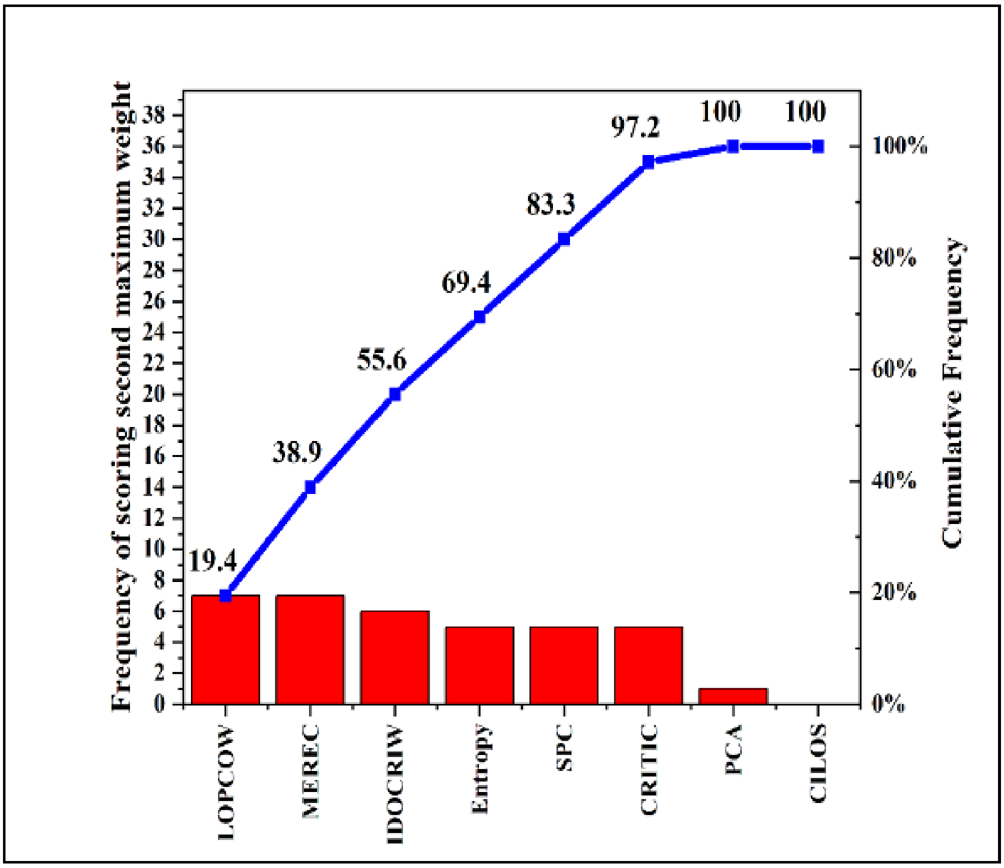


Figure 9.4 Pareto chart for number of times weighting method scored second maximum

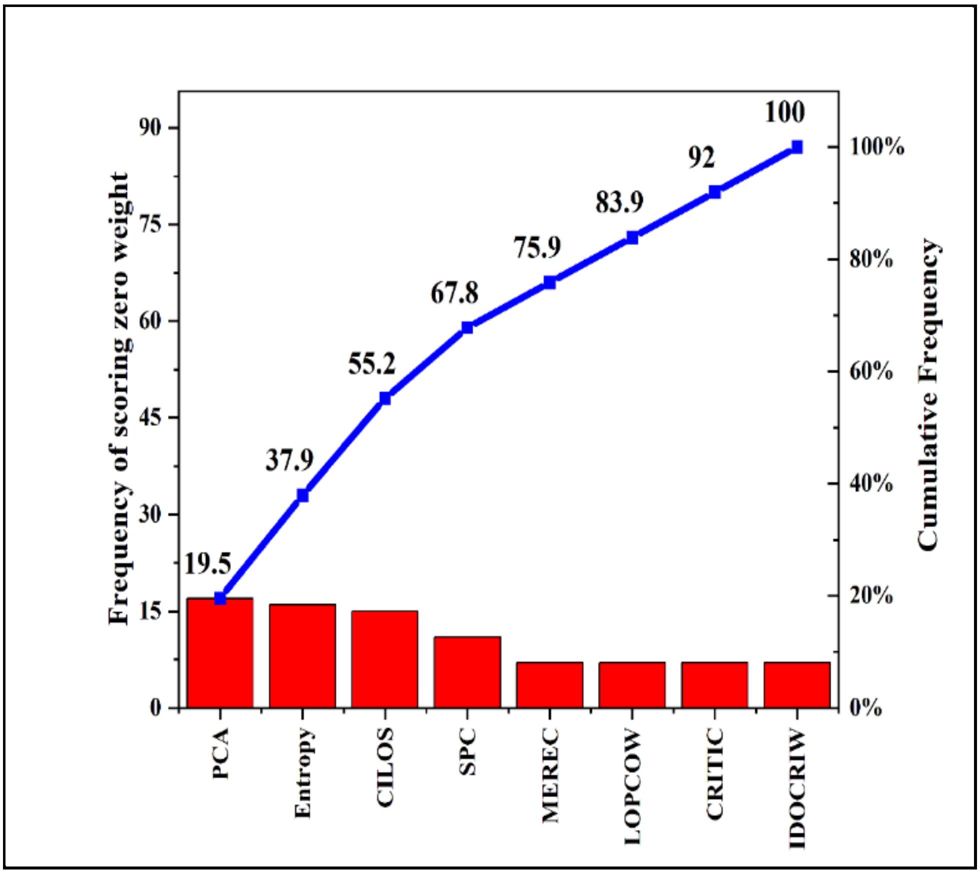


Figure 9.5 Pareto chart for number of times weighting method scored zero

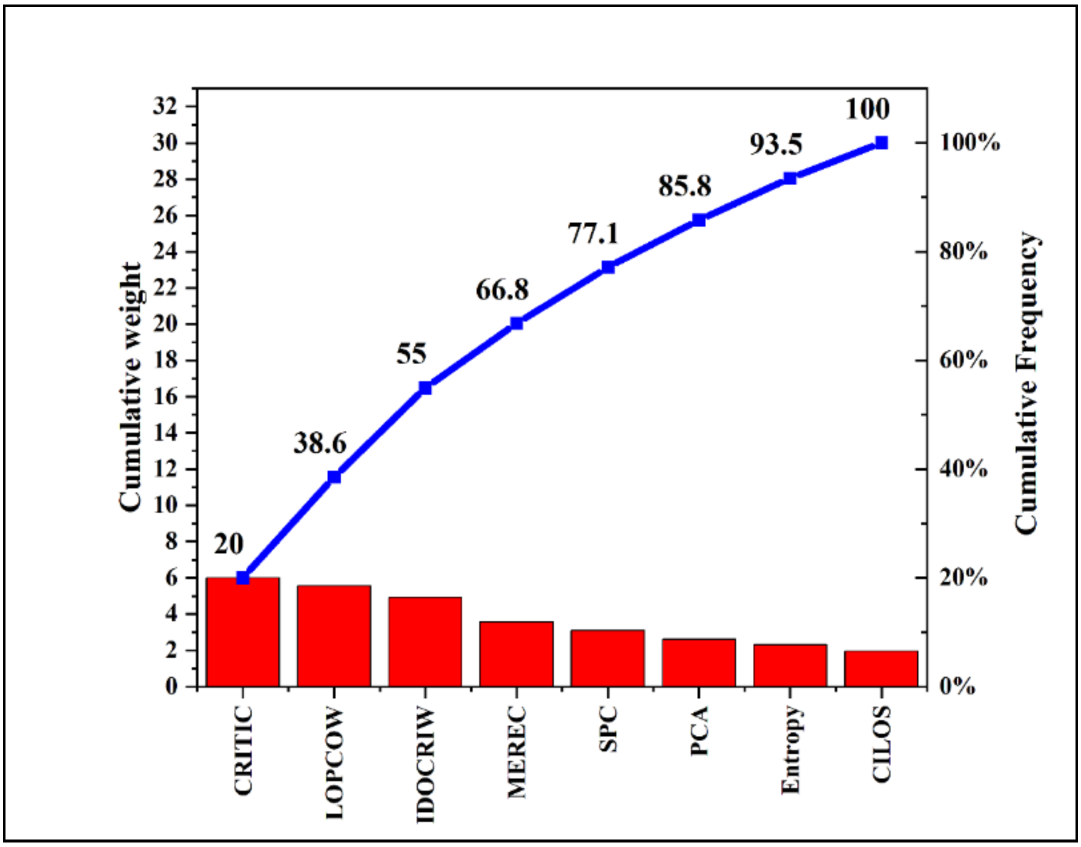


Figure 9.6 Pareto chart for cumulative weight

9.3 Identification of the superior MCDM method

For ensuring accurate and reliable decision outcomes **it** is crucial to select suitble MCDM method. Given that different MCDM methods employ distinct mathematical principles and ranking mechanisms, their effectiveness varies across decision problems.

Aggregated ranking results

This subsection presents Tables 9.37 – 9.76, summarizing the aggregated ranking results obtained through the ensemble methodology for multiple MCDM techniques. Each table corresponds to a specific weighting method and demonstrates how these six MCDM approaches rank the given alternatives under the influence of a single weighting methods. Additionally, ranks of CURLI and PEG methods are also utilized in this ensemble methodology along with the ranks of six different MCDM methods to generate the ensembled aggregate rankings. The results are derived from five distinct decision making problems, ensuring a comprehensive evaluation of the effectiveness of the MCDM methods. However, it is important to note that CURLI and PEG do not directly depend on weighting methods. Instead, these two methods serve as comparative tools, providing an overview of how different MCDM techniques perform under diverse weighting schemes, offering valuable insights into their relative effectiveness.

3D printer nozzle selection problem

Table 9.37 to 9.44 reveal consistent dominance of alternative A_4, which ranks first across all scenarios and universal underperformance of A_1, which ranks last in every case. CI values range from

0.685 (PCA, IDOCRIW) to 0.788 (SPC), with all methods exhibiting high TL from 0.930 to 1.000, indicating reliable and consistent rankings across MCDM techniques. Analysis of method weight distributions reveals that PARIS, CURLI, DNMA and PEG frequently receive the highest weights, such as PARIS with 0.934 in IDOCRIW and CURLI with 0.479 in CRITIC, highlighting their dominant influence on decision making. These patterns collectively indicate that ensemble ranking models favour a few consistently performing methods while marginalizing methods with weaker alignment across scenario.

Table 9.37 Entropy based aggregate ranking (CI: 0.725, TL: 1.000)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	8.000	8	MACONT (0.000)
A_2	3.000	3	PARIS (0.250)
A_3	6.000	6	OPTBIAS (0.000)
A_4	1.000	1	DNMA (0.250)
A_5	2.000	2	PROBID (0.000)
A_6	7.000	7	EAMR (0.250)
A_7	5.000	5	CURLI (0.250)
A_8	4.000	4	PEG (0.000)

Table 9.38 CRITIC based aggregate ranking (CI: 0.768, TL: 0.957)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	7.999	8	MACONT (0.001)
A_2	3.289	3	PARIS (0.256)
A_3	5.983	6	OPTBIAS (0.000)
A_4	1.000	1	DNMA (0.007)
A_5	2.004	2	PROBID (0.000)
A_6	6.733	7	EAMR (0.001)
A_7	4.986	5	CURLI (0.479)
A_8	4.006	4	PEG (0.257)

Table 9.39 MEREC based aggregate ranking (CI: 0.784, TL: 0.968)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	6.784	7	MACONT (0.007)
A_2	4.082	4	PARIS (0.465)
A_3	5.526	5	OPTBIAS (0.077)
A_4	1.078	1	DNMA (0.438)
A_5	5.679	6	PROBID (0.001)
A_6	2.433	2	EAMR (0.000)
A_7	7.849	8	CURLI (0.004)
A_8	2.569	3	PEG (0.008)

Table 9.40 PCA based aggregate ranking (CI: 0.685, TL: 0.948)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	8.000	8	MACONT (0.008)
A_2	3.397	3	PARIS (0.000)
A_3	5.603	6	OPTBIAS (0.000)

A_4	1.000	1	DNMA (0.000) PROBID (0.024) EAMR (0.000) CURLI (0.541) PEG (0.428)
A_5	2.039	2	
A_6	6.938	7	
A_7	5.459	5	
A_8	3.564	4	

Table 9.41 SPC based aggregate ranking (CI: 0.788, TL: 0.968)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	6.038	6	MACONT (0.018) PARIS (0.004) OPTBIAS (0.448) DNMA (0.000) PROBID (0.409) SPC - EAMR (0.113) CURLI (0.005) PEG (0.004)
A_2	2.317	2	
A_3	3.064	3	
A_4	1.117	1	
A_5	7.837	8	
A_6	7.038	7	
A_7	4.053	4	
A_8	4.536	5	

Table 9.42 LOPCOW based aggregate ranking (CI: 0.763, TL: 0.973)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	7.948	8	MACONT (0.022) PARIS (0.006) OPTBIAS (0.001) DNMA (0.020) PROBID (0.001) EAMR (0.002) CURLI (0.477) PEG (0.472)
A_2	3.568	4	
A_3	5.487	6	
A_4	1.020	1	
A_5	2.158	2	
A_6	6.996	7	
A_7	5.345	5	
A_8	3.479	3	

Table 9.43 CILOS based aggregate ranking (CI: 0.757, TL: 0.930)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	7.900	8	MACONT (0.167) PARIS (0.255) OPTBIAS (0.000) DNMA (0.478) PROBID (0.000) EAMR (0.100) CURLI (0.000) PEG (0.000)
A_2	5.434	5	
A_3	2.912	3	
A_4	1.000	1	
A_5	6.632	7	
A_6	6.033	6	
A_7	2.511	2	
A_8	3.578	4	

Table 9.44 IDOCRIW based aggregate ranking (CI: 0.685, TL: 0.984)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	8.000	8	MACONT (0.000) PARIS (0.934) OPTBIAS (0.024) DNMA (0.018) PROBID (0.024) EAMR (0.000) CURLI (0.000) PEG (0.000)
A_2	6.964	7	
A_3	5.066	5	
A_4	1.000	1	
A_5	2.000	2	
A_6	5.923	6	
A_7	4.048	4	
A_8	3.000	3	

Piston material selection problem

Table 9.45 through 9.52 identify A_7 as the top-ranked alternative and A_6 as second, suggesting broad agreement on their suitability. CI values range from 0.716 (MEREC) to 0.774 (LOPCOW), with TL values remaining high (0.931–0.997), affirming the reliability of rankings. Weight distribution reveals frequent dominance by DNMA, PROBID and OPTBIAS across most methods, such as OPTBIAS and DNMA receiving equal weights of 0.330 in CRITIC and OPTBIAS with 0.314 in CILOS. PEG gains notable weight of 0.319, while CURLI consistently receives zero weight. MACONT, although present in several aggregations, has low to moderate influence except under MEREC and LOPCOW. This pattern shows consistent alignment favoring A_7 and A_6, despite varying weighting schemes. High TL values affirm the reliability of the decision framework. Exclusion of CURLI method suggests limited fit for this problem. The dominance of key methods reflects strong compatibility with the selection criteria.

Table 9.45 Entropy based aggregate ranking (CI: 0.750, TL: 0.950)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	4.969	5	MACONT(0.067)
A_2	6.251	6	PARIS(0.375)
A_3	7.998	8	OPTBIAS(0.375)
A_4	6.750	7	DNMA(0.031)
A_5	3.749	4	PROBID(0.001)
A_6	1.933	2	EAMR(0.000)
A_7	1.067	1	CURLI(0.000)
A_8	3.282	3	PEG(0.152)

Table 9.46 CRITIC based aggregate ranking (CI: 0.762, TL: 0.997)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	3.001	3.0	MACONT(0.000)
A_2	5.989	6.0	PARIS(0.011)
A_3	4.988	5.0	OPTBIAS(0.330)
A_4	3.978	4.0	DNMA(0.330)
A_5	6.999	7.0	PROBID(0.330)
A_6	2.045	2.0	EAMR(0.000)
A_7	1.001	1.0	CURLI(0.000)
A_8	7.999	8.0	PEG(0.000)

Table 9.47 MEREC based aggregate ranking (CI: 0.716, TL: 0.953)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	3.001	3	MACONT(0.287)
A_2	5.024	5	PARIS(0.424)
A_3	6.025	6	OPTBIAS(0.004)
A_4	4.000	4	DNMA(0.265)
A_5	7.220	7	PROBID(0.019)
A_6	1.713	2	EAMR(0.001)
A_7	1.287	1	CURLI(0.000)
A_8	7.731	8	PEG(0.000)

Table 9.48 PCA based aggregate ranking (CI: 0.740, TL: 0.974)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	4.319	4	MACONT(0.001)
A_2	6.320	6	PARIS(0.367)
A_3	3.010	3	OPTBIAS(0.000)
A_4	4.704	5	DNMA(0.316)
A_5	6.648	7	PROBID(0.008)
A_6	1.999	2	EAMR(0.308)
A_7	1.001	1	CURLI(0.000)
A_8	8.000	8	PEG(0.000)

Table 9.49 SPC based aggregate ranking (CI: 0.748, TL: 0.977)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	3.340	3	MACONT(0.000)
A_2	6.047	6	PARIS(0.348)
A_3	3.663	4	OPTBIAS(0.000)
A_4	5.049	5	DNMA(0.314)
A_5	7.613	8	PROBID(0.024)
A_6	2.000	2	EAMR(0.314)
A_7	1.000	1	CURLI(0.000)
A_8	7.288	7	PEG(0.000)

Table 9.50 LOPCOW based aggregate ranking (CI: 0.774, TL: 0.931)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	4.852	5	MACONT(0.249)
A_2	6.148	6	PARIS(0.250)
A_3	2.502	3	OPTBIAS(0.043)
A_4	4.148	4	DNMA(0.104)
A_5	6.852	7	PROBID(0.104)
A_6	2.498	2	EAMR(0.249)
A_7	1.000	1	CURLI(0.000)
A_8	8.000	8	PEG(0.000)

Table 9.51 CILOS based aggregate ranking (CI: 0.755, TL: 0.989)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	3.000	3	MACONT(0.029)
A_2	6.000	6	PARIS(0.029)
A_3	4.941	5	OPTBIAS(0.314)
A_4	4.000	4	DNMA(0.314)
A_5	7.000	7	PROBID(0.314)
A_6	2.059	2	EAMR(0.000)
A_7	1.000	1	CURLI(0.000)
A_8	8.000	8	PEG(0.000)

Table 9.52 IDOCRIW based aggregate ranking (CI: 0.756, TL: 0.941)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	4.895	5	MACONT(0.053)

A_2	6.401	6	PARIS(0.385) OPTBIAS(0.216) DNMA(0.026) PROBID(0.001) EAMR(0.000) CURLI(0.000) PEG(0.319)
A_3	7.997	8	
A_4	6.601	7	
A_5	3.242	3	
A_6	1.947	2	
A_7	1.053	1	
A_8	3.864	4	

Cobot selection problem

The result across Tables 9.53 to 9.60, consistently highlight alternative A_6 as the most robust and superior choice, securing rank 1 in all cases. The rankings exhibit strong CI values between 0.898 and 0.918 and TL values from 0.972 to 0.983, reinforcing their reliability. Alternatives A_1 and A_{11} emerge as competitive contenders, frequently occupying second or third ranks, particularly where methods such as MACONT, PARIS, OPTBIAS, DNMA and PROBID dominate the weight distribution. The influence of these five MCDM methods is notably stronger, while CURLI and PEG consistently receive negligible weights, exerting minimal impact. The fluctuation in ranks for alternatives such as A_{13} and consistently low performance of A_8 demonstrate sensitivity to method weighting.

Table 9.53 Entropy based aggregate ranking (CI: 0.901, TL: 0.972)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	4.215	4	MACONT(0.213) PARIS(0.230) OPTBIAS(0.222) DNMA(0.063) PROBID(0.222) EAMR(0.041) CURLI(0.008) PEG(0.000)
A_2	8.598	8	
A_3	11.344	12	
A_4	7.132	7	
A_5	9.571	10	
A_6	1.000	1	
A_7	9.216	9	
A_8	12.985	13	
A_9	10.719	11	
A_{10}	4.963	5	
A_{11}	3.347	3	
A_{12}	5.454	6	
A_{13}	2.456	2	

Table 9.54 CRITIC based aggregate ranking(CI: 0.917, TL: 0.983)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	2.057	2	MACONT(0.159) PARIS(0.190) OPTBIAS(0.168) DNMA(0.198) PROBID(0.203) EAMR(0.078) CURLI(0.003) PEG(0.001)
A_2	8.538	8	
A_3	5.068	5	
A_4	7.008	7	
A_5	11.996	12	
A_6	1.168	1	
A_7	8.870	9	
A_8	12.994	13	
A_9	4.387	4	
A_{10}	9.502	10	
A_{11}	3.133	3	
A_{12}	6.045	6	
A_{13}	10.233	11	

Table 9.55 MEREC based aggregate ranking(CI: 0.916, TL: 0.972)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	3.314	3	MACONT (0.100) PARIS (0.207) OPTBIAS (0.213) DNMA(0.206) PROBID(0.213) EAMR(0.051) CURLI(0.005) PEG(0.005)
A_2	8.257	8	
A_3	3.805	4	
A_4	9.971	11	
A_5	11.530	12	
A_6	1.000	1	
A_7	8.139	7	
A_8	12.984	13	
A_9	4.692	5	
A_{10}	8.418	9	
A_{11}	3.313	2	
A_{12}	6.043	6	
A_{13}	9.534	10	

Table 9.56 PCA based aggregate ranking(CI: 0.917, TL: 0.979)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	4.855	4	MACONT (0.152) PARIS (0.191) OPTBIAS (0.161) DNMA(0.211) PROBID(0.190) EAMR(0.089) CURLI(0.007) PEG(0.000)
A_2	8.147	8	
A_3	6.228	7	
A_4	5.850	6	
A_5	12.002	12	
A_6	1.161	1	
A_7	9.261	9	
A_8	12.987	13	
A_9	3.373	3	
A_{10}	9.453	10	
A_{11}	2.020	2	
A_{12}	5.464	5	
A_{13}	10.200	11	

Table 9.57 SPC based aggregate ranking(CI: 0.918, TL: 0.978)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	3.234	2	MACONT(0.141) PARIS(0.206) OPTBIAS(0.207) DNMA(0.199) PROBID(0.207) EAMR(0.029) CURLI(0.004) PEG(0.008)
A_2	9.498	9	
A_3	3.629	4	
A_4	10.259	11	
A_5	10.955	12	
A_6	1.000	1	
A_7	5.977	6	
A_8	12.985	13	
A_9	4.742	5	
A_{10}	8.899	8	
A_{11}	3.468	3	
A_{12}	6.527	7	
A_{13}	9.827	10	

Table 9.58 LOPCOW based aggregate ranking(CI: 0.918, TL: 0.977)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	5.198	5	MACONT(0.166) PARIS(0.187) OPTBIAS(0.217) DNMA(0.179) PROBID(0.203) EAMR(0.041) CURLI(0.005) PEG(0.002)
A_2	9.894	11	
A_3	4.382	4	
A_4	8.511	9	
A_5	11.980	12	
A_6	1.000	1	
A_7	7.950	7	
A_8	12.987	13	
A_9	3.815	3	
A_{10}	8.479	8	
A_{11}	2.244	2	
A_{12}	5.345	6	
A_{13}	9.215	10	

Table 9.59 CILOS based aggregate ranking(CI: 0.908, TL: 0.973)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	2.438	2	MACONT(0.077) PARIS(0.194) OPTBIAS(0.167) DNMA(0.192) PROBID(0.198) EAMR(0.166) CURLI(0.006) PEG(0.000)
A_2	7.055	7	
A_3	7.952	8	
A_4	9.083	10	
A_5	12.004	12	
A_6	1.333	1	
A_7	10.506	11	
A_8	12.987	13	
A_9	5.617	5	
A_{10}	6.973	6	
A_{11}	2.456	3	
A_{12}	4.116	4	
A_{13}	8.481	9	

Table 9.60 IDOCRIW based aggregate ranking(CI: 0.898, TL: 0.974)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	5.211	6	MACONT(0.196) PARIS(0.215) OPTBIAS(0.247) DNMA(0.064) PROBID(0.247) EAMR(0.023) CURLI(0.009) PEG(0.000)
A_2	9.081	9	
A_3	11.329	12	
A_4	7.096	7	
A_5	9.016	8	
A_6	1.000	1	
A_7	9.398	10	
A_8	12.982	13	
A_9	10.848	11	
A_{10}	3.741	3	
A_{11}	4.237	4	
A_{12}	4.733	5	
A_{13}	2.330	2	

Drone selection problem

Aggregate rankings derived from Table 9.61 to Table 9.68 identify alternative A_2 as the best alternative, securing the first rank. Alternatives A_3 and A_6 also demonstrate stable performance, frequently appearing within the top three positions. The methods contributing the highest weights across tables are typically DNMA, PARIS and PROBID, while MACONT often receives negligible or zero weight. The CI and TL values reported in these tables remain high (CI: 0.684–0.795; TL: 0.932–0.968), ensuring the robustness and reliability of the aggregated rankings.

Table 9.61 Entropy based aggregate ranking(CI: 0.795, TL: 0.952)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	7.952	8	MACONT(0.000) PARIS(0.316) OPTBIAS(0.141) DNMA(0.287) PROBID(0.243) EAMR(0.004) CURLI(0.001) PEG(0.007)
A_2	1.900	1	
A_3	2.589	3	
A_4	5.343	5	
A_5	6.972	7	
A_6	2.341	2	
A_7	5.378	6	
A_8	3.525	4	

Table 9.62 CRITIC based aggregate ranking(CI: 0.684, TL: 0.958)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	5.438	6	MACONT(0.000) PARIS(0.189) OPTBIAS(0.003) DNMA(0.788) PROBID(0.008) EAMR(0.005) CURLI(0.003) PEG(0.003)
A_2	1.000	1	
A_3	3.396	3	
A_4	6.974	7	
A_5	7.961	8	
A_6	4.008	4	
A_7	2.051	2	
A_8	5.172	5	

Table 9.63 MEREC based aggregate ranking(CI: 0.789, TL: 0.943)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	7.998	8	MACONT(0.000) PARIS(0.234) OPTBIAS(0.185) DNMA(0.253) PROBID(0.252) EAMR(0.077) CURLI(0.000) PEG(0.000)
A_2	1.253	1	
A_3	2.739	3	
A_4	5.536	6	
A_5	6.689	7	
A_6	2.086	2	
A_7	4.797	4	
A_8	4.901	5	

Table 9.64 PCA based aggregate ranking(CI: 0.757, TL: 0.944)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	2.693	3	MACONT(0.000) PARIS(0.307) OPTBIAS(0.000)
A_2	1.000	1	
A_3	2.693	2	

A_4	7.000	7	DNMA(0.193)
A_5	5.500	6	PROBID(0.307)
A_6	5.500	5	EAMR(0.000)
A_7	3.614	4	CURLI(0.193)
A_8	8.000	8	PEG(0.000)

Table 9.65 SPC based aggregate ranking(CI: 0.779, TL: 0.944)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	7.994	8	MACONT(0.000)
A_2	1.926	1	PARIS(0.325)
A_3	2.329	3	OPTBIAS(0.078)
A_4	5.408	6	DNMA(0.301)
A_5	6.934	7	PROBID(0.230)
A_6	2.036	2	EAMR(0.065)
A_7	4.396	4	CURLI(0.000)
A_8	4.977	5	PEG(0.001)

Table 9.66 LOPCOW based aggregate ranking(CI: 0.753, TL: 0.932)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	7.992	8	MACONT(0.000)
A_2	1.190	1	PARIS(0.072)
A_3	2.249	2	OPTBIAS(0.023)
A_4	6.127	6	DNMA(0.426)
A_5	4.706	5	PROBID(0.351)
A_6	3.611	4	EAMR(0.127)
A_7	3.551	3	CURLI(0.001)
A_8	6.575	7	PEG(0.000)

Table 9.67 CILOS based aggregate ranking(CI: 0.726, TL: 0.968)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	3.691	4	MACONT(0.000)
A_2	1.000	1	PARIS(0.305)
A_3	3.308	3	OPTBIAS(0.000)
A_4	6.306	6	DNMA(0.389)
A_5	7.992	8	PROBID(0.303)
A_6	5.002	5	EAMR(0.000)
A_7	2.002	2	CURLI(0.002)
A_8	6.699	7	PEG(0.000)

Table 9.68 IDOCRIW based aggregate ranking(CI: 0.784, TL: 0.940)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	7.998	8	MACONT(0.000)
A_2	1.041	1	PARIS(0.219)
A_3	2.001	2	OPTBIAS(0.332)
A_4	4.147	4	DNMA(0.020)
A_5	6.761	7	PROBID(0.190)
A_6	5.222	6	EAMR(0.238)
A_7	3.733	3	CURLI(0.000)
A_8	5.097	5	PEG(0.000)

EDM oil selection problem

Based on the aggregate rankings from Tables 9.69 to 9.76, alternative A_1 consistently emerges as the best choice for this problem, securing the first rank in six out of eight weighting methods (entropy, CRITIC, PCA, SPC, LOPCOW, CILOS and IDOCRIW) and placing second only in MEREC. This consistent performance is driven by high-weight contributions from MCDM methods such as MACONT, DNMA, PROBID, EAMR and occasionally OPTBIAS and PARIS. Alternative A_8 stands out as a strong runner-up, ranking first under MEREC and second in most other methods, making it a reliable second ranked alternative. Alternatives A_2, A_4 and A_7 show moderate performance with ranks between third and fifth, while A_5, A_6 and especially A_9 consistently rank lower, indicating weaker suitability. Overall, A_1 demonstrates the most robust and stable performance across all objective weighting methods with high CI and TL values, making it the most preferred alternative for EDM oil selection.

Table 9.69 Entropy based aggregate ranking(CI: 0.720, TL: 0.995)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	1.000	1	MACONT(0.013) PARIS(0.013) OPTBIAS(0.000) DNMA(0.487) PROBID(0.487) EAMR(0.000) CURLI(0.000) PEG(0.000)
A_2	6.000	6	
A_3	4.000	4	
A_4	3.000	3	
A_5	7.973	8	
A_6	9.000	9	
A_7	5.000	5	
A_8	2.000	2	
A_9	10.000	10	
A_{10}	7.027	7	

Table 9.70 CRITIC based aggregate ranking(CI: 0.850, TL: 1.000)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	1.000	1	MACONT(0.250) PARIS(0.000) OPTBIAS(0.250) DNMA(0.250) PROBID(0.000) EAMR(0.250) CURLI(0.000) PEG(0.000)
A_2	3.000	3	
A_3	6.000	6	
A_4	4.000	4	
A_5	8.000	8	
A_6	9.000	9	
A_7	5.000	5	
A_8	2.000	2	
A_9	10.000	10	
A_{10}	7.000	7	

Table 9.71 MEREC based aggregate ranking(CI: 0.813, TL: 1.000)

Alternative	R^*	Aggregate rank	Method (weight)
A_1	2.000	2	MACONT(0.250) PARIS(0.250) OPTBIAS(0.250) DNMA(0.000)
A_2	4.000	4	
A_3	6.000	6	
A_4	3.000	3	

A_5	9.000	9	PROBID(0.000) EAMR(0.250) CURLI(0.000) PEG(0.000)
A_6	8.000	8	
A_7	5.000	5	
A_8	1.000	1	
A_9	10.000	10	
A_{10}	7.000	7	

Table 9.72 PCA based aggregate ranking(CI: 0.850, TL: 1.000)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	1.000	1	MACONT(0.250) PARIS(0.250) OPTBIAS(0.000) DNMA(0.250) PROBID(0.250) EAMR(0.000) CURLI(0.000) PEG(0.000)
A_2	3.000	3	
A_3	5.000	5	
A_4	6.000	6	
A_5	9.000	9	
A_6	8.000	8	
A_7	4.000	4	
A_8	2.000	2	
A_9	10.000	10	
A_{10}	7.000	7	

Table 9.73 SPC based aggregate ranking(CI: 0.746, TL: 1.000)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	1.000	1	MACONT(0.001) PARIS(0.000) OPTBIAS(0.001) DNMA(0.499) PROBID(0.499) EAMR(0.000) CURLI(0.000) PEG(0.000)
A_2	6.000	6	
A_3	4.000	4	
A_4	3.000	3	
A_5	9.001	9	
A_6	8.000	8	
A_7	5.000	5	
A_8	2.000	2	
A_9	9.999	10	
A_{10}	7.000	7	

Table 9.74 LOPCOW based aggregate ranking(CI: 0.850, TL: 1.000)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	1.000	1	MACONT(0.200) PARIS(0.200) OPTBIAS(0.200) DNMA(0.200) PROBID(0.000) EAMR(0.200) CURLI(0.000) PEG(0.000)
A_2	3.000	3	
A_3	6.000	6	
A_4	5.000	5	
A_5	8.000	8	
A_6	9.000	9	
A_7	4.000	4	
A_8	2.000	2	
A_9	10.000	10	
A_{10}	7.000	7	

Table 9.75 CILOS based aggregate ranking(CI: 0.829, TL: 1.000)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	1.000	1	MACONT(0.250)

A_{2}	3.000	3	PARIS(0.000) OPTBIAS(0.000) DNMA(0.250) PROBID(0.250) EAMR(0.250) CURLI(0.000) PEG(0.000)
A_{3}	5.000	5	
A_{4}	7.000	7	
A_{5}	10.000	10	
A_{6}	8.000	8	
A_{7}	4.000	4	
A_{8}	2.000	2	
A_{9}	9.000	9	
A_{10}	6.000	6	

Table 9.76 IDOCRIW based aggregate ranking(CI: 0.913, TL: 1.000)

Alternative	$R*$	Aggregate rank	Method (weight)
A_{1}	1.000	1	MACONT(0.143) PARIS(0.143) OPTBIAS(0.143) DNMA(0.143) PROBID(0.143) EAMR(0.143) CURLI(0.000) PEG(0.143)
A_{2}	4.000	4	
A_{3}	6.000	6	
A_{4}	3.000	3	
A_{5}	8.000	8	
A_{6}	9.000	9	
A_{7}	5.000	5	
A_{8}	2.000	2	
A_{9}	10.000	10	
A_{10}	7.000	7	

Comparative analysis of MCDM methods based on ensemble aggregate weights

This subsection presents a comparative evaluation of MCDM methods based on ensemble aggregate weights across different decision problems. Table 9.77 summarizes the weight distribution among MCDM methods and their overall contribution to the decision making process. It highlights how frequently each method receives the highest or second-highest weight, instances where a method is assigned no weight and the total cumulative weight allocated across all cases. Additionally, the table quantifies influence of each method, thus providing a clear assessment of their relative effectiveness across various decision scenarios. The data reveals that methods like DNMA, PARIS, OPTBIAS, and PROBID consistently secure higher weights, reflecting their stability and broad applicability. In contrast, methods such as PEG and CURLI often receive lower or no weights, indicating limited contribution to effective decision making. This reinforces the earlier correlation findings, where these methods also exhibited strong agreement across rankings. The table also facilitates identification of methods that maintain balance between consistency and adaptability across different problem structures. Weight dominance by a method across diverse problems signifies its robustness and reliability. The presence of zero-weight assignments also helps in pinpointing methods that may not suit certain types of decision contexts. This comprehensive weighting analysis thus serves as a practical guide for method selection based on decision environment. Moreover, it supports the development of hybrid frameworks by highlighting complementary strengths among superior methods.

Figure 9.7 highlights that DNMA and PARIS are the most dominant MCDM methods, as they receive the highest weight most frequently (15 times each), indicating their strong influence in ranking determination. Figure 9.8 further confirms the effectiveness of DNMA with the highest cumulative weight contribution (8.959), followed closely by PARIS (8.802). PROBID (6.456%) ranks third in terms of impact, while PEG (1.81) has the least influence. Additionally, CURLI (21 instances) and PEG (25 instances) have the highest occurrences of zero weights, indicating lower reliability in consistently contributing to the decision making process. Conversely, DNMA has one of the lowest occurrences of zero weights (4 times), reinforcing its stability across multiple selection problems.

Table 9.77 Comparison of MCDM methods using ensemble aggregate weights and performance metrics

Case studies	MACONT	PARIS	OPTBIAS	DNMA	PROBID	EAMR	CURLI	PEG
3D Printer nozzle material selection	0.000	0.250	0.000	0.250	0.000	0.250	0.250	0.000
	0.001	0.256	0.000	0.007	0.000	0.001	0.479	0.257
	0.007	0.465	0.077	0.438	0.001	0.000	0.004	0.008
	0.008	0.000	0.000	0.000	0.024	0.000	0.541	0.428
	0.018	0.004	0.448	0.000	0.409	0.113	0.005	0.004
	0.022	0.006	0.001	0.020	0.001	0.002	0.477	0.472
	0.167	0.255	0.000	0.478	0.000	0.100	0.000	0.000
	0.000	0.934	0.024	0.018	0.024	0.000	0.000	0.000
Piston material selection	0.067	0.375	0.375	0.031	0.001	0.000	0.000	0.152
	0.000	0.011	0.330	0.330	0.330	0.000	0.000	0.000
	0.287	0.424	0.004	0.265	0.019	0.001	0.000	0.000
	0.001	0.367	0.000	0.316	0.008	0.308	0.000	0.000
	0.000	0.348	0.000	0.314	0.024	0.314	0.000	0.000
	0.249	0.250	0.043	0.104	0.104	0.249	0.000	0.000
	0.029	0.029	0.314	0.314	0.314	0.000	0.000	0.000
	0.053	0.385	0.216	0.026	0.001	0.000	0.000	0.319
Cobot selection	0.213	0.230	0.222	0.063	0.222	0.041	0.008	0.000
	0.159	0.190	0.168	0.198	0.203	0.078	0.003	0.001
	0.100	0.207	0.213	0.206	0.213	0.051	0.005	0.005
	0.152	0.191	0.161	0.211	0.190	0.089	0.007	0.000
	0.141	0.206	0.207	0.199	0.207	0.029	0.004	0.008
	0.166	0.187	0.217	0.179	0.203	0.041	0.005	0.002
	0.077	0.194	0.167	0.192	0.198	0.166	0.006	0.000
	0.196	0.215	0.247	0.064	0.247	0.023	0.009	0.000
Drone selection	0.000	0.316	0.141	0.287	0.243	0.004	0.001	0.007
	0.000	0.189	0.003	0.788	0.008	0.005	0.003	0.003
	0.000	0.234	0.185	0.253	0.252	0.077	0.000	0.000
	0.000	0.307	0.000	0.193	0.307	0.000	0.193	0.000
	0.000	0.325	0.078	0.301	0.230	0.065	0.000	0.001
	0.000	0.072	0.023	0.426	0.351	0.127	0.001	0.000
	0.000	0.305	0.000	0.389	0.303	0.000	0.002	0.000
	0.000	0.219	0.332	0.020	0.190	0.238	0.000	0.000
EDM oil selection	0.013	0.013	0.000	0.487	0.487	0.000	0.000	0.000
	0.250	0.000	0.250	0.250	0.000	0.250	0.000	0.000
	0.250	0.250	0.250	0.000	0.000	0.250	0.000	0.000
	0.250	0.250	0.000	0.250	0.250	0.000	0.000	0.000
	0.001	0.000	0.001	0.499	0.499	0.000	0.000	0.000
	0.200	0.200	0.200	0.200	0.000	0.200	0.000	0.000
	0.250	0.000	0.000	0.250	0.250	0.250	0.000	0.000
	0.143	0.143	0.143	0.143	0.143	0.143	0.000	0.143

Frequency of scoring maximum weight	5	15	12	15	13	5	4	1
Frequency of scoring second maximum weight	5	11	3	7	6	3	1	5
Frequency of scoring zero weight	12	4	11	3	6	12	21	25
Cumulative weight	3.47	8.802	5.04	8.959	6.456	3.465	2.003	1.81
Contribution (%)	8.67	22.00	12.60	22.39	16.14	8.66	5.01	4.52

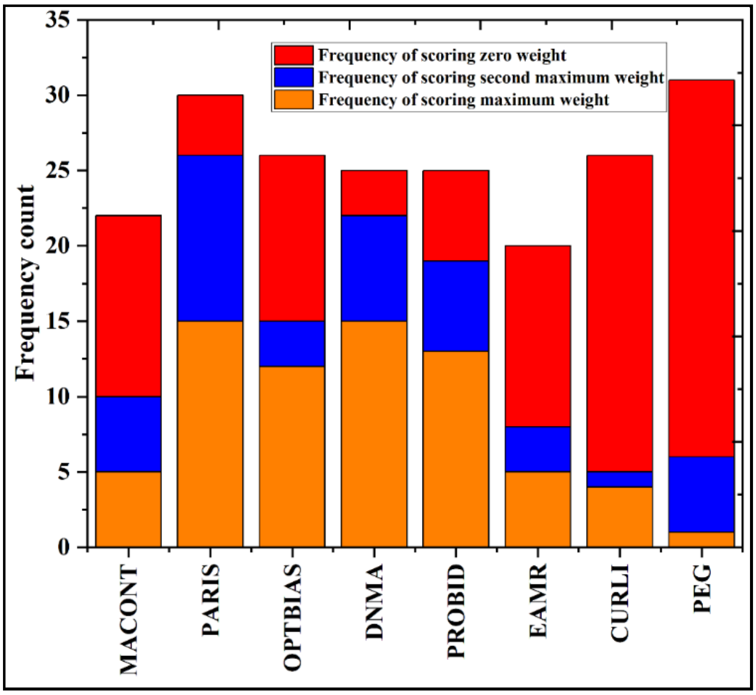


Figure 9.7 Dominant MCDM method

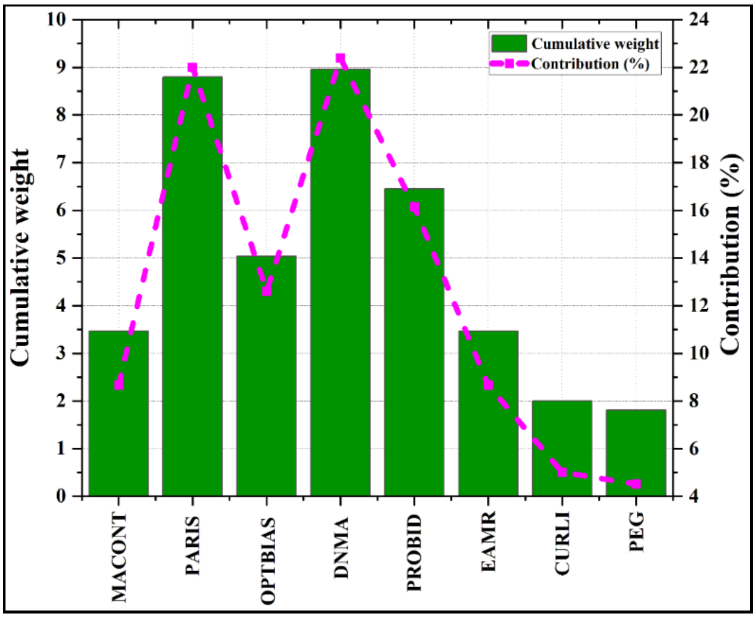


Figure 9.8 Weight contribution of different MCDM method

Pareto analysis for identification of superior MCDM methods

While the previous sections evaluate MCDM methods based on aggregate rankings, frequency of maximum assigned weight and cumulative contribution, a structured prioritization approach is necessary to extract the most influential techniques. Pareto analysis provides a systematic way to distinguish the most effective methods by identifying those that consistently contribute the most to ranking determination. Unlike weighting methods, which focus on assigning relative importance to criteria, MCDM methods directly influence the final ranking outcomes by processing decision matrices under different computational principles. This makes it crucial to identify methods that not only exhibit strong overall performance but also maintain consistency across diverse decision problems. The Pareto principle is employed to analyze the dominance and superiority of different MCDM methods in these manufacturing environment. Figure 9.9 presents the Pareto chart for the number of times each MCDM method scored the maximum weight, providing insight into which techniques most frequently influenced ranking decisions. DNMA and PARIS emerge as the most dominant methods, each securing the highest assigned weight 15 times, followed by PROBID (13 times) and OPTBIAS (12 times), with the cumulative Pareto curve revealing that these methods account for over 70% of the total occurrences, reinforcing their reliability.

Figure 9.10 further refines the analysis by considering how often each method ranks as the second most influential, showing that PARIS, DNMA and PROBID continue to demonstrate stability by frequently appearing in the second rank, indicating that their influence is not limited to only extreme cases but remains consistently high across different scenarios. A critical aspect of MCDM evaluation is identifying methods that occasionally contribute nothing to the decision making process, as shown in Figure 9.11, which presents the Pareto chart for the number of times each method scores zero weight. PEG (25 occurrences) and CURLI (21 occurrences) exhibit the highest number of zero-weight assignments, suggesting their limited applicability across different decision problems, whereas DNMA and PARIS, with only four and three, zero-weight occurrences, respectively, reinforce their stability and robustness in decision analysis. To quantify the overall significance of each method, Figure 9.12 illustrates the cumulative weight assigned to each MCDM method across all decision problems, where higher cumulative weights indicate stronger overall influence in ranking determination. DNMA (8.959), PARIS (8.802) and PROBID (6.456) secure the highest cumulative weights, reinforcing their significant role, while PEG (1.81) and CURLI (2.003) register the lowest cumulative contributions, confirming their weaker impact. Overall, while considering the contribution of each method, DNMA leads with a 22.39%, followed by PARIS (22.00%) and PROBID (16.14%), underscoring their dominance in decision making effectiveness, whereas PEG, with the lowest contribution (4.52%), remains the least impactful. The Pareto curve highlights that a small subset of methods accounts for the majority of decision influence and further validating their prioritization. The overall results from the Pareto analysis establish DNMA and PARIS as the most effective MCDM methods, demonstrating dominance across multiple metrics, including maximum assigned weight frequency, cumulative contribution and minimal occurrences of zero weights, reinforcing their reliability across different decision matrices as the preferred choices for robust decision making. In contrast, PEG and CURLI exhibit inconsistencies, frequently receiving zero-weight assignments and accumulating the lowest total contributions, indicating their limited applicability. Among all, DNMA emerges as the superior MCDM method, leading in cumulative weights, securing the highest ranking weight most frequently and maintaining superior stability, making it the most influential technique for ranking determination. Its methological structure proves highly compatible with various weighting methods and decision problems, making it a consistently effective choice. PARIS shows similar flexibility, especially in handling complex trade-offs between multiple criteria. PROBID also performs reliably, often ranking just below the top methods and serving as a dependable alternative when results are close. On the other hand, PEG and CURLI frequently show weak performance, likely due to their limited ability to adapt to different data structures. Their high number of zero-weight assignments and low total contribution suggest they are less relevant in broad decision making contexts.

The Pareto analysis clearly shows that a small group of methods, mainly DNMA, PARIS and PROBID, accounts for most of the influence on final rankings. For practical applications, focusing on these proven methods can improve decision quality while keeping the process efficient. This approach supports the development of more streamlined and reliable MCDM frameworks based on consistent performance across diverse scenarios.

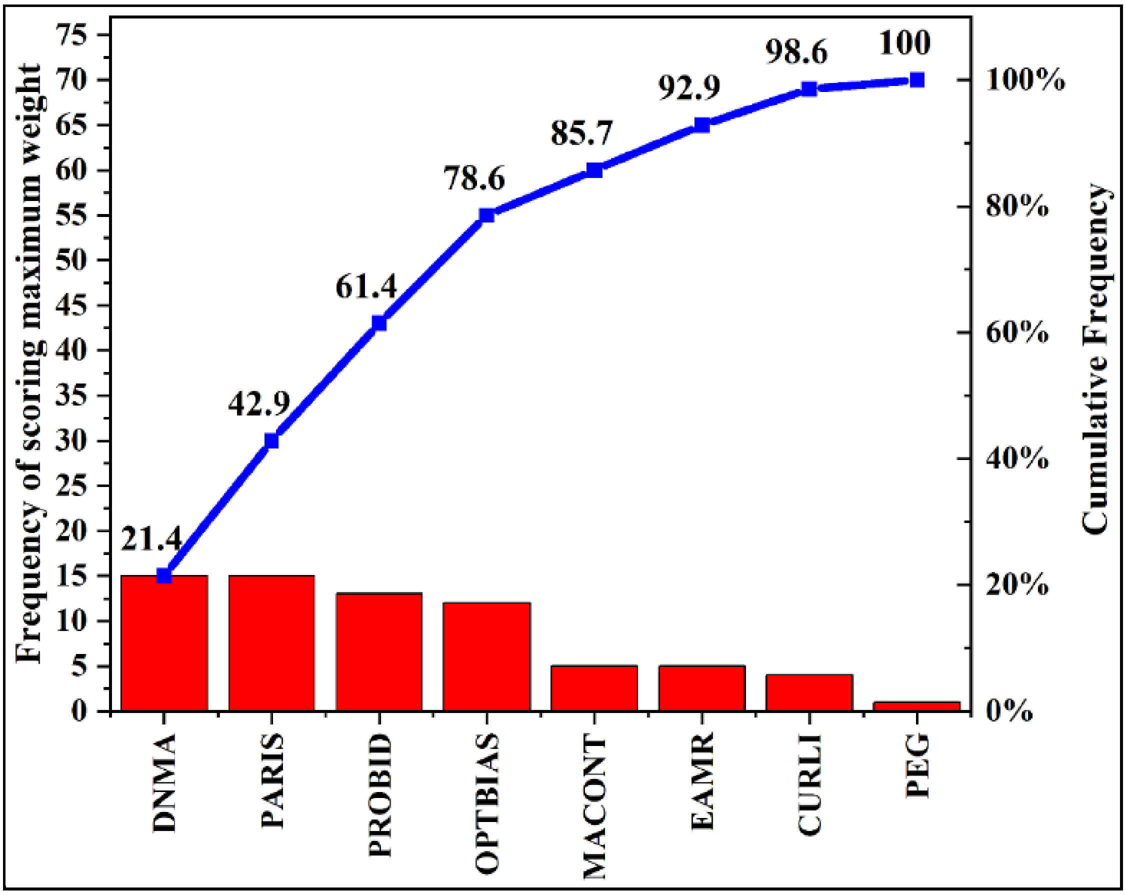


Figure 9.9 Pareto chart for number of times MCDM method scored maximum

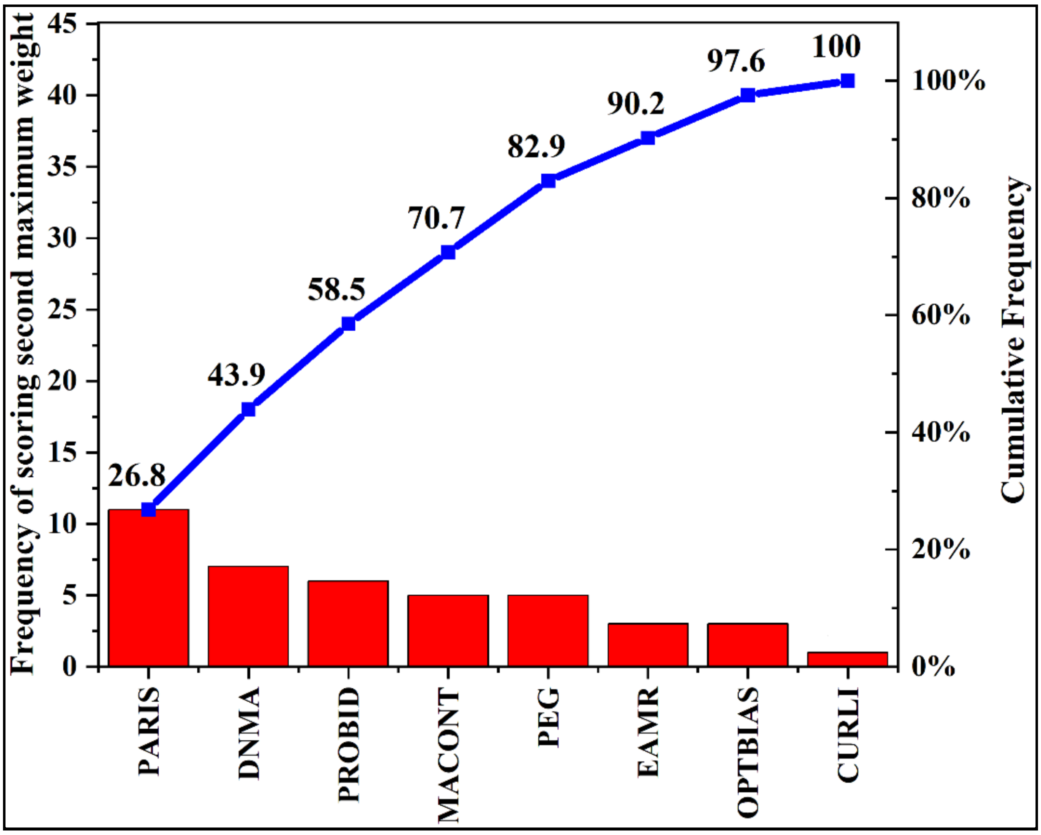


Figure 9.10 Pareto chart for number of times MCDM method scored second maximum

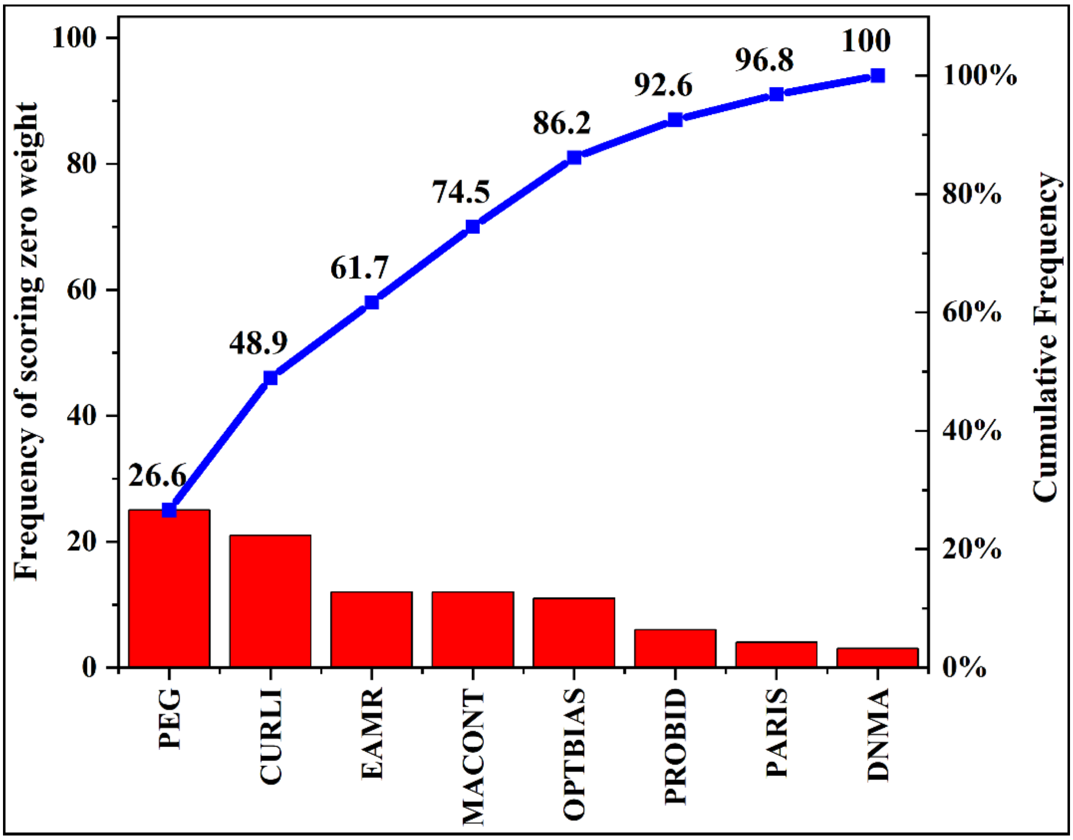


Figure 9.11 Pareto chart for number of times weighting method scored zero weight

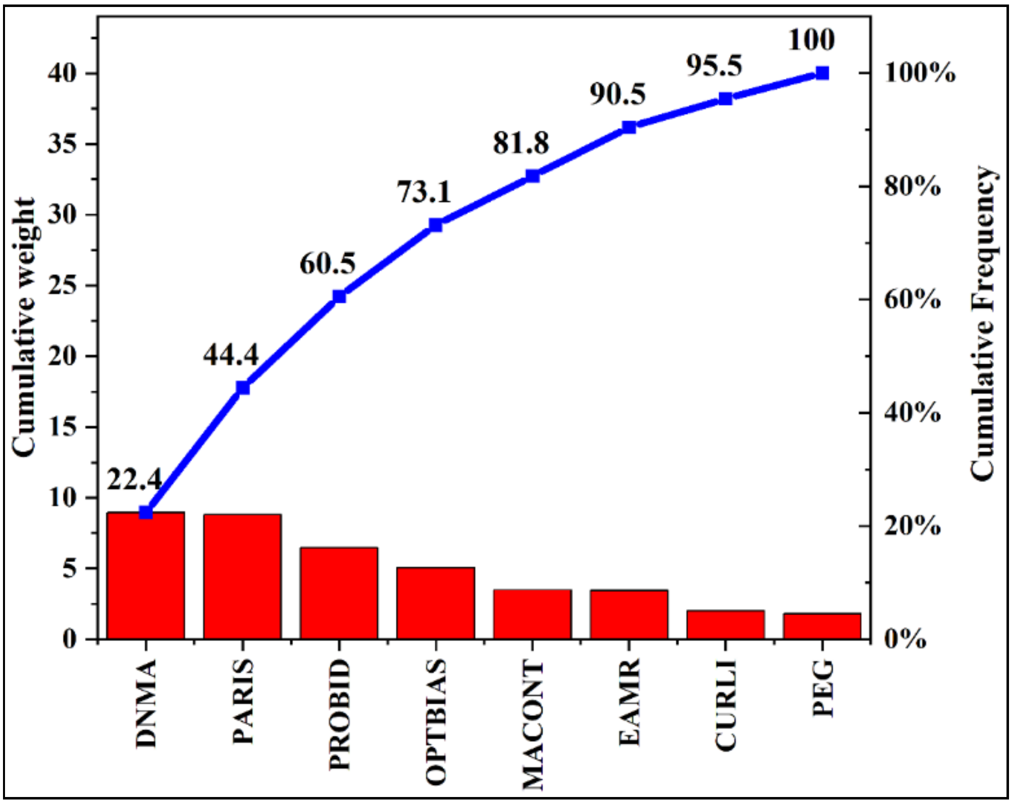


Figure 9.12 Pareto chart for cumulative weight

9.4 Identification of the superior MCDM method under equal weighting condition

Identifying the superior MCDM method under equal weighting conditions is a critical step in validating and reinforcing the consistency of previous findings, where DNMA emerged as the superior MCDM method and PARIS was a strong second contender. The primary rationale behind this analysis is to eliminate potential biases introduced by different weighting schemes and ensure that the superior performance of DNMA is not an artifact of a particular weight distribution but a reflection of its intrinsic mathematical robustness. Evaluating all MCDM methods under equal weighting conditions provides a neutral ground where each method is assessed solely based on its computational ability to generate stable and reliable rankings across multiple decision making problems considered in this study. This approach ensures methodological neutrality, offering a consistent basis for comparative evaluation across diverse scenarios. It also facilitates the identification of universally applicable methods that maintain high performance regardless of external weighting influences. Such validation strengthens the credibility of the selected MCDM techniques for deployment in complex decision making environments.

3D printer nozzle material selection

Table 9.78 presents the equal weight-based aggregate ranking with CI and TL equal to 0.740 and 0.958, respectively, indicating high reliability. A_4 ranks first followed by A_5, while A_1 ranks last. The aggregation is driven mainly by DNMA with weight equal to 0.497 and PARIS, 0.493, with negligible input from MACONT, PROBID, EAMR (0.000) and minimal influence from CURLI and PEG.

Table 9.78 Equal weight based aggregate ranking (CI: 0.740, TL: 0.958)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	8.000	8	MACONT(0.000) PARIS(0.493) OPTBIAS(0.001) DNMA(0.497) PROBID(0.000) EAMR(0.000) CURLI(0.003) PEG(0.004)
A_2	6.973	7	
A_3	4.011	4	
A_4	1.494	1	
A_5	1.514	2	
A_6	6.004	6	
A_7	3.017	3	
A_8	4.989	5	

Piston material selection

Table 9.79 displays the CI of 0.744 and TL of 0.976, indicating strong reliability. A_7 ranks first, followed by A_6, while A_8 is the least preferred. The rankings are primarily influenced by PARIS (0.437) and DNMA (0.437), with minor contributions from PROBID (0.089) and MACONT (0.023). Methods such as CURLI and PEG have no influence and OPTBIAS (0.002) and EAMR (0.012) contribute minimally.

Table 9.79 Equal weight based aggregate ranking (CI: 0.744, TL: 0.976)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	3.023	3	MACONT(0.023) PARIS(0.437) OPTBIAS(0.002) DNMA(0.437) PROBID(0.089) EAMR(0.012) CURLI(0.000) PEG(0.000)
A_2	6.045	6	
A_3	4.913	5	
A_4	4.114	4	
A_5	6.905	7	
A_6	2.000	2	
A_7	1.000	1	
A_8	8.000	8	

Cobot selection problem

Table 9.80 illustrates a high CI of 0.912 and TL of 0.971. A_6 is the top-ranked alternative and A_8 is the least preferred. The ranking is influenced most by DNMA, PARIS and OPTBIAS. PROBID (0.118) adds moderate influence, whereas CURLI (0.007) and PEG (0.001) have negligible impact.

Table 9.80 Equal weight based aggregate ranking (CI: 0.912, TL: 0.971)

Alternative	$R*$	Aggregate rank	Method (weight)
A_1	2.681	3	MACONT(0.138) PARIS(0.207) OPTBIAS(0.157) DNMA(0.227) PROBID(0.118) EAMR(0.145) CURLI(0.007) PEG(0.001)
A_2	6.547	6	
A_3	6.940	7	
A_4	7.941	8	
A_5	11.764	12	
A_6	1.275	1	
A_7	8.700	9	
A_8	12.985	13	

A_9	4.311	4	
A_{10}	9.310	10	
A_{11}	2.391	2	
A_{12}	6.009	5	
A_{13}	10.147	11	

Drone selection problem

Table 9.81 provides a very high reliability result. A_6 ranks first followed by A_7 indicating a clear winner. In contrast, A_5 and A_4 are the least preferred. The ranking is dominated by DNMA and PARIS, with minor influence from PROBID (0.058) and OPTBIAS (0.021), while MACONT, CURLI and PEG have negligible impact. The minimal contribution from PEG, CURLI and EAMR suggests their ranking did not align well with the dominant evaluation trends in this scenario. The concentration of influence in a few methods may indicate potential methodological bias or relevance. Despite this, the high consistency index supports the credibility of the ranking outcome.

Table 9.81 Equal weight based aggregate ranking (CI: 0.713, TL: 0.957)

Alternative	*R**	Aggregate rank	Method (weight)
A_1	5.328	6	MACONT(0.000) PARIS(0.405) OPTBIAS(0.021) DNMA(0.504) PROBID(0.058) EAMR(0.005) CURLI(0.001) PEG(0.006)
A_2	2.896	3	
A_3	4.334	4	
A_4	6.891	7	
A_5	7.901	8	
A_6	1.045	1	
A_7	2.278	2	
A_8	5.328	5	

EDM oil selection problem

Table 9.82 shows the equal weight-based ranking with CI and TL equal to 0.900 and 1.000, respectively, indicating high confidence and perfect trust. A_1 ranks first, followed by A_8 and A_2. Six out of eight methods share equal weight, 0.167, with no input from CURLI and PEG, reflecting strong consensus and balanced evaluation among those six methods. The exclusion of CURLI and PEG, indicates a well-aligned decision environment where methodological consensus ensures stable results.

Table 9.82 Equal weight based aggregate ranking (CI: 0.900, TL: 1.000)

Alternative	*R**	Aggregate rank	Method (weight)
A_1	1.000	1.000	MACONT(0.167) PARIS(0.167) OPTBIAS(0.167) DNMA(0.167) PROBID(0.167) EAMR(0.167) CURLI(0.000) PEG(0.000)
A_2	3.000	3.000	
A_3	6.000	6.000	
A_4	4.000	4.000	
A_5	8.000	8.000	
A_6	9.000	9.000	
A_7	5.000	5.000	
A_8	2.000	2.000	
A_9	10.000	10.000	
A_{10}	7.000	7.000	

Table 9.83 Comparison of MCDM methods using ensemble aggregate weights under equal weighting conditions and performance metrics

Case studies	MACONT	PARIS	OPTBIAS	DNMA	PROBID	EAMR	CURLI	PEG
3D Printer nozzle material selection	0.000	0.493	0.001	0.497	0.000	0.000	0.003	0.004
Piston material selection	0.023	0.437	0.002	0.437	0.089	0.012	0.000	0.000
Cobot selection	0.138	0.207	0.157	0.227	0.118	0.145	0.007	0.001
Drone selection	0.000	0.405	0.021	0.504	0.058	0.005	0.001	0.006
EDM oil selection	0.167	0.167	0.167	0.167	0.167	0.167	0.000	0.000
Frequency of scoring maximum weight	1	2	1	5	1	1	0	0
Frequency of scoring second maximum weight	0	3	0	0	1	0	0	0
Frequency of scoring zero weight	2	0	0	0	1	1	2	2
Cumulative weight	0.328	1.709	0.348	1.832	0.432	0.329	0.011	0.011
Contribution (%)	6.56	34.18	6.96	36.64	8.64	6.58	0.22	0.22

The dominant MCDM method under equal weighting conditions is illustrated in Figure 9.13, confirming the superior performance of OPTBIAS. Additionally, the weight contribution of each MCDM method under equal weighting conditions, presented in Figure 9.14, further reinforces these findings. The contribution percentage and weight dominance of each MCDM method, as depicted in Table 9.83, highlight that DNMA has the highest contribution percentage (36.64%), the highest cumulative weight (1.832) and the most frequent maximum weight scores (five times). Furthermore, DNMA never recorded a zero-weight score, reinforcing its consistency and robustness.

The Pareto analysis provides additional validation for this conclusion. Figure 9.15 highlights the number of times each MCDM method scores the maximum weight, where DNMA leads, while Figure 9.16 displays the number of times each method secures the second-highest weight, further demonstrating the superior performance of DNMA method. The robustness of DNMA is further validated by Figure 9.17, which confirms that it never records a zero-weight instance, unlike other MCDM methods. The cumulative weight distribution among MCDM methods, shown in Figure 9.18 illustrates the clear dominance of DNMA over the other methods

Ultimately, the results confirm that DNMA is the superior MCDM method under equal weighting conditions. Its mathematical superiority is evident in its ability to generate the most stable and reliable rankings across diverse decision problems, reaffirming its dominance as the superior

MCDM method. While PARIS remains a strong second choice, with a contribution percentage of 34.18% and a cumulative weight of 1.709, it falls short of DNMA in terms of frequency of maximum scores and overall weight distribution dominance. The Pareto analysis, illustrated in Figures 9.15 to 9.18, further supports this conclusion by demonstrating that DNMA not only outperforms other methods in direct comparisons but also maintains a significant lead over its closest competitor. This finding aligns with previous research conclusions and strengthens confidence in recommending DNMA as the preferred method for decision making applications, particularly in scenarios requiring a high degree of ranking accuracy and consistency.

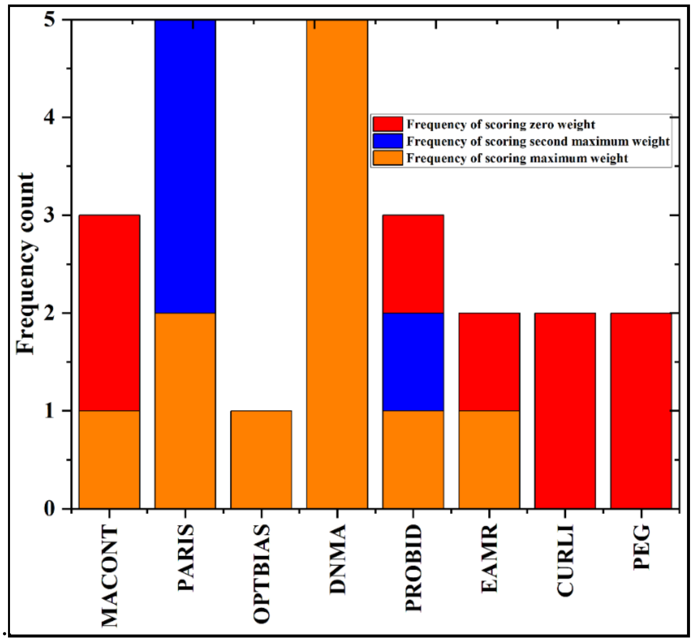


Figure 9.13 Dominant MCDM method under equal weighting condition

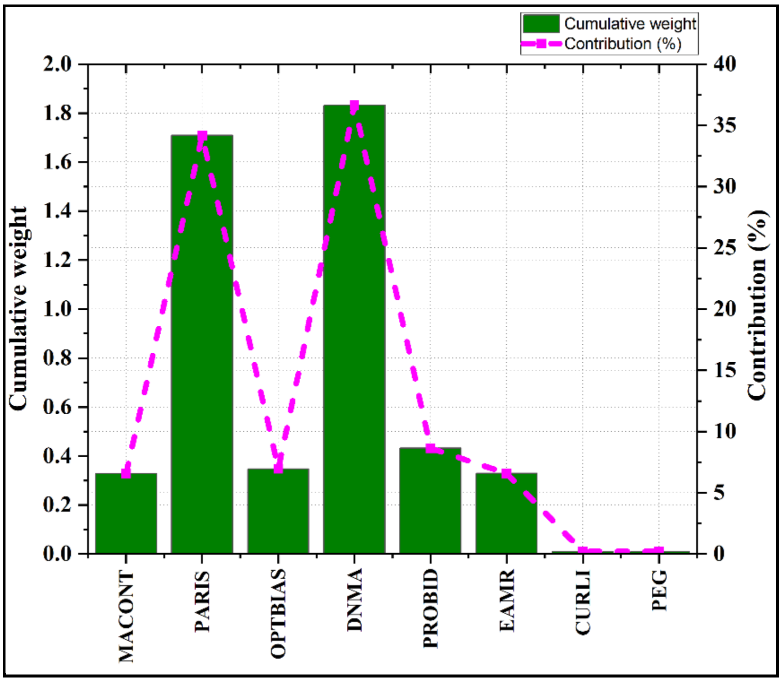


Figure 9.14 Weight contribution of MCDM methods under equal weighting conditions

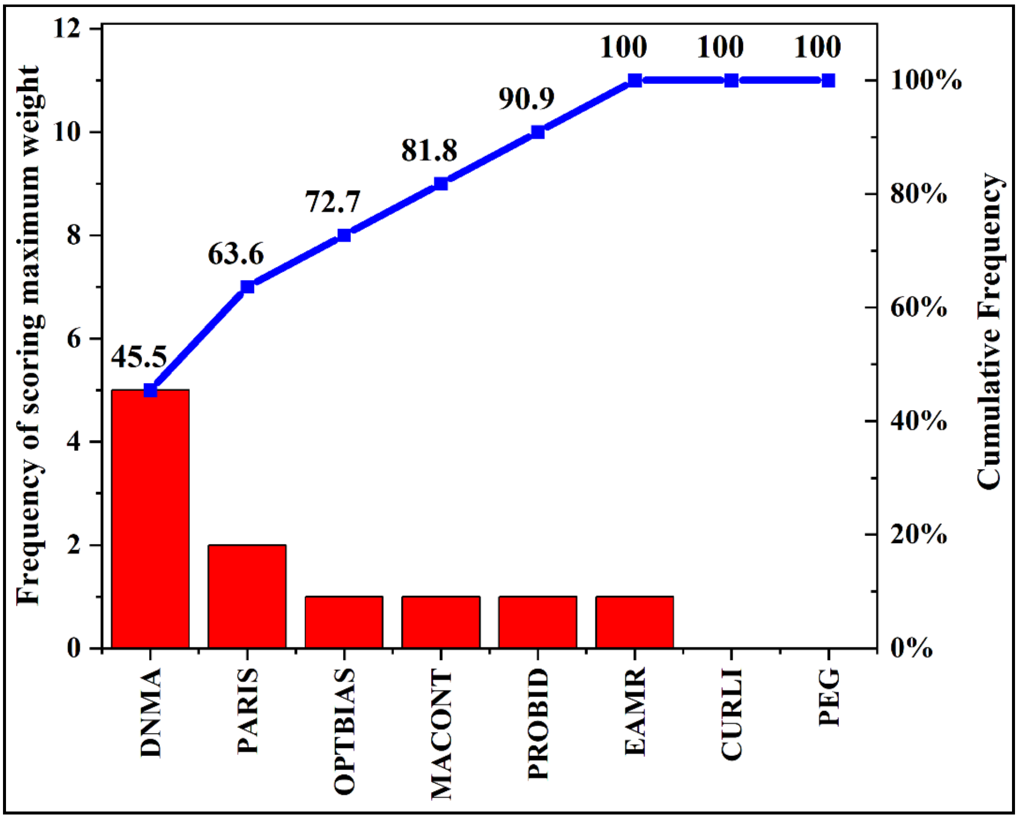


Figure 9.15 Pareto chart for number of times MCDM method scored maximum under equal weighting condition

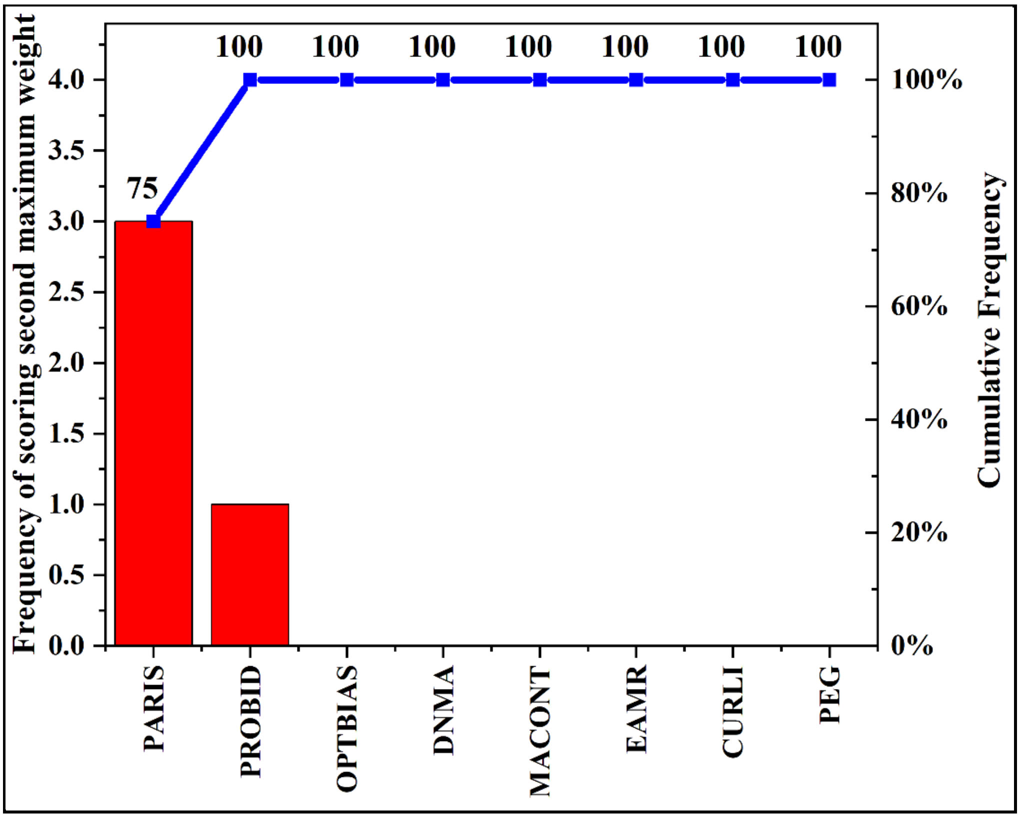


Figure 9.16 Pareto chart for number of times MCDM method scored second maximum under equal weighting condition

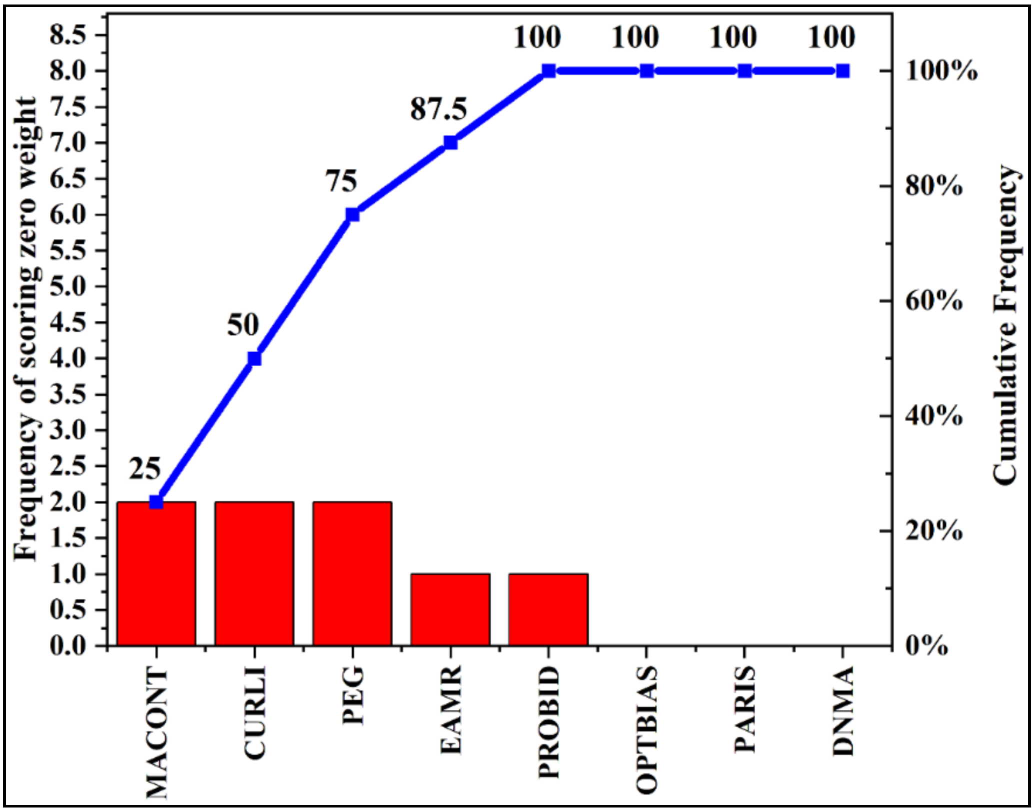


Figure 9.17 Pareto chart for number of times weighting method scored zero weight under equal weighting condition

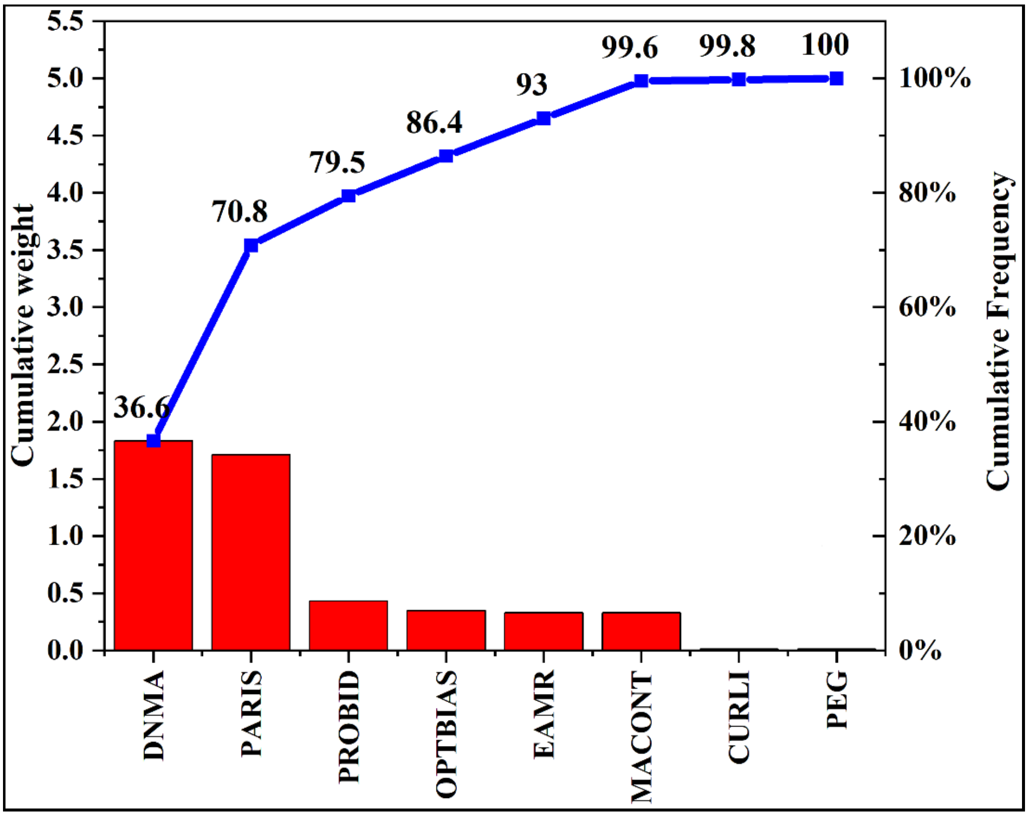


Figure 9.18 Pareto chart for cumulative weight under equal weighting condition for different MCDM methods

10. CONCLUSIONS

In this research work, eight newly developed MCDM methods in the form of MACONT, PROBID, PARIS, OPTBIAS, DNMA, EAMR, CURLI and PEG along with the eight weighting methods such as entropy, CRITIC, MEREC, PCA, SPC, LOPCOW, CILOS and IDOCRIW are used to solve real time decision making problems that exist in the manufacturing environment such as nozzle, piston, drone, cobot and EDM oil selection. The following conclusions are drawn, based on the derived solutions and extensive comparative and sensitivity analysis of these considered methods for each problems:

a) In the 3D printer nozzle material selection, tungsten carbide (A_4) is ranked highest, while brass (A_1) performs poorly. DNMA stands out as the best method due to its consistent results across different weighting methods. It reliably ranks A_4 as the top choice, demonstrating stability and minimal sensitivity to changes in the weighting. DNMA is well correlated with other techniques, attesting to its accuracy. DNMA is also more efficient with fewer operations compared to MACONT and CURLI.

b) A_7 (AISI 4140 steel) is highest ranked for material selection of piston. DNMA is established to be superior as it ranks A_7 as the top choice invariably under different weighting techniques, i.e. entropy, CRITIC and LOPCOW. It exhibits strong correlation with other techniques and provides accuracy with minimum fluctuations, particularly under entropy, MEREC, PCA and SPC. DNMA is more stable, reliable, and less operation-intensive and therefore it is more efficient.

c) A_6 (Elfin-P) is the top ranked in the matter of cobot selection. DNMA shows highest correlation values for the top performers A_6 and A_{11}. DNMA remains consistent and stable across all levels. It is also more efficient and requires fewer operations than other methods like CURLI.

d) For the drone ranking, Power Vision Power Eye (A_2) performs best. DNMA is the most stable method, with consistent ranking under different situations. It is consistently ranked as first ranked alternative. DNMA is stable, particularly under weighting situations like CRITIC, MEREC and IDOCRIW. Although EAMR is operationally more efficient, DNMA offers a better performance vs. computational complexity trade-off and hence is the most stable method overall.

e) For EDM oil selection, the highest rank is Spark SPO-A (A_1). DNMA ranks A_1 as top performing alternative for all weighting situations. It shows stable performance in distinguishing between top and lower-performing alternatives. Despite fluctuations in middle-tier rankings, DNMA remains stable at the top ranks and excels with different weighting methods. Unlike methods such as CURLI and PEG, which lack reliability, DNMA provides dependable results. While it has a higher computational complexity than EAMR, it offers a good balance between reliability and efficiency.

f) Each method is useful for ranking the alternatives and resolving manufacturing decision making problems in real time and helps rank the alternatives. This research rigorously identifies

CRITIC as the most suitable weighting method and DNMA as the effective and suitable MCDM method for achieving reliable and consistent decision outcomes across diverse selection problems.

One of the main limitations of this research is that it focuses only on a selected set of newly developed MCDM methods and specific objective weighting techniques without considering traditional or fuzzy-based methods, which are often more suitable for handling uncertainty and imprecise data in practical situations. While the study identifies DNMA as a reliable and efficient method based on comparative and sensitivity analyses, this conclusion is drawn from a fixed group of decision problems in the manufacturing sector. As a result, the findings may not be applicable to a wider range of decision making environments, especially those involving subjective judgments or qualitative data. Furthermore, the study gives limited attention to the actual implementation challenges of these methods, such as ease of use, time complexity on large-scale problems and adaptability to changes in real-time decision making. Moreover, the reliance on a limited number of manufacturing problems, despite their diversity, may restrict the broader applicability of the conclusions, particularly in more dynamic or non-manufacturing decision making scenarios.

Apart from above mentioned limitations, comparison with traditional and well established MCDM methods were not conducted. These methods use crisp quantitative data only, without addressing robustness under incomplete data. Environmental and social impact criteria were not considered, despite their significance in present day manufacturing setting. Exploring very large data set problems was not analyzed and group decision making was not considered.

In future work, several directions can be explored to address these limitations. To better handle vagueness and uncertainty in input data, fuzzy logic can be added. The use of additional sensitivity analysis approaches could improve final rankings. Investigating the impact of different normalization techniques may also enhance the fairness and accuracy of evaluations. With rapid advancements in artificial intelligence and deep learning, MCDM frameworks can be further refined and adapted to leverage these technologies for more intelligent decision support. There remains a significant gap in finding suitable MCDM method for a specific engineering problem, which calls for developing a structured guidelines or selection frameworks. Moreover, the application of these MCDM methods can be extended beyond manufacturing to domains such as finance, environmental assessment and business operations. The development of an expert system combining these methods could facilitate faster and more reliable decision making by automating complex evaluations and reducing the potential for human error. In Industry 4.0, future usage will involve these MCDM models combined with cyber-physical systems, IoT-based manufacturing, digital twins, and smart factory settings in order to enable real-time, data-driven decision-making as well as adaptive optimization.

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Sarkar chatterjee
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Multidiscipline Modeling in Materials and Structures

An integrated MCDM approach for dielectric fluid selection during electrical discharge machining of aluminum bronze alloy

Saikat Chatterjee
Department of Production Engineering, Faculty of Engineering and Technology, Jadavpur University, Kolkata, India
Partha Protim Das
Department of Mechanical Engineering, Sikkim Manipal Institute of Technology, Sikkim Manipal University, Gangtok, India, and
Shankar Chakraborty
Department of Production Engineering, Jadavpur University, Kolkata, India

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Abstract

Purpose – In electrical discharge machining (EDM) process, EDM oil used as a dielectric fluid plays an important role in determining quality of the machining operation, serving as a medium to generate controlled electrical discharges, quenching medium to cool down and solidify the eroded gaseous particles, removal of solidified waste, and lubrication medium to absorb and remove the heat generated at the machining zone. Due to presence of numerous decisive factors, no single dielectric fluid (mainly in the form of EDM oil) meets all the required characteristics during a real-time EDM operation. Thus, this paper proposes application of an integrated methodology to select the most appropriate EDM oil for enhanced machining performance during deep-hole drilling of aluminum bronze alloy.

Design/methodology/approach – A good dielectric fluid should possess several characteristics, like low cost, non-toxicity, low viscosity, good wetting property, high flash and fire points to avoid fire hazards, chemically non-corrosive, high electric strength and specific gravity, minimal aromatics and good quenching behavior. In this paper, performance of 10 alternative EDM oils is evaluated based on six selection criteria. Integrated determination of objective criteria weights (IDOCRIW) method is adopted to compute the criteria weights, whereas double normalization-based multiple aggregation (DNMA) approach is applied to identify the best-suited EDM oil from the candidate alternatives.

Findings – Spark SPO-A EDM oil appears as the most suitable dielectric fluid, followed by Fine Spark 110. Contrarily, Exxsol D80 emerges as the worst choice.

Originality/value – The robustness of the adopted methodology is finally validated through sensitivity analysis studies. It can thus be applied to solve any of the decision-making problems with high degree of accuracy and consistency.

Keywords Dielectric fluid, EDM oil, Multi-criteria decision-making, ISOCRIW, DNMA

Paper type Research paper

1. Introduction

Electrical discharge machining (EDM) is one of the most extensively used non-traditional material removal processes (Ho and Newman, 2003) in many of the modern-day technologically advanced manufacturing industries. It utilizes thermal energy to remove material from any electrically conductive workpiece regardless of its hardness and toughness by means of a series of sparks generated between the tool (also called as electrode) and workpiece in presence of a dielectric fluid. The electrode is made to move slowly toward the workpiece until the gap between it and workpiece is small enough to ionize the dielectric to

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produce short duration discharges (Papazoglou *et al.*, 2021). These electrical discharges create tiny craters on the workpiece surface, causing material removal through erosive action. EDM is widely employed for generation of die cavities, deep small and micro-holes, various intricate shape geometries, and also precision machining of materials which are extremely difficult-to-cut using conventional machining processes (Das and Chakraborty, 2020). It started to gain attention as an efficient machining process in the early 1940s when the Lazarenko brothers discovered the decisive role of the dielectric fluid (Kunieda *et al.*, 2005). Since then, it has experienced intense upgrading and development. Despite machining conductive materials, the present-day EDM is also able to generate complex features and shape geometries in many of the semi-conductive, metal matrix and ceramic composite materials. Generally, EDM can be classified as die-sinking EDM, wire-EDM, micro-EDM, powder-mixed EDM and dry EDM. In die-sinking EDM, the electrode and workpiece are completely submerged in a dielectric fluid (Farooq *et al.*, 2024). Wire-EDM employs a thin metallic wire continuously travelling with the help of microprocessor-controlled guideways, thereby enabling it to generate complicated 3-D profiles on the workpiece (Das *et al.*, 2019; Farooq *et al.*, 2022a). The working principle of micro-EDM is almost similar to that of die-sinking EDM; the only difference is that in micro-EDM, the diameter of the electrode is in microns (Das *et al.*, 2022). In powder-mixed EDM, suitable abrasive materials in form of powder are proportionately mixed with the dielectric fluid causing faster sparking and erosive action resulting in higher material removal rate (MRR) and better surface quality of the machined components (Das and Chakraborty, 2021; Farooq *et al.*, 2022b; Sana *et al.*, 2024). In dry EDM, high-pressure gas or air is supplied through a thin-walled pipe used as electrode, helping in removal of debris from the machining zone (Gholipoor *et al.*, 2015). In this process, use of dielectric fluid is minimized to avoid its perilous effect during the machining operation.

EDM process can also be classified based on the type of dielectric fluid utilized, i.e. hydrocarbon and EDM oil dielectric fluids, water and water-based dielectric fluids, gaseous-based dielectric fluids and powder-mixed dielectric fluids. Dielectric fluid is an insulating material acting as a poor conductor of electricity and when placed in an electric field, practically no current is allowed to flow as it does not have any loosely bound or free electron which can drift through. Dielectric fluid separates the tool and the workpiece. At the time of machining, with the spark produced, a stream of current flows with the dielectric getting ionized to form a path from the tool to the workpiece. The dielectric medium ruptures the current flow as the gap between the tool and the workpiece increases. It has already been experimented that selection of suitable dielectric fluid is extremely important with respect to enhanced machining performance and quality of the end products. The dielectric fluid in EDM process thus has the following functions (Chakraborty *et al.*, 2015):

(1) It serves as a medium to produce controlled electrical discharges.

(2) It acts as a quenching medium to cool down and solidify the eroded gaseous particles generated from the discharges.

(3) It helps in removing the solidified waste from the machining zone based on dielectric filtration system.

(4) It also works as a lubrication medium to absorb and remove the heat generated by the discharges from the machining zone.

Generally, hydrocarbon oil or EDM oil is used in die-sinking EDM, while deionized water is utilized in wire- and micro-EDM processes (Jeswani, 1981). Commonly used dielectric fluids, like EDM oil cause several problems during actual machining operation, such as air pollution, degradation of dielectric properties, carbon particles adhesion, health hazards, etc. These disadvantageous features of EDM oils all together impede stable electrical discharges between the electrode and workpiece resulting in inferior machining efficiency. Several types of EDM oil are available in the market having varying compositions and properties. In order to perform as a good dielectric medium, an EDM oil should be low in cost, non-toxic, chemically non-corrosive, and has low viscosity and good wetting property, high flash and fire points to avoid fire hazards, high electric strength for proper insulation, and good quenching behavior (Ming *et al.*, 2022). Selection of the most suitable EDM oil for a specific machining application from a pool of available alternatives can thus be regarded as a typical multi-criteria decision-making (MCDM) problem, involving evaluation of several criteria (EDM oil properties) which are often conflicting in nature, requiring trade-offs. In a recent work, Alam *et al.* (2021) solved a sustainable dielectric fluid selection problem considering six alternatives, i.e. jatropha oil, waste vegetable oil, sunflower oil, waste palm oil blended with kerosene, bio-dielectric fluid and canola oil, based on seven properties, such as density, viscosity, thermal conductivity, specific heat, flash point, breakdown voltage and dielectric constant. The corresponding criteria weights had been first estimated using standard deviation method and sunflower oil had been singled out as the best dielectric fluid while applying proximity index value method as an MCDM tool, resulting in sustainable EDM operation. Asif *et al.* (2023) extensively studied the effect of eco-friendly and biodegradable surfactant additives on MRR, surface roughness, tool wear rate (TWR) and overcut during EDM operation on titanium alloy. Considerable improvements of those responses had justified addition of the surfactants, thus validating the adopted approach for one-step sustainable machining.

The past researchers have already explored applications of several MCDM methods, and also highlighted their dominance in solving complex decision-making problems in various domains of engineering and management. Nila and Roy (2023) proposed a hybrid MCDM framework combining fuzzy set theory, full consistency method (FUCOM), logarithmic percentage change-driven objective weighting (LOPCOW) and Dombi Bonferroni (DOBI) operator for solving a third-party logistics provider selection problem. Shao *et al.* (2023) developed a decision framework for solving a tidal current power plant site selection problem integrating analytic hierarchy process (AHP), fuzzy group decision-making AHP, criteria importance through intercriteria correlation (CRITIC) and VIKOR (Vlse Kriterijumska Optimizacija I Kompromisno Resenje in Serbian) methods. Combining entropy method with evaluation based on distance from average solution (EDAS) technique, Chatterjee and Chakraborty (2023) identified the best material for 3D printer nozzle. Ghorui *et al.* (2023) endeavored to fuse pentagonal intuitionistic fuzzy number with AHP and technique for order preference by similarity to ideal solution (TOPSIS) to single out the best cloud service provider. Dai *et al.* (2024) demonstrated the application of combined stochastic multicriteria acceptability analysis (SMAA) and multi-attributive border approximation area comparison (MABAC) methods to solve a healthcare supplier selection problem. The earlier researchers have also demonstrated the advantages of MCDM methods in solving cutting fluid selection problems for different machining operations. Rao and Patel (2010) applied preference ranking organization method for enrichment evaluation (PROMETHEE) for selecting suitable cutting fluid for a cylindrical grinding operation. Abhang and Hameedullah (2012) combined TOPSIS and AHP to select the best cutting fluid for turning of EN31 steel with tungsten carbide inserts. Prasad and Chakraborty (2016) presented the application of quality function deployment-based model for cutting fluid selection for drilling and honing operations. Prasad and Chakraborty (2018) employed a modified similarity-based approach as a multi-objective optimization tool for selection of suitable cutting fluids for gear cutting and turning operations. Özakin (2023) presented a comparative analysis among four different MCDM methods, i.e. TOPSIS, VIKOR, multi-objective optimization based on ratio analysis (MOORA) and reference ideal method (RIM) while solving a cutting fluid selection problem. Based on the derived results, it was concluded that there had been a strong rank correlation between VIKOR and MOORA methods, whereas TOPSIS had not been strongly correlated with other MCDM methods. Acknowledging the immense potentiality of MCDM methods in efficiently solving cutting fluid selection problems, the past researchers explored applications of different MCDM techniques, like TOPSIS (Dhanalakshmi and Rameshbabu, 2021; Sofuoğlu, 2021; Dwivedi and Sharma, 2024), preference selection index (Attri *et al.*, 2014), complex proportional assessment (COPRAS) (Goswami and Behera, 2021), additive ratio assessment (ARAS) (Goswami and Behera, 2021), range of value (ROV) (Madić *et al.*, 2016), VIKOR (Dhanalakshmi and Rameshbabu, 2021) for the said purpose.

Based on wide acceptance of different MCDM methods and requirement of selecting the best suited dielectric fluid for efficient EDM operation, this paper attempts to hybridize integrated determination of objective criteria weights (IDOCRIW) with double normalization-based multiple aggregation (DNMA) method to identify the best EDM oil from a set of ten feasible alternatives based on six pivotal criteria during deep-hole drilling on aluminum bronze alloy. Aluminum bronze alloy contains approximately 80–90% copper, 8–14% aluminum, 2–4% iron and very small quantities of nickel, silicon, manganese and zinc. IDOCRIW, proposed by Zavadskas and Podvezko (2016), combines the advantageous features of both entropy (Zou *et al.*, 2006) and criterion impact loss (CILOS) (Mirkin, 1974) methods. It has been observed that in entropy method, weight calculated for a specific criterion is higher when there are large variations in its value against the considered alternatives. On the other hand, weight for a criterion estimated using CILOS method is comparatively small as it considers the significant loss of each criterion importance. Thus, combining criteria weights computed using both entropy and CILOS methods would provide an objective weight while overcoming limitations of one method being compensated by the other. DNMA (Liao and Wu, 2020) involves realistic normalization of criteria values based on both linear and vector normalization techniques, thus eliminating chances of any bias in the derived normalized values. It further considers the Euclidian distances of all the alternatives from the ideal solution for their subsequent ranking. Overall, the integrated approach combining IDOCRIW and DNMA methods would act as a powerful MCDM tool for solving high-dimensional decision-making problems involving multiple criteria and alternatives. To the best of authors' knowledge, this integrated approach is applied for the first time to solve a synthetic EDM oil selection problem while fulfilling the given machining requirements. Its performance in estimating the objective criteria weights and ranking of the alternatives is further analyzed through sensitivity analyses. The framework explaining IDOCRIW-DNMA-based selection of EDM oil is portrayed in Figure 1.

The structure of this paper is as follows: The mathematical formulations of IDOCRIW and DNMA methods are presented in Section 2, followed by the solution of a real-time EDM oil selection problem in Section 3. The comparative analysis and sensitivity analysis are provided in Section 4. Section 5 concludes the paper.

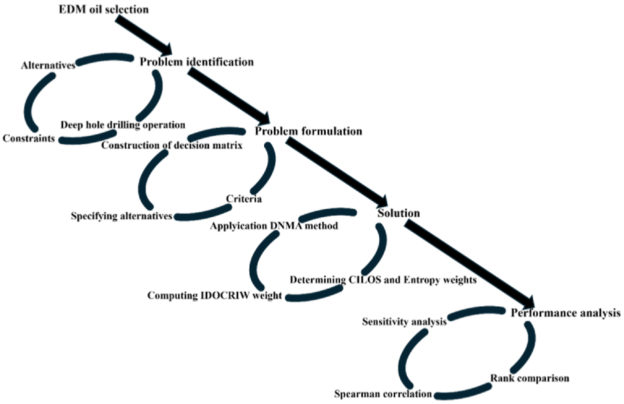

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Figure 1. Framework for EDM oil selection based on the integrated methodology

2. Methods

2.1 Entropy method

Entropy method (Zou *et al.*, 2006) is based on the existing information of various criteria to determine their weights, leading to better objectified results. To present its mathematical formulations, consider the following decision matrix with m alternatives and n criteria.

$$X = \left[x_{ij}\right]_{m\times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}$$

where x_{ij} denotes the performance of ith alternative against jth criterion. It has the following procedural steps:

Step 1: To eradicate influences of different dimensions in criteria values, the decision matrix is first normalized using the following equations:

$$P_{ij} = \frac{x_{ij}}{\sqrt{\sum\limits_{i=1}^{m} {x_{ij}}^2}}, \text{for beneficial criteria} \tag{1}$$

$$P_{ij} = 1 - \frac{x_{ij}}{\sqrt{\sum\limits_{i=1}^{m} {x_{ij}}^2}}, \text{for non} - \text{beneficial criteria} \tag{2}$$

Step 2: The definition of entropy of jth criterion is explained using Eq. (3)

$$e_j = -\frac{1}{\ln m}\sum_{i=1}^{m} f_{ij}\ln\left(f_{ij}\right), j = 1, 2, \ldots, n \tag{3}$$

where $f_{ij} = \frac{P_{ij}}{\sum_{i=1}^{m} P_{ij}}$, when $f_{ij} = 0$, $\ln(f_{ij}) = 0$.

Step 3: The entropy weight (E_j) of jth criterion is determined as follows:

$$E_j = \frac{1 - e_j}{\sum\limits_{j=1}^{n}\left(1 - e_j\right)} \tag{4}$$

where $0 \le E_j \le 1$ and $\sum_{j=1}^{n} E_j = 1$.

2.2 CILOS method

CILOS method, defined by Mirkin (1974), is another promising approach to determine objective criteria weights considering significance loss of each criterion. The steps involved are given as below:

Step 1: Transformation of the nonbeneficial criteria into beneficial criteria using Eq. (5).

$$t_{ij} = \frac{\min\limits_{i} x_{ij}}{x_{ij}} \tag{5}$$

Values of beneficial criteria require no change.

Step 2: Normalization of the transformed matrix as follows:

$$r_{ij} = \frac{t_{ij}}{\sum\limits_{i=1}^{m} t_{ij}} \tag{6}$$

Step 3: Development of the square matrix $A = |a_{tj}|$, by rearranging the rows with the maximum normalized values in each criteria column. Thus, the diagonals in square matrix A contain the maximum criterion values obtained in the normalized matrix.

Step 4: Formulation of a relative loss matrix L based on the square matrix A, in which each row corresponds to the row in which the criterion has the maximum value.

$$L_{ij} = \frac{r_j - a_{ij}}{r_j} = \frac{a_{ii} - a_{ij}}{a_{ii}}, L_{ii} = 0;\ i,j = 1, 2, \ldots, m \tag{7}$$

where $r_j = \max_i r_{ij} = r_{k_j j}$, k_j is the number of row of column j where the maximum value is located.

Step 5: Development of F matrix based on the relative loss matrix, as defined below:

$$F = \begin{bmatrix} -\sum_{i=1}^{n} L_{i1} & L_{12} & \ldots & L_{1n} \\ L_{21} & -\sum_{i=1}^{n} L_{i2} & \ldots & L_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ L_{m1} & L_{m2} & \ldots & -\sum_{i=1}^{n} L_{in} \end{bmatrix} \tag{8}$$

Step 6: Formation of the following linear equation, as given below:

$$Fq^T = 0 \tag{9}$$

Solving the above equation would result in criteria weights (q_j), where $\sum_{j=1}^{n} q_j = 1$.

2.3 IDOCRIW

IDOCRIW, proposed by Zavadskas and Podvezko (2016), is a combination of entropy and CILOS methods. It is employed to calculate objective weight of a criterion while combining its weights estimated using both entropy and CILOS methods.

$$w_j = \frac{E_j q_j}{\sum_{j=1}^{n} E_j q_j} \tag{10}$$

where E_j and q_j are the weights estimated using entropy and CILOS methods for jth criterion respectively, and w_j is the combined weight of jth criterion.

These objective weights would exhibit deviations of individual criteria values as obtained by entropy method, but at the same time, significance of the criterion would be reduced caused by higher losses compared to other criteria.

2.4 DNMA

DNMA (Liao and Wu, 2020) has been developed as a versatile MCDM tool for solving complex decision-making problems. Its unique strength lies in its flexible normalization procedure, adeptly dealing with diverse data types and criteria through both linear and vector normalization techniques. This adaptability allows it to prioritize solutions perfectly aligned with the desired outcomes, making it ideal for situations with clear goals. DNMA is based on a nuanced approach, going beyond the traditional MCDM methods by effectively balancing both the positive and negative aspects (beneficial and non-beneficial criteria) while solving a decision-making problem. This acknowledgment of trade-offs facilitates informed decisions even in the face of contrasting criteria. Moreover, its integration with three distinct aggregation operators ensures a comprehensive evaluation from multiple perspectives. Its credibility is also rooted in a solid theoretical foundation, and its versatility extends across various domains, from finance (Demir, 2022) and healthcare (Liao *et al*., 2019) to technology selection (Hezam *et al*., 2022) and is further enhanced by the recent advancements, like hesitant fuzzy DNMA (Zhang *et al*., 2020) and CRITIC-based weighting (Lai and Liao, 2021). To present the procedural steps of DNMA approach, consider a decision matrix, $X = [x_{ij}]_{m \times n}$ with m alternatives and n criteria.

Step 1: Normalization of the decision matrix

In this step, the initial decision matrix is normalized using Eqs. (11) and (12). Equation (11) is adopted for target-based linear normalization, whereas Eq. (12) is considered for target-based vector normalization.

$$n_{ij}^{1} = 1 - \frac{\left|x_{ij} - r_j\right|}{\max\left\{\max_{i} x_{ij}, r_j\right\} - \min\left\{\min_{i} x_{ij}, r_j\right\}} \tag{11}$$

$$n_{ij}^{2} = 1 - \frac{\left|x_{ij} - r_j\right|}{\sqrt{\sum_{i=1}^{m} \left(x_{ij}\right)^2 + \left(r_j\right)^2}} \tag{12}$$

where $r_j = \begin{cases} \max\limits_{i} x_{ij} \text{for beneficial criteria} \\ \min\limits_{i} x_{ij} \text{for non} - \text{beneficial criteria} \end{cases}$

Step 2: Determination of the weight adjustment coefficient

To achieve a trade-off between the evaluation criteria, their weight values are adjusted based on Eq. (13).

$$w_j^{\sigma} = \frac{\sigma_j}{\sum_{j=1}^{n} \sigma_j} \tag{13}$$

In Eq. (13), σ_j represents the standard deviation of jth criterion, calculated using the following equation:

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}\left(\frac{x_{ij}}{\underset{i}{\max} x_{ij}} - \frac{1}{m}\sum_{i=1}^{m}\left(\frac{x_{ij}}{\underset{i}{\max} x_{ij}}\right)\right)^2}{m}} \tag{14}$$

Finally, using Eq. (15), the adjusted criterion weight is determined, as shown below:

$$\widetilde{w}_j = \frac{\sqrt{w_j^{\sigma}.w_j}}{\sum_{j=1}^{n}\sqrt{w_j^{\sigma}.w_j}} \tag{15}$$

where w_j is the criterion weight obtained using IDOCRIW method.

Step 3: Aggregation

Based on the weight adjustment coefficients and values of the normalized decision matrix, three linear aggregation operators, i.e. complete compensatory model (CCM), uncompensatory model (UCM) and incomplete compensatory model (ICM), as respectively provided in Eqs. (16), (17) and (18), are employed to compute the corresponding utility values of all the alternatives under consideration. Thereby, three subordinate ranks of alternative a_i can be derived when its utility values, $u_1(a_i)$, $u_2(a_i)$ and $u_3(a_i)$ are arranged in descending, ascending and descending orders, respectively.

$$u_1(a_i) = \sum_{j=1}^{n}\widetilde{w}_j\frac{n_{ij}^{1}}{\underset{i}{\max} n_{ij}^{1}} \tag{16}$$

$$u_2(a_i) = \underset{j}{\max}\widetilde{w}_j\left(1 - \frac{n_{ij}^{1}}{\underset{i}{\max} n_{ij}^{1}}\right) \tag{17}$$

$$u_3(a_i) = \prod_{j}\left(\frac{n_{ij}^{2}}{\underset{i}{\max} n_{ij}^{2}}\right)^{\widetilde{w}_j} \tag{18}$$

Step 4: Integration of the utility values and ranking of the alternatives

Finally, Eq. (19) calculates the comprehensive utility value for each of the alternatives by adding its normalized utility values estimated based on CCM, UCM and ICM aggregators.

$$
\begin{aligned}
S_i = \overline{\omega}_1 & \sqrt{\varphi\left(\frac{u_1^N(a_i)}{\max\limits_i u_1^N(a_i)}\right)^2 + (1-\varphi)\left(\frac{m - r_1(a_i) + 1}{m}\right)^2} \\
& - \overline{\omega}_2 \sqrt{\varphi\left(\frac{u_2^N(a_i)}{\max\limits_i u_2^N(a_i)}\right)^2 + (1-\varphi)\left(\frac{r_2(a_i)}{m}\right)^2} \\
& + \overline{\omega}_3 \sqrt{\varphi\left(\frac{u_3^N(a_i)}{\max\limits_i u_3^N(a_i)}\right)^2 + (1-\varphi)\left(\frac{m - r_3(a_i) + 1}{m}\right)^2}
\end{aligned}
\tag{19}
$$

$$
u_y^N(a_i) = \frac{u_y(a_i)}{\sqrt{\sum_{i=1}^{m}\left(u_y(a_i)\right)^2}}, y = 1, 2, 3
$$

where $\overline{\omega}_1, \overline{\omega}_2$ and $\overline{\omega}_3$ are the weights assigned to CCM, UCM and ICM aggregators, respectively with $\overline{\omega}_1 + \overline{\omega}_2 + \overline{\omega}_3 = 1$. The parameter $\varphi\,(\varphi \in 0, 1)$ represents the relative significance of the subordinate utility value and subordinate rank, and $r_1(a_i)$, $r_2(a_i)$ and $r_3(a_i)$ are the subordinate ranks of *i*th alternative derived based on CCM, UCM and ICM aggregators, respectively. In this paper, the value of φ is considered as 0.5. Finally, all the alternatives are ranked in decreasing order of their S_i values, the best alternative having the maximum S_i score.

3. EDM oil selection using IDOCRIW-DNMA-based approach

As mentioned earlier, this paper presents application of an integrated approach combining IDOCRIW and DNMA methods for solving an EDM oil selection problem, while performing deep-hole drilling on aluminum bronze alloy. For the said purpose, ten EDM oil alternatives and six evaluation criteria are considered. These criteria are viscosity (C_1) (cSt at 40 °C), dielectric strength (C_2) (kV/mm), flash point (C_3) (°C), specific gravity (C_4), aromatics (C_5) (% by weight) and cost (C_6) (USD/l). Among these criteria, C_1, C_5 and C_6 are nonbeneficial in nature (requiring their lower values), whereas the remaining criteria are beneficial for which higher values are preferred. Viscosity of an EDM oil is a critical criterion influencing its flow and flushing ability during the machining operation. Low viscosity oils are ideal during deep-hole EDM operation as they efficiently promote material removal, preventing debris buildup and enhancing surface quality, while EDM oils having moderate viscosity strike a balance between flushing and electrode stability, minimizing wear and ensuring smoother finishes (Li *et al.*, 2019). On the other hand, high viscosity EDM oils are less effective in chip removal, leading to higher surface roughness and increased electrode wear, making them unsuitable for deep-hole EDM applications (Triyono *et al.*, 2018). Dielectric strength measures the EDM oil's ability to withstand electrical breakdown, a crucial factor in preventing short circuits during real-time machining operations. EDM oils with high dielectric strength are preferred for work materials, like aluminum bronze alloy due to their higher conductivity, minimizing risk of short circuits. Conversely, lower dielectric strength would increase the risk of short circuits, adversely affecting machining stability and overall performance (Jeavudeen *et al.*, 2020). The flash point of an EDM oil indicates the temperature at which it ignites, an important safety consideration during high temperature EDM operations. EDM oils with high flash point provide a wider safety margin, particularly important during deep-hole EDM with increased heat generation (Ming *et al.*, 2022). On the other hand, EDM oils with lower flash point require strict safety precautions and increased awareness of potential fire hazards. Specific gravity is the measure of how denser an EDM oil is as compared to water, impacting performance of

EDM operation. A higher specific gravity EDM oil may have several benefits, such as improved flushing and debris removal, better thermal conductivity, and enhanced stability during machining operations (Ishfaq *et al.*, 2022). The level of aromatics in an EDM oil indicates the proportion of various aromatic compounds within its overall weight. This can vary based on the specific oil type. Opting for an EDM oil with less aromatics is a wise decision. It not only promotes a safer workplace and reduces environmental impact but also ensures smoother machining operation dissipating the heat more effectively (Pragadish *et al.*, 2023). Lastly, cost of an EDM oil is considered as an important criterion for selection as it is directly proportional to the total machining cost.

Based on the identified criteria, ten feasible EDM oils, i.e. Spark SPO-A (A_1), Diel 7500 (A_2), Lubricut EDM SX2 (A_3), Lubrall EDM 90 (A_4), RBM oil (A_5), EDM-244 (A_6), IPOL SEO 450 (A_7), Fine Spark 110 (A_8), Exxsol D80 (A_9) and Extro EDM Plus 222 (A_{10}) are shortlisted from a pool of synthetic EDM oils available in the market. They possess specific characteristics and benefits and are well-known for their widespread industrial applications. Spark SPO-A has comparatively low cost and viscosity, making it a good alternative for better flushing while producing smoother surface finish. With higher dielectric strength, flash point and specific gravity, Diel 7500 as a dielectric fluid assists in reducing short circuits, enhances safety and improves flushing. Lubricut EDM SX2 is a better alternative as dielectric fluid compared to others in terms of its aromatics presence. In addition to being one of the cheapest EDM oils, Lubrall EDM 90 also offers low aromatic presence, allowing safer working environment. Similarly, RBM oil also falls under the low-cost category of EDM oils along with higher dielectric strength. EDM-244 is known for its low aromatics with comparatively high specific gravity. IPOL SEO 450 offers higher dielectric strength at low cost making it more suitable for machining tougher materials with minimum electrode wear and better surface quality. With low aromatics and cost, Fine Spark 110 EDM oil provides better environment to work upon. Exxsol D80 has low viscosity, higher dielectric strength and specific gravity, allowing it to withstand any chance of electrical breakdown, thus preventing short circuits during machining. Extro EDM Plus 222 is one of the EDM oils that offers lower viscosity at comparatively low cost, thus making it more suitable for deep-hole drilling with better flushing ability.

Based on the websites/catalogs of different manufacturers of EDM oil, the initial decision matrix of Table 1 is now developed consisting of ten feasible EDM oil alternatives evaluated against six criteria. To calculate objective weights of the considered criteria, IDOCRIW which combines entropy and CILOS methods is first employed. The corresponding criteria weights, estimated based on entropy, CILOS and IDOCRIW methods, are provided in Table 2. From Table 2, it can be noticed that IDOCRIW method assigns maximum weight (0.4366) to

Table 1. Decision matrix for synthetic EDM oil selection

EDM oil	C_1	C_2	C_3	C_4	C_5	C_6
A_1	2	45	140	0.77	0.01	2
A_2	2	45	110	0.776	0.1	2.4
A_3	2.4	46	105	0.75	0.01	4.57
A_4	3	40	120	0.81	0.01	0.96
A_5	4	46	93	0.764	0.24	1.4
A_6	2.45	45	110	0.77	0.01	14.89
A_7	2.3	46	110	0.758	0.1	1.63
A_8	2.3	46	105	0.8	0.01	1.42
A_9	1.4	46	77	0.809	0.5	8.18
A_{10}	1.9	45	93	0.764	0.24	2.29

Source(s): Authors' own work

Table 2. Entropy, CILOS and IDOCRIW weights

Weight	C_1	C_2	C_3	C_4	C_5	C_6
Entropy	0.0321	0.0007	0.0098	0.0003	0.5975	0.3596
CILOS	0.3364	0.2656	0.2300	0.0648	0.0446	0.0587
IDOCRIW	0.1773	0.0029	0.0369	0.0003	0.4366	0.3459

Source(s): Authors’ own work

aromatics (C_5) criterion. Cost (C_6) is the next significant criterion, and importance of specific gravity (C_4) is the least.

Now, employing the procedural steps of DNMA method, the decision matrix of Table 1 is normalized using both linear and vector normalization approaches, based on Eqs. (11) and (12), respectively. These normalized values are provided in Table 3. In the next step, using Eq. (13), the adjusted weight coefficients for the six evaluation criteria under consideration are estimated as 0.1859, 0.0113, 0.0701, 0.0030, 0.3941 and 0.3356, respectively. Based on these weight adjusted coefficients and normalized values of the decision matrix, and applying Eqs. (16)-(18), the corresponding utility values of all the candidate EDM oils are computed using three different aggregation operators, i.e. CCM, UCM and ICM, as shown in Table 4. In Table 4, based on the computed utility values, the alternative EDM oils are subsequently ranked in descending, ascending and descending orders for CCM, UCM and ICM aggregators, respectively. Finally, the comprehensive utility values for each of the alternative EDM oils are calculated using Eq. (19), considering values of different tuning parameters as $\phi = 0.5$, $\varpi_1 = 0.6$, $\varpi_2 = 0.1$ and $\varpi_3 = 0.3$. Ten EDM oils are subsequently ranked in decreasing order of their S_i values. It can be clearly noticed from Figure 2 that Spark SPO-A EDM oil emerges out as the best dielectric fluid having the maximum comprehensive utility score, followed by Fine Spark 110. On the other hand, Exxsol D80 is the least preferred choice for the said deep-hole drilling operation. Moderately low viscosity and cost, and lowest aromatics; and moderately high dielectric strength and specific gravity, and highest flashing point are responsible for the superiority of Spark SPO-A over the competing EDM oil alternatives under consideration.

To validate effectiveness of all the considered EDM oils, the corresponding experiments are carried out employing an EDM setup (Make: Sparkonix, India, Model S50 ZNC) based on a Box–Behnken design (BBD) plan on aluminum bronze alloy of 3 mm thickness and brass electrode with 300 μm diameter. The EDM setup is shown in Figure 3. During generation of deep-holes on the said material, gap voltage {25, 35, 45 V}, peak current {0.5, 1.5, 2.5 A} and pulse-on time {5, 8, 11 μs} are considered as the input parameters, while MRR and TWR are the responses. Each of the EDM parameters is set at three distinct operating levels to study their effects on the responses. While performing EDM experiments, the flushing pressure of the dielectric is maintained at 0.25 kgcm^{-2}. A BBD plan is more preferred than a normal factorial technique to develop higher-order response surfaces using fewer runs (Beg and Akhter, 2021). It uses 12 middle edge nodes and 3 center nodes to fit a second-order equation. The results of 15 EDM experiments while utilizing Spark SPO-A as the dielectric medium are provided in Table 5.

4. Comparative and sensitivity analyses

Table 6 summarizes the results of DNMA method compared to other popular MCDM techniques, such as evaluation by an area-based method of ranking (EAMR) (Keshavarz-Ghorabaee *et al.*, 2016), MABAC (Pamučar and Ćirović, 2015), mixed aggregation by comprehensive normalization technique (MACONT) (Wen *et al.*, 2020), ARAS (Zavadskas and Turskis, 2011), and measurement of alternatives and ranking according to compromise solution (MARCOS) (Stević *et al.*, 2020). It is worthwhile to mention here that in all the cases,

Table 3. Linear and vector normalized values

	Linear normalization						Vector normalization					
EDM oil	C_1	C_2	C_3	C_4	C_5	C_6	C_1	C_2	C_3	C_4	C_5	C_6
A_1	0.7692	0.8333	1.0000	0.3333	1.0000	0.9253	0.9243	0.9926	1.0000	0.9829	1.0000	0.9430
A_2	0.7692	0.8333	0.5238	0.4333	0.8163	0.8966	0.9243	0.9926	0.9136	0.9855	0.8551	0.9211
A_3	0.6154	1.0000	0.4444	0.0000	1.0000	0.7408	0.8739	1.0000	0.8992	0.9743	1.0000	0.8022
A_4	0.3846	0.0000	0.6825	1.0000	1.0000	1.0000	0.7982	0.9556	0.9424	1.0000	1.0000	1.0000
A_5	0.0000	1.0000	0.2540	0.2333	0.5306	0.9684	0.6721	1.0000	0.8647	0.9803	0.6297	0.9759
A_6	0.5962	0.8333	0.5238	0.3333	1.0000	0.0000	0.8676	0.9926	0.9136	0.9829	1.0000	0.2366
A_7	0.6538	1.0000	0.5238	0.1333	0.8163	0.9519	0.8865	1.0000	0.9136	0.9777	0.8551	0.9633
A_8	0.6538	1.0000	0.4444	0.8333	1.0000	0.9670	0.8865	1.0000	0.8992	0.9957	1.0000	0.9748
A_9	1.0000	1.0000	0.0000	0.9833	0.0000	0.4817	1.0000	1.0000	0.8186	0.9996	0.2111	0.6043
A_{10}	0.8077	0.8333	0.2540	0.2333	0.5306	0.9045	0.9369	0.9926	0.8647	0.9803	0.6297	0.9271

Source(s): Authors' own work

Table 4. Ranking of EDM oils using IDOCRIW-DNMA method

EDM oil	CCM $u_1(a_i)$	Rank	UCM $u_2(a_i)$	Rank	ICM $u_3(a_i)$	Rank	Utility value (S_i)	Rank
A_1	0.9282	1	0.0429	1	0.9661	1	0.8895	1
A_2	0.8131	4	0.0724	3	0.8955	6	0.6743	4
A_3	0.7996	6	0.0870	5	0.8989	5	0.6188	6
A_4	0.8521	3	0.1144	6	0.9545	3	0.7391	3
A_5	0.5639	8	0.1859	8	0.7599	8	0.4004	8
A_6	0.5521	9	0.3356	9	0.5966	9	0.3163	9
A_7	0.8111	5	0.0724	3	0.9021	4	0.6724	5
A_8	0.8851	2	0.0644	2	0.9623	2	0.8228	2
A_9	0.3618	10	0.3941	10	0.4511	10	0.1720	10
A_{10}	0.6907	7	0.1850	7	0.7944	7	0.4928	7

Source(s): Authors' own work

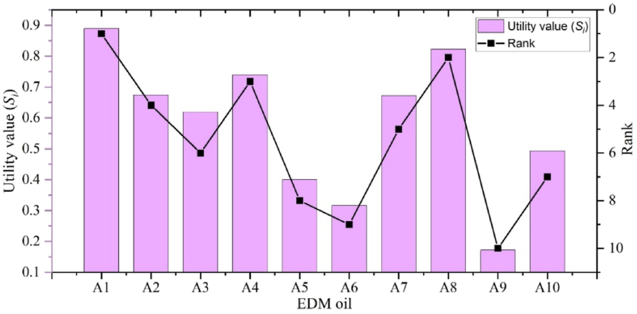

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Figure 2. Ranking of EDM oils

the criteria weights are considered as determined using IDOCRIW method. Table 6 reveals that all these methods except MACONT identify Spark SPO-A (A_1) as the most favorable EDM oil, followed by Fine Spark 110 (A_8). While MACONT picks out Fine Spark 110 (A_8) as the best EDM oil, and Spark SPO-A (A_1) as the second best choice. On the other hand, Exxsol D80 (A_9) is the least preferred choice as suggested by all the MCDM methods. Figure 4 portrays the computed Spearman's rank correlation coefficients between the considered MCDM methods while solving the said EDM oil selection problem. The Spearman's rank correlation is basically a statistical metric to access the degree of similarity between two ranking patterns (Więckowski and Sałabun, 2023). Its value nearer to 1 signifies a positive rank correlation, indicating that the two considered ranking patterns are almost similar. On the other hand, a value of -1 indicates a negative rank correlation. From Figure 4, it can be reassured that all the considered MCDM methods, i.e. DNMA, EAMR, MABAC, MACONT, ARAS and MARCOS provide almost similar rankings to the EDM oils, with rank correlation coefficients closer to 1. It is also interesting to note that DNMA behaves exactly similar to MABAC. Thus, the above findings evidently reveal consistency of DNMA method in identifying the best as well as worst EDM oils. The pros and cons of all the MCDM methods considered in this paper are highlighted in Table 7.

Furthermore, a sensitivity analysis is performed to investigate the effect of changing criteria weights on the ranking patterns derived using DNMA method. It basically strives to evaluate reliability, consistency and robustness in the ranking order obtained by the adopted

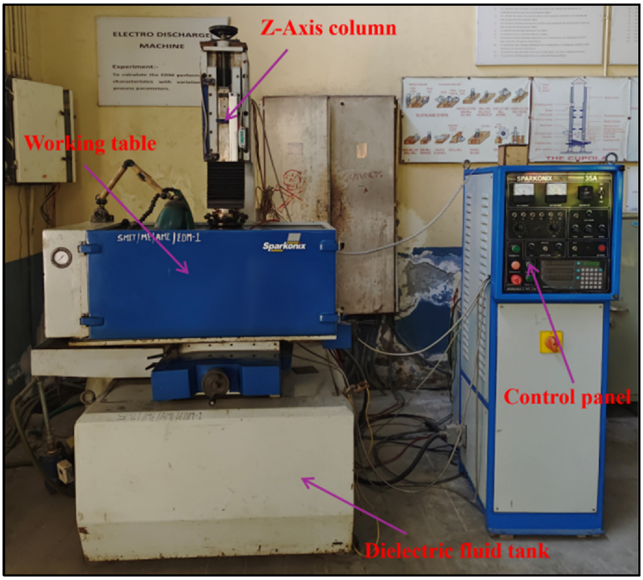

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Figure 3. Photograph of the EDM setup

Table 5. Experimental details

Run	Gap voltage (V)	Peak current (A)	Pulse-on time (μs)	MRR (mg/min)	TWR (mg/min)
1	35	1.5	8	42.4574	24.7297
2	45	0.5	8	12.3184	10.2405
3	25	2.5	8	44.0587	23.5847
4	35	2.5	11	24.5498	22.2737
5	35	1.5	8	44.5683	23.8622
6	45	2.5	8	39.927	21.4534
7	45	1.5	11	27.8757	21.0382
8	35	1.5	8	43.1689	22.7101
9	25	1.5	5	29.925	19.6458
10	25	1.5	11	44.0587	23.5847
11	25	0.5	8	16.0359	26.6655
12	45	1.5	5	11.7097	28.8274
13	35	0.5	5	25.5871	23.136
14	35	0.5	11	9.0449	19.0492
15	35	2.5	5	24.5498	22.2737

Source(s): Authors' own work

methodology. For this purpose, equal criteria weights along with seven different objective weighting methods, like entropy, CRITIC (Diakoulaki *et al.*, 1995), method based on the removal effects of criteria (MEREC) (Keshavarz-Ghorabaee *et al.*, 2021), principal component analysis (PCA) (Wold *et al.*, 1987), symmetry point of criterion (SPC) (Gligorić *et al.*, 2023), logarithmic percentage change-driven objective weighting (LOPCOW) (Ecer and Pamucar, 2022) and CILOS are considered. These criteria weights are provided in Table 8.

Table 6. Rank comparison against other MCDM methods

EDM oil	DNMA	EAMR	MABAC	MACONT	ARAS	MARCOS
A_1	1	1	1	2	1	1
A_2	4	6	4	7	8	8
A_3	6	5	6	4	4	4
A_4	3	3	3	3	3	3
A_5	8	9	8	8	7	7
A_6	9	8	9	6	5	5
A_7	5	4	5	5	6	6
A_8	2	2	2	1	2	2
A_9	10	10	10	10	10	10
A_{10}	7	7	7	9	9	9

Source(s): Authors' own work

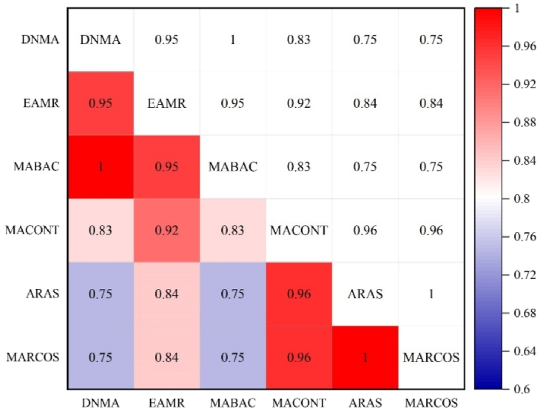

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Figure 4. Correlation heatmap between different MCDM methods

Based on these criteria weights and applying DNMA method, the rankings of all the EDM oils are obtained, as illustrated in Figure 5. Figure 5 depicts that alternatives A_1 (Spark SPO-A) and A_8 (Fine Spark 110) receive the top two rank positions for all the weight sets considering different weighting scenarios. On the other hand, alternative A_9 (Exxsol D80) appears as the least preferred EDM oil in 8 out of 9 weight sets (88.89%). Thus, IDOCRIW-DNMA approach evolves out as a powerful MCDM tool, providing consistent, reliable and robust selection decisions.

The effects of variations of φ, and $\overline{\varpi}_1$, $\overline{\varpi}_2$ and $\overline{\varpi}_3$ values used in Eq. (19) while calculating the comprehensive utility scores of the alternative EDM oils are analyzed in Figures 6 and 7, respectively. Figure 6 provides the derived ranking patterns at varying values of φ (increasing from 0 to 1 at step size 0.1). It is interesting to note that the rankings of the considered EDM oils almost remain unchanged at different φ values, except at $\varphi = 0.9$ and $\varphi = 1$, where minor variations are noticed. Figure 7 presents variations in ranking patterns at different combinations of $\overline{\varpi}_1$, $\overline{\varpi}_2$ and $\overline{\varpi}_3$, i.e. weights assigned to CCM, UCM and ICM aggregator respectively, such that they must always add up to one. It is revealed from Figure 7 that in all

Table 7. Pros and cons of the considered MCDM methods

Method	Pros	Cons
DNMA	(a) It eliminates the partialities of the single normalization technique through reasonable combination of both linear and vector normalization techniques (b) It shows higher reliability and consistency against other utility-based ranking methods because of double normalization techniques, three aggregation operators and utility integration approach (c) The decision makers can adjust weights of the subordinate tuning parameters to reflect their preferences on "group utility" and "individual regret" of the alternatives	(a) Adjustment of tuning parameters may sometimes become challenging (b) It cannot deal with qualitative evaluation criteria
EAMR	(a) It is not affected by any associated tuning parameter (b) It is computationally simple and easy to implement	(a) It is not applicable to those problems having only beneficial or non-beneficial criteria
MABAC	(a) It provides consistent results in the event of changes in the measurement units used to display criteria values of the alternatives (b) It provides stable solutions arising due to change in the type of criteria formulation	(a) It cannot effectively handle qualitative criteria in the decision-making process
MACONT	(a) It integrates three linear normalization techniques based on criterion type to minimize deviation in the normalized values (b) It applies two aggregation operators to achieve multi-aspect and reliable results considering compensation and non-compensation effects among the criteria (c) It allows the decision makers to adjust the tuning parameters, enhancing its application scope	(a) The steps involved are mathematically complicated (b) Adjustment of the tuning parameters may sometimes be challenging
ARAS	(a) It measures the degree of the alternative utility by comparison of the variant analyzed with the ideal solution (b) It is mathematically simple to apply	(a) It cannot deal with qualitative criteria
MARCOS	(a) It is based on testing the reference values of the alternatives in relation to the ideal solutions employing a comprehensive rational and reasonable methodology (b) Its robustness and stability in dynamic environments is excellent	(a) This method cannot handle the qualitative evaluation criteria

Source(s): Authors' own work

the considered scenarios, alternative A_1 (Spark SPO-A) continues to receive the top rank, followed by alternative A_8 (Fine Spark 110), while A_9 (Exxsol D80) remains as the least preferred EDM oil for deep-hole drilling on aluminum bronze alloy. From the above analysis, it can be stated that the tuning parameters as considered in Eq. (19), i.e. φ, $\overline{\varpi}_1$, $\overline{\varpi}_2$ and $\overline{\varpi}_3$ have minimal impacts on the ranking patterns of the said EDM oil selection problem.

Table 8. Different criteria weight sets for sensitivity analysis

Weighting method	C_1	C_2	C_3	C_4	C_5	C_6
Equal	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667
Entropy	0.0321	0.0007	0.0098	0.0003	0.5975	0.3596
CRITIC	0.1440	0.1910	0.1264	0.2093	0.1648	0.1645
MEREC	0.2708	0.0090	0.2609	0.0027	0.3193	0.1373
PCA	0.2569	0.2814	0.0991	0.1308	0.1147	0.1171
SPC	0.0230	0.0046	0.0089	0.0019	0.7562	0.2055
LOPCOW	0.1947	0.2265	0.1346	0.0741	0.1714	0.1988
CILOS	0.3364	0.2656	0.2300	0.0648	0.0446	0.0587

Source(s): Authors' own work

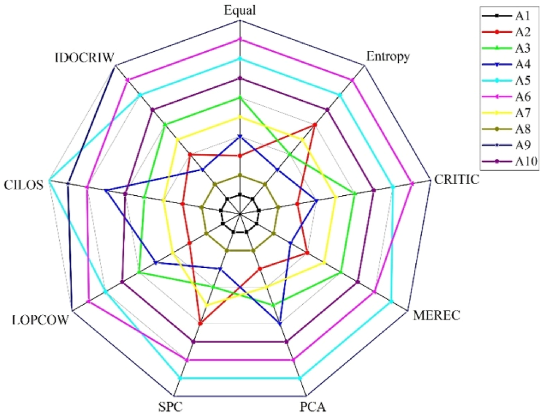

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Figure 5. Rankings of EDM oils using different weighting methods

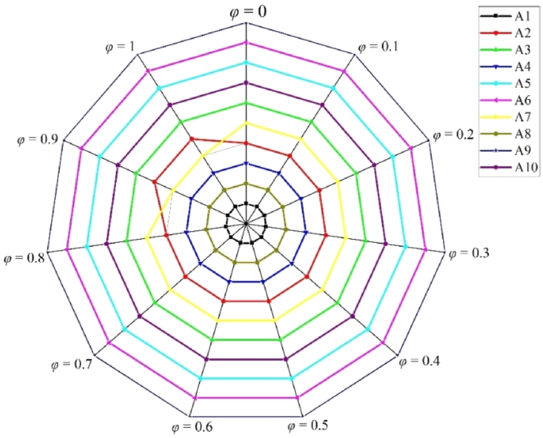

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Figure 6. Effects of variations of φ on rankings of EDM oils

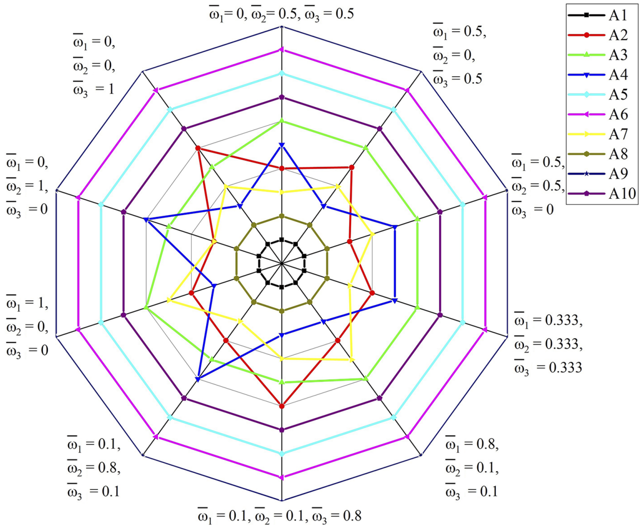

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Figure 7. Effects of variations of $\overline{\omega}_1$, $\overline{\omega}_2$ and $\overline{\omega}_3$ values on rankings of EDM oils

5. Conclusions

This paper presents application of an integrated IDOCRIW-DNMA approach for solving an EDM oil selection problem based on real-time data. The objective criteria weights are calculated using IDOCRIW method and the feasible EDM oils are subsequently ranked employing DNMA method. On the basis of the analyzed results, the following conclusions can be framed:

1. IDOCRIW assigns maximum importance to "aromatics" criterion, followed by "cost". "Specific gravity" is the least important criterion.
2. DNMA identifies Spark SPO-A and Exxsol D80 as the best and the worst preferred EDM oils, respectively for deep-hole drilling on aluminum bronze material. Spark SPO-A has moderately low viscosity and cost, and lowest aromatics; and moderately high dielectric strength and specific gravity, and highest flashing point.
3. A comparative analysis with other MCDM methods reveals solution accuracy of the adopted methodology.
4. Its consistency and robustness is validated through sensitivity analysis studies at varying values of different tuning parameters.
5. It has been experimented that application of Spark SPO-A as an ideal EDM oil results in 5–8% and 7–10% improvements in the average MRR and TWR values against other dielectrics.

As a future scope, this approach may be extended for parametric optimization of an EDM process, selection of electrode material etc. The future scope also includes comparing its ranking performance against other newly developed MCDM techniques, like combined compromise solution (CoCoSo), multi-attributive ideal-real comparative analysis (MAIRCA), ordinal priority approach (OPA) etc. which are not considered here due to paucity of space. Application of DNMA may be explored while integrating it with different uncertainty models, like fuzzy set, intuitionistic fuzzy set, grey numbers, etc. to precisely deal with qualitative data in the decision-making process.

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Further reading

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Corresponding author

Shankar Chakraborty can be contacted at: s_chakraborty00@yahoo.co.in

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An LOPCOW-OPTBIAS-based integrated approach for cobot selection in manufacturing assembly operations

Saikat Chatterjee and Partha Protim Das*

Department of Mechanical Engineering,
Sikkim Manipal Institute of Technology,
Sikkim Manipal University,
Sikkim-737136, India
Email: saikatchatterjee007@gmail.com
Email: parthaprotimdas@ymail.com
*Corresponding author

Shankar Chakraborty

Department of Production Engineering,
Jadavpur University,
Kolkata-700032, India
Email: s_chakraborty00@yahoo.co.in

Abstract: Nowadays, collaborative robots (cobots) have gained much popularity in manufacturing industries to assist in various assembly operations. However, selecting the most suitable cobot can be challenging due to abundance of many viable options in the market. In this paper, an integrated approach combining logarithmic percentage change-driven objective weighting (LOPCOW) and ordering preference targeting at bi-ideal average solutions (OPTBIAS) methods is proposed. Based on a real-time illustrative example consisting of 13 alternatives and 6 evaluation criteria, OPTBIAS method identifies Elfin-P as the most approsite cobot model for the considered assembly operation. The effectiveness of this integrated approach is validated against other popular multi-criteria decision making (MCDM) techniques and objective criteria weighting methods. A sensitivity analysis with respect to variations in the criteria weights also proves robustness of the adopted approach. Thus, it can act as a potent MCDM tool in effectively selecting the most suitable assembly cobot for a given application.

Keywords: cobot selection; decision making; LOPCOW; OPTBIAS; comparative analysis.

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Biographical notes: Saikat Chatterjee is an Assistant Professor in the Department of Mechanical Engineering at Sikkim Manipal Institute of Technology, Sikkim Manipal University. He earned his Bachelor's in Mechanical Engineering from Rajiv Gandhi Prodyogiki Vishwavidyalaya in Bhopal in 2010, and Master's in Mechanical Engineering from

Jadavpur University in 2013. He is currently pursuing his PhD in Production Engineering at Jadavpur University. His research interests include multi criteria decision-making methods, manufacturing processes, and material selection, among other topics.

Partha Protim Das is working as an Assistant Professor in the Department of Mechanical Engineering at Sikkim Manipal Institute of Technology, Sikkim Manipal University. He received his Bachelor's in Mechanical Engineering from Annamalai University in 2013, Master's in Design and Manufacturing from NIT Silchar in 2015. He was awarded with PhD (Engineering) degree from Jadavpur University in 2021. He has published more than 50 research articles in various international journals of repute. His research interest includes decision making methods, soft computing techniques, optimisation artificial intelligence techniques, and machine learning algorithms in machining environment.

Shankar Chakraborty is a Professor in Production Engineering Department of Jadavpur University. He had been awarded with PhD (Engineering) degree from Jadavpur University in 1994. His research interests include applications of different multi-criteria decision-making methods, optimisation of machining processes, and development of MIS and ERP systems for diverse engineering applications. He has guided several PG and PhD (Engineering) theses and published more than 200 research papers in International journals. He is also an Associate Editors of several international journals. Since the last three years, he is among the top 2% global scientists declared by the prestigious Stanford University.

1 Introduction

Assembly is the process of connecting individual components or sub-assemblies to develop a finished product with the help of conventional methods (like fastening, riveting, seaming, soldering etc.) or specialised equipment (such as robotic arms or assembly machines). Assembly can be performed either manually or using automated processes. Manual assembly requires human labour, whereas, automated assembly can be performed by machines with minimal human intervention. Automated assembly has become an essential step in the manufacturing process for high-volume production, where efficiency and speed are of critical issue (Cherubini et al., 2016). Use of appropriate tools and equipment can make the assembly process more efficient and accurate, helping to ensure that the finished product should meet the required quality standards. However, existing manual assembly operations in a manufacturing shop floor have several limitations, including inconsistencies and variability due to differences in skill level, human error, safety risks, limited productivity, and lack of flexibility. These may result in quality issues, increased waste, production delays, injuries, lost time and increased costs. To address these constraints, several manufacturers are resorting to automated processes, including the deployment of collaborative robots or cobots, to increase efficiency, efficacy, and safety in their assembly operations.

Assembly cobots (Colgate et al., 1996; Peshkin et al., 2001) have the potential to overcome many of the current constraints of manual assembly methods on the factory shop floor. They can do tasks faster and more efficiently than humans, resulting in increased output and throughput, as well as enhanced quality and decreased waste. They are especially useful for repetitive or complicated activities that would take human workers a long time to complete. They can accomplish jobs with great accuracy and precision, maintaining consistency while minimising variability in assembly operations (Faccio et al., 2019). They can also collaborate with human operators to provide a safe and ergonomic workplace. They can carry out jobs with great accuracy and precision, maintaining consistency while minimising variability in assembly operations (Faccio et al., 2019). They can also collaborate with human operators to provide a safe and ergonomic workplace. Because cobots are very adaptable and can be programmed to do an extensive variety of jobs, they are well suited for a wide range of assembly operations. Although they may have greater upfront expenses, they can deliver a considerable long-term return on investment.

Assembly cobots and industrial robots are both extensively used to automate assembly operations on manufacturing shop floors. There are, nevertheless, numerous significant variations between them. Assembly cobots are engineered to collaborate with human employees, whereas industrial robots normally work alone. Assembly cobots are typically outfitted with safety features like sensors and cameras that detect the presence of humans and alter their motions accordingly. On the other hand, industrial robots require safety barriers or cages to avoid accidents. Assembly cobots are meant to be highly flexible and versatile, allowing them to be readily reprogrammed or reconfigured to suit changing production demands. Industrial robots, on the other hand, are frequently designed for specific tasks and may be difficult to reprogramme for numerous use. Assembly cobots are often smaller and more mobile than industrial robots, which are large and immobile. This makes cobots more suitable for smaller workstations and duties requiring movement throughout the manufacturing floor (Matheson et al., 2019). Cobots are also easy to merge into prevailing production lines, requiring less advanced training to operate. Industrial robots are often built to bear larger loads than assembly cobots, which are better suited to light assembly activities. Cobots feature optimised specifications for assembly jobs, such as large payload capacity, extended reach, excellent repeatability, and low weight.

Overall, assembly cobots offer greater flexibility, mobility and cost-effectiveness than industrial robots. While both types of robots have their own advantages and limitations, cobots are well-suited for a variety of assembly operations, and can help manufacturers to optimise their production processes, and improve efficiency and quality in the shop floor. Assembly cobots can be classified into different categories based on their design, functionality and application. Cobots can be categorised based on their payload capacity (maximum weight they can handle) into three main classes, i.e. low payload (up to 5 kg), medium payload (up to 10 kg) and high payload (up to 50 kg) (https://www.marketsandmarkets.com). They can also be classified depending on their mobility (ability to move around the manufacturing floor) into two main groups, e.g. stationary cobots (fixed at one location) and mobile cobots (can move around the shop floor). Cobots can again be classified into three groups based on their physical form factor, which refers to their shape and size, i.e., articulated cobots (having multiple joints and can move in a wide range of directions), Cartesian cobots (can move in straight lines along X, Y and Z axes) and SCARA cobots (having two parallel joints that allow them to move in a horizontal plane). Based on degree of autonomy (level of human intervention), there are semi-autonomous cobots and fully autonomous cobots. They can also be classified based on the specific task they are designed to perform, like assembly, pick-and-place operations, welding, material handling and spray painting. Overall, the classification of assembly cobots helps the manufacturers to choose the right type of cobot for their specific needs and applications. By understanding different categories of cobots, manufacturers can optimise their assembly operations, and improve productivity, quality and safety in the shop floor. As a result, the most crucial decision to make when contemplating and addressing a cobot selection problem is to determine what kind of applications and operations the cobot is utilised for. For example, when selecting an assembly cobot, some of the criteria that may be considered include payload capacity, accuracy, repeatability, power consumption and cost. Each of these criteria has a different level of importance depending on the specific requirement and objective of the assembly operation. Moreover, improving one criterion often comes at the expense of another, making it difficult to identify the best solution that satisfies all the criteria. Hence, assembly cobot selection can be considered as a typical multi-criteria decision making (MCDM) problem as it involves evaluation of several criteria which are often conflicting or require trade-offs.

Keeping in mind the immense requirements to select the most appropriate cobot from a set of feasible options for performing assembly operations in an automobile industry, two recently developed MCDM tools, i.e. LOPCOW and OPTBIAS are integrated for the first time in this paper. LOPCOW is employed to estimate objective weights of the considered evaluation criteria based on their relative importance, while OPTBIAS is adopted to determine the ranking order of the alternative assembly cobots for the given task. There are several added advantages of LOPCOW over the other objective criteria weighting techniques (like entropy method and CRITIC method), such as not being affected by the negative values of raw data in the decision matrix, no limitation on the criterion type and ability to eliminate the difference caused by the data size while expressing the mean square value of the data as a percentage of their standard deviations. On the other hand, OPTBIAS excels over the existing MCDM techniques with respect to reduction in computational burden while making maximum use of the Pareto-optimal solutions. It basically takes into account the relative importance of distances between the Pareto-optimal solutions, and bi-ideal solutions and average solution. By weighting information of the top and bottom third of the ideal points, it constructs bi-positive and bi-negative ideal points, ensuring full use of the solution set while reducing the risk of ordering inconsistency. Overall, it offers a more efficient and effective approach for solving high-dimensional MCDM problems. In this paper, the performance of LOPCOW with respect to criteria weight measurement is contrasted with that of entropy and CRITIC methods. Similarly, the ranking behaviour of the combined method (LOPCOW-OPTBIAS) is also compared with that of other integrated approaches. A sensitivity analysis is finally performed to validate its ranking stability under varying criteria weighting scenarios. To the best of the authors' knowledge, it is the first application of LOPCOW-OPTBIAS for solving an assembly cobot selection problem for an automobile industry based on real-time data.

The structure of this paper is as follows: Literature survey is presented in Section 2, followed by the mathematical formulations of LOPCOW and OPTBIAS methods in Section 3. A real-time assembly cobot selection problem is solved in Section 4 along with a comparative analysis in Section 5 and sensitivity analysis in Section 6. Section 7 mentions the managerial implications and Section 8 concludes the paper.

2 Literature review

MCDM methods, providing a systematic and structured framework, helps the decision makers in assessing different available options and making an informed decision based on a comprehensive and unbiased evaluation of all the relevant criteria. The process of selecting an assembly cobot from a vast array of options available in the market for a specific task has already garnered considerable attention from the researchers. With a wide range of MCDM techniques available and pressing need to accurately address this issue, the past studies have explored the use of different MCDM techniques to effectively solve cobot selection problems for varying industrial applications.

2.1 Cobot selection

Bahadir (2017) proposed a model to aid in estimating importance weight of criteria and alternative evaluations in a single group decision making environment, and applied VIKOR for final selection of cobot. Mecheri and Greene (2019) first shortlisted some specific criteria for evaluating various cobots and employed an improved MCDM algorithm to select the most suitable cobot for a manufacturing/service industry. Bhalaji et al. (2021) adopted DEMATEL method to analyse the risk factors influencing human-robot interaction during an assembly operation. A detailed comparison of different MCDM methods used for selection of cobot is provided in Table 1. Accorsi et al. (2019) proposed a generalised methodology to support the study of technical and economic feasibility of implementing cobots in a food catering industry. Cohen et al. (2022) provided a review of the concerns connected to cobot acquisition and implementation, as well as a productivity study to support the same concern. Based on a comprehensive review, Silva et al. (2022) identified those evaluation criteria significantly influencing the cobot selection decision. It can be noticed that the available literature on cobot selection is notably limited, with only a handful of studies focusing on applications of MCDM techniques for the said purpose. To address this gap in knowledge, a separate review is also conducted on the applications of different MCDM tools for solving human-robot and industrial robot selection problems.

Table 1 Application of different MCDM methods for cobot selection

Authors	*Methodology*	*Workdone*
Bahadir (2017)	VIKOR	Selection of cobot
Mecheri and Greene (2019)	AHP	Selection of cobot
Bhalaji et al. (2021)	DEMATEL	Analysis of risk factors influencing human-robot interaction
This paper	LOPCOW and OPTBIAS	Selection of cobot

2.2 Industrial robot selection

Athawale and Chakraborty (2011) compared the ranking performance of several MCDM methods while solving a robot selection problem for pick-n-place operation, and concluded that almost all the adopted approaches would result in identification of the same robot as the best choice. Chatterjee et al. (2014) investigated the application feasibilities of two preference dominance-based MCDM techniques for selecting the best robots within the given manufacturing environments. Adakane and Narkhede (2014) adopted three different MCDM techniques, i.e. AHP, TOPSIS and PROMETHEE to choose the best robot alternative for powder coating operation. Chakraborty et al. (2014) validated the applicability and usefulness of WASPAS method as an MCDM tool for solving robot selection problems. Other studies have also employed different MCDM methods for the same purpose, like QUALIFLEX (Xue et al., 2016), AHP (Mirfakhradi et al., 2016; Breaz et al., 2017; Simion et al., 2018), TOPSIS (Mirfakhradi et al., 2016; Chodha et al., 2022), PROMETHEE (Sen et al., 2016), WSM (Karande et al., 2016), WPM (Karande et al., 2016), WASPAS (Karande et al., 2016), MOORA (Karande et al., 2016), EDAS (Yalçin and Uncu, 2019), SMART (Suszyński and Rogalewicz, 2020), COPRAS (Goswami et al., 2021), ARAS (Goswami et al., 2021), CoCoSo (Kumar et al., 2022), CODAS (Shanmugasundar et al., 2022), MABAC (Shanmugasundar et al., 2022) and TARO (Bairagi, 2022). Thus, it can be concluded that although there are applications of different MCDM tools and criteria weighting techniques for solving industrial robot and cobot selection problems, they suffer from several disadvantages, like complicated computational steps, dependency on data, inconsistent decisions etc. To resolve these issues, this paper proposes hybridisation of two newly developed MCDM tools, i.e. LOPCOW and OPTBIAS for solving an assembly cobot selection problem for an automobile industry based on real-time data.

3 Methods

3.1 LOPCOW

It is a recently proposed approach for measuring objective criteria weights having several advantageous features as compared to its peer ones while providing more acceptable solutions (Ecer and Pamucar, 2022). It avoids huge differences between the criteria values, which have often been encountered with other techniques, like entropy method. It is not affected by negative values of raw data in the decision matrix. In this method, there is no limitation on the criterion type as it can offer a suitable solution for both the beneficial and non-beneficial criteria. It also eliminates the difference caused by the size of the data while expressing the mean square value of the data as a percentage of their standard deviations. The following are the steps for LOPCOW:

Step 1 Construct the initial decision matrix with n alternatives and m criteria.

$$X = \left[X_{ij}\right]_{n\times m} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{1}$$

where x_{ij} denotes the performance of i^{th} alternative with respect to j^{th} criterion.

Step 2 Normalise the elements of the decision matrix using linear normalisation technique.

$$V = \left[v_{ij} \right]_{n \times m} = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1m} \\ v_{21} & v_{22} & \cdots & v_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ v_{n1} & v_{n2} & \cdots & v_{nm} \end{bmatrix}$$

$$v_{ij} = \frac{x_{\max} - x_{ij}}{x_{\max} - x_{\min}}, \text{ if } j \text{ is a non-beneficial criterion} \tag{2}$$

$$v_{ij} = \frac{x_{ij} - x_{\min}}{x_{\max} - x_{\min}}, \text{ if } j \text{ is a beneficial criterion} \tag{3}$$

where v_{ij} is the linear normalised value of x_{ij}.

Step 3 Calculate the percentage value (P_j) of each criterion while taking the natural log of the ratio of the mean square value of the criterion by its standard deviation, and multiplying by 100. It helps in eliminating differences in the size of the data.

$$P_j = \left| \ln \left(\frac{\sqrt{\frac{\sum_{i=1}^{n} v_{ij}^{2}}{n}}}{\sigma_j} \right) \times 100 \right| \tag{4}$$

where σ_j is the standard deviation of jth criterion.

Step 4 Compute the objective criteria weights.

$$w_j = \frac{P_i}{\sum_{j=1}^{m} P_j} \tag{5}$$

where w_j is the weight assigned to jth criterion.

3.2 OPTBIAS

The OPTBIAS (Dai et al., 2023) method is employed for multi-objective optimisation by ranking a set of Pareto-optimal solutions based on their distance to several reference points, including bi-positive, bi-negative ideal solutions, and an average solution. It differs from TOPSIS with respect to defining the reference points and measuring the relative distance. OPTBIAS identifies bi-positive and bi-negative ideal points while extracting information from the top and bottom third of the ideal points, while TOPSIS considers either the best or worst value of each criterion to define the reference points. Additionally, it takes into account the relative importance of distances between the Pareto-optimal solutions and reference points, using a weighted Euclidean distance measure, while TOPSIS employs a standard Euclidean distance measure. Finally, OPTBIAS aims to reduce computational complexity while making maximum use of the Pareto-optimal solutions, whereas, TOPSIS may become computationally complex while dealing with high-dimensional problems. In this method, the ranking of each alternative is based on its distance to the reference points. The closer a solution is to a bi-positive ideal solution, higher is its ranking. On the contrary, the closer a solution is to a bi-negative ideal solution or average solution, the worse is its ranking. The following are the steps for using OPTBIAS:

Step 1 From the initial decision matrix, develop the following matrix using vector normalisation procedure.

$$R = \left[r_{ij}\right]_{n\times m} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix} \tag{6}$$

where r_{ij} is the vector normalised value of x_{ij}.

Step 2 Formulate the weighted normalised decision matrix (Y) by multiplying each element of the normalised decision matrix with the corresponding criteria weights.

$$Y = \left[y_{ij}\right]_{nm} = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1m} \\ y_{21} & y_{22} & \cdots & y_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ y_{n1} & y_{n2} & \cdots & y_{nm} \end{bmatrix} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdots & w_m r_{1m} \\ w_1 r_{21} & w_2 r_{22} & \cdots & w_m r_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ w_1 r_{n1} & w_2 r_{n2} & \cdots & w_m r_{nm} \end{bmatrix} \tag{7}$$

Step 3 Identification of the corresponding reference points, i.e. bi-positive (BP) ideal, bi-negative (BN) ideal and average (A) solutions using the following equations:

$$\begin{aligned} SA_{(p)} &= \begin{Bmatrix} Max(y_j), & j \in B' \\ Min(y_j), & j \in C \end{Bmatrix} \\ &= \left\{ y_{(p)1}, y_{(p)2}, y_{(p)3}, \ldots, y_{(p)m} \right\},\ p \in \{1, 2, \ldots, n\} \end{aligned} \tag{8}$$

$$BP_{(k)} = \begin{cases} SA_{(p)|p=1} & k = 1 \\ \displaystyle\sum_{p=2}^{n/3} \frac{SA_{(p)}}{p} & k = 2 \end{cases} \tag{9}$$

$$BN_{(k)} = \begin{cases} SA_{(p)|p=n} & k = 1 \\ \displaystyle\sum_{p=n+1-(n/3)}^{n-1} \frac{SA_{(p)}}{n-p+1} & k = 2 \end{cases} \tag{10}$$

where $k = \begin{cases} 1 & n < 6 \\ 1, 2 & n \geq 6 \end{cases}$

$$A = \left[\overline{y_j}\right]_m = \left[\overline{y_1}\,\overline{y_2}\ldots\overline{y_m}\right] = \left[\frac{\sum_{i=1}^{n} y_{(i)1}}{n}\;\frac{\sum_{i=1}^{n} y_{(i)2}}{n}\ldots\frac{\sum_{i=1}^{n} y_{(i)m}}{n}\right] \tag{11}$$

where $SA_{(p)}$ represents the combination of p^{th} best value for each criterion among all the considered alternatives. For example, $SA_{(1)}$ consists of the best value for each criterion with respect to all the alternatives (i.e. maximum value for beneficial (B') criterion and minimum value for cost (C) criterion), assigned with rank one ideal solution, also known as the most 'positive' ideal solution. Similarly, $SA_{(2)}$ denotes the second-best value for each criterion among all the alternatives, and so on. Thus, $SA_{(n)}$ signifies the most 'negative' ideal solution (minimum value for beneficial (B') criterion and maximum value for cost (C) criterion). On the other hand, $\text{Max}(y_j)$ and $\text{Min}(y_j)$ represent the p^{th} maximum and minimum values of j^{th} weighted normalised data (i.e. y_j) for each criterion respectively, k denotes the first and second positive and negative ideal solutions respectively, $(n\backslash 3)$ is an integer quotient of n divided by 3 ignoring the remainder and $\overline{y_j}$ is the average weighted normalised value for j^{th} criterion.

Step 4 Computation of the Euclidean distances RP, RN and RA from j^{th} criterion to the bi-positive ideal, bi-negative ideal and average solutions respectively for each alternative.

$$RP = \left[RP_i\right]_n = \begin{bmatrix} RP_1 \\ RP_2 \\ \vdots \\ RP_n \end{bmatrix}, RP_i = \begin{cases} \sum_{k=1}^{2}\sqrt{\sum_{j=1}^{m}\left(y_{ij} - BP_{(k)j}\right)^2} & n \geq 6 \\ \sqrt{\sum_{j=1}^{m}\left(y_{ij} - BP_{(1)j}\right)^2} & n < 6 \end{cases} \tag{12}$$

$$RN = \left[RN_i\right]_n = \begin{bmatrix} RN_1 \\ RN_2 \\ \vdots \\ RN_n \end{bmatrix}, RN_i = \begin{cases} \sum_{k=1}^{2}\sqrt{\sum_{j=1}^{m}\left(y_{ij} - BN_{(k)j}\right)^2} & n \geq 6 \\ \sqrt{\sum_{j=1}^{m}\left(y_{ij} - BN_{(1)j}\right)^2} & n < 6 \end{cases} \tag{13}$$

$$RA = \left[RA_i\right]_n = \begin{bmatrix} RA_1 \\ RA_2 \\ \vdots \\ RA_n \end{bmatrix} = \begin{bmatrix} \sqrt{\sum_{j=1}^{m}\left(y_{1j} - \overline{y_j}\right)^2} \\ \sqrt{\sum_{j=1}^{m}\left(y_{2j} - \overline{y_j}\right)^2} \\ \vdots \\ \sqrt{\sum_{j=1}^{m}\left(y_{nj} - \overline{y_j}\right)^2} \end{bmatrix} \tag{14}$$

Step 5 Development of the final performance score matrix (*PS*) for each alternative.

$$PS = \left[PS_i\right]_n = \begin{bmatrix} PS_1 \\ PS_2 \\ \vdots \\ PS_n \end{bmatrix} = \begin{bmatrix} \exp\left(\dfrac{B_1}{3}\right) + \dfrac{RA_1}{2n} \\ \exp\left(\dfrac{B_2}{3}\right) + \dfrac{RA_2}{2n} \\ \vdots \\ \exp\left(\dfrac{B_n}{3}\right) + \dfrac{RA_n}{2n} \end{bmatrix} \tag{15}$$

$$B = \left[B_i\right]_n = \begin{bmatrix} B_1 \\ B_2 \\ \vdots \\ B_n \end{bmatrix} = \begin{bmatrix} \dfrac{RN_1}{RP_1} \\ \dfrac{RN_2}{RP_2} \\ \vdots \\ \dfrac{RN_n}{RP_n} \end{bmatrix} \tag{16}$$

where *B* is the ratio of the Euclidean distances *RN* and *RP*. The alternative having the maximum *PS* value is identified as the best option among the set of candidate solutions.

4 Assembly cobot selection using LOPCOW-OPTBIAS method

To demonstrate the application of the integrated LOPCOW-OPTBIAS approach in solving an assembly cobot selection problem, an illustrative example consisting of 13 alternative cobot models is considered in this paper, which are appraised with respect to six evaluation criteria, i.e. payload (C_1) (in kg), reach (C_2) (in mm), repeatability (C_3), weight (C_4) (in kg), power consumption (C_5) (in W) and cost (C_6) (in USD). Among them, C_1 and C_2 are beneficial in nature having their higher values preferred, while C_3, C_4, C_5 and C_6 are non-beneficial (cost) attributes requiring their lower values. Payload refers to the maximum load that a cobot can lift, carry or manipulate during a given assembly operation. It determines the type and size of the object that the cobot can handle, avoiding any potential safety hazard or limitation in the assembly process. Reach represents the distance that a cobot can outstretch from its base, including length of its arms and end-effectors. The reach of a cobot is supposed to be an important criterion determining size of the workspace and number of assembly operations that it can perform. Repeatability refers to the precision with which a cobot can perform the same assembly operation with minimum deviation from the target. It also plays a crucial role while selecting a cobot for a given assembly operation requiring higher accuracy and consistency. Repeatability enables cobots to precisely position parts on a constant basis, reducing assembly errors and maintaining integrity of the finished products. Repetitive assembly jobs also necessitate consistent execution, and higher repeatability allows the cobots to complete operations with the same level of accuracy, resulting in uniform product quality and lower variation in outcomes. Weight refers to the weight of the cobot itself, affecting mobility, flexibility and its ease of operation. A lightweight cobot can always be easily moved and repositioned to different assembly stations, while a heavier cobot may be more limited in its mobility. Power consumption denotes the amount of power that a cobot consumes during its operation. It significantly affects operating cost and energy efficiency of a cobot. Cost refers to the price of cobot, including both the initial investment cost and any ongoing maintenance or operating cost. It may be treated as the most important criterion influencing overall affordability and cost-effectiveness of a specific assembly operation. Table 2 provides the initial decision matrix, containing 13 alternatives and six criteria, considered in this paper for solving the assembly cobot selection problem using LOPCOW-OPTBIAS approach. The information regarding technical specifications of these assembly cobots is accumulated from various catalogues/websites of the concerned manufacturers (http://cobotsguide.com).

Table 2 Decision matrix for the assembly cobot selection problem

Cobot		*Criteria*					
		C_1	C_2	C_3	C_4	C_5	C_6
		Payload (kg)	*Reach (mm)*	*Repeatability (mm)*	*Weight (kg)*	*Power consumption (W)*	*Cost (USD)*
A_1	Universal Robots UR5	5	850	0.03	20.7	250	45,000
A_2	Yaskawa Motoman HC10DP	10	1200	0.05	58	500	39,000
A_3	DENSO VP6242	2.5	432	0.02	15	300	30,000
A_4	F&P Robotics F&P ILD	5	900	0.1	16	200	30,000
A_5	Stäubli TX2-60	4.5	670	0.02	52	700	50,000
A_6	Elfin-P	3	590	0.02	19	100	15,000
A_7	Fanuc CR-4Ia	4	550	0.01	48	500	30,000
A_8	LBR iisy 3 R760	3	760	0.1	22.8	450	80,000
A_9	Aubo-i3	3	625	0.05	16	150	20,000
A_{10}	DOOSAN-M0609	6	900	0.03	27.5	850	30,000
A_{11}	Techman-TM5-700	6	700	0.05	22.1	220	20,000
A_{12}	CRB 15000	5	950	0.03	28	580	28,000
A_{13}	KAWASAKI-RS007L	7	930	0.03	36	850	30,000

To estimate objective weights of the six evaluation criteria, LOPCOW method is first adopted. Applying equations (2) to (5), the corresponding criteria weights are determined, as provided in Table 3. It can be noted that cost (C_6) has the maximum priority weight, followed by repeatability (C_3). Now, employing the procedural steps of OPTBIAS method, the decision matrix of Table 2 is normalised using vector normalisation approach. The computed bi-positive ideal, bi-negative ideal and average solutions are provided in Table 4. Table 5 exhibits the corresponding values of the Euclidean distances of the alternative assembly cobots from the positive ideal solution, negative ideal solution and average solutions. This table also provides values of *B* (ratio of the Euclidean distances of *RN* and *RP*) and overall performance scores (*PS*) of all the cobot alternatives. It can be clearly noticed from Table 5 that Elfin-P model occupies the top position in the ranking list with the maximum performance score, followed by Techman-TM5-700 model. On the other hand, minimum preference is assigned to LBR iisy 3 R760 model for the given assembly operation. Relatively low cost, repeatability, weight and power consumption, and moderate payload and reach justify selection of Elfin P model as the most suitable assembly cobot.

Table 3 Criteria weights measured using LOPCOW method

Weight	C_1	C_2	C_3	C_4	C_5	C_6
	0.1023	0.1497	0.1994	0.1684	0.1442	0.2359

Table 4 Bi-positive ideal, bi-negative ideal and average solutions

Bi-positive ideal solution	$BP_{(1)}$	0.0535	0.0624	0.0111	0.0216	0.0080	0.0258
	$BP_{(2)}$	0.0374	0.0525	0.0240	0.0260	0.0157	0.0408
Bi-negative ideal solution	$BN_{(1)}$	0.0134	0.0225	0.1108	0.0833	0.0680	0.1378
	$BN_{(2)}$	0.0174	0.0326	0.0877	0.0733	0.0643	0.0857
Average solution	A	0.0263	0.0402	0.0460	0.0421	0.0348	0.0592

Table 5 Ranking of the assembly cobots using LOPCOW-OPTBIAS

Cobots	*RP*	*RN*	*RA*	*B*	*PS*	*Rank*
A1	0.1071	0.2087	0.0298	1.9485	1.9157	6
A_2	0.1692	0.1751	0.0557	1.0347	1.4140	11
A_3	0.1063	0.2444	0.0406	2.2979	2.1526	3
A_4	0.1962	0.2033	0.0708	1.0361	1.4152	10
A_5	0.1835	0.1714	0.0533	0.9341	1.3673	12
A_6	0.0856	0.2797	0.0531	3.2677	2.9740	1
A_7	0.1378	0.2234	0.0467	1.6214	1.7186	7
A_8	0.2934	0.1380	0.1028	0.4705	1.1738	13
A_9	0.1096	0.2382	0.0419	2.1728	2.0648	4
A_{10}	0.1325	0.2031	0.0375	1.5330	1.6684	8
A_{11}	0.0948	0.2280	0.0339	2.4057	2.2311	2
A_{12}	0.0984	0.2098	0.0225	2.1326	2.0366	5
A_{13}	0.1384	0.1977	0.0401	1.4280	1.6112	9

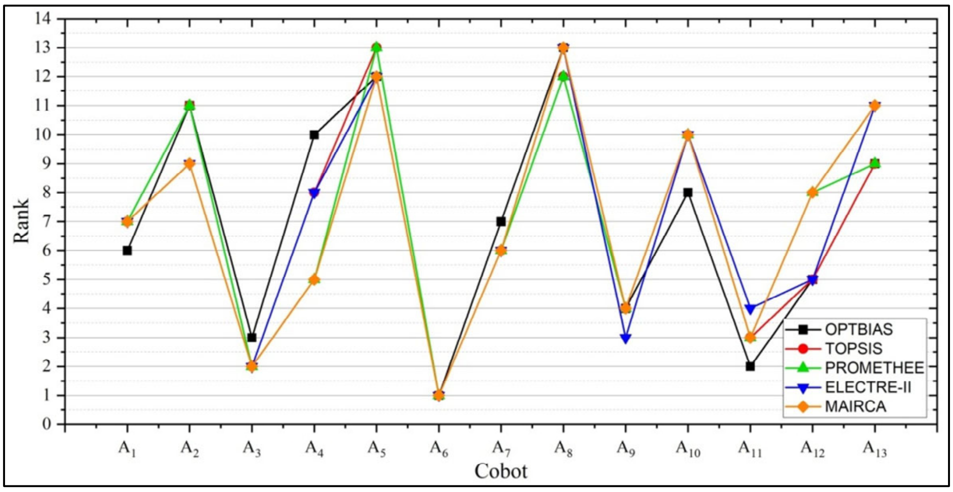
5 Comparison with other MCDM methods

This section offers a comprehensive comparative analysis of the ranking performance of the integrated LOPCOW-OPTBIAS approach against some of the popular MCDM techniques, like TOPSIS, PROMETHEE-II, ELECTRE-II and MAIRCA, and validates its appropriateness in solving assembly cobot selection problems. It is worthwhile to mention here that in all the cases, criteria weights are estimated using LOPCOW method.

5.1 Based on ranking of the alternatives

Figure 1 depicts the rankings of the alternative assembly cobots derived using LOPCOW-OPTBIAS and other considered MCDM techniques. Although there are discrepancies in the intermediate rankings of different cobots, Elfin-P is identified as the top-ranked model by all the MCDM techniques. Therefore, OPTBIAS along with LOPCOW performs particularly well in selecting the best assembly cobot based on the quantitative information considered in this problem.

Figure 1 Rankings of alternative cobots using different MCDM techniques (see online version for colours)



5.2 Based on correlation between the ranking patterns

Figure 2 portrays the Spearman's rank correlation coefficients calculated considering the ranks derived employing LOPCOW-OPTBIAS and other popular MCDM techniques, revealing a high degree of similarity with TOPSIS, PROMETHEE, ELECTRE-II and MAIRCA methods. It can be unveiled that the corresponding coefficient values are extremely high (> 0.85) proving its capability in extracting almost exact ranking patterns for the considered cobot alternatives against other MCDM techniques.

5.3 Based on Gini index

In this paper, Gini indexes (Trung, 2022) are considered to determine the superiority of cobot alternative A_6 over the others based on the application of different MCDM techniques. These indexes, provided in Table 6, are usually employed to appraise stability of different MCDM techniques in ranking of the alternatives. A Gini index of 0 denotes that the rank of a particular alternative is consistent across all MCDM methods, while a value of 1 implies complete discrepancy in rankings. While comparing two alternatives, the one with a smaller Gini index should always be preferred. In this case, alternative A_6 has a Gini index of 0, meaning that it has been identified as the best alternative by all the MCDM techniques under consideration. Conversely, alternative A_4 has the highest Gini index, proving it as the least stable, having maximum discrepancies in its rank positions across all the five MCDM techniques. Thus, it can be concluded that alternative A_6 is the most stable and preferred choice, while alternative A_4 is the least stable one.

Figure 2 Spearman rank's correlation coefficients between different MCDM techniques (see online version for colours)

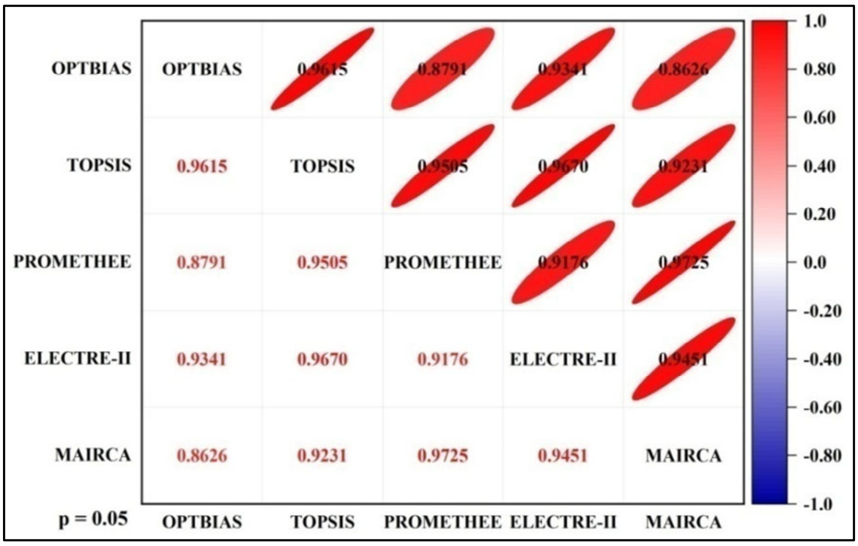


Table 6 Gini indexes for the cobot alternatives

Cobot	A_1	A_2	A_3	A_4	A_5	A_6	A_7
Gini index	0.0555	0.1666	0.0555	0.3611	0.0833	0	0.0555
Alternative	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	
Gini index	0.0833	0.0555	0.1111	0.1111	0.25	0.1666	

Table 7 Number of computation steps in OPTBIAS method

Steps	*Computation*
Normalised matrix	$P \times C$
Weighted matrix	$P \times C$
First positive-ideal solution	C
Second positive-ideal solution	C
First negative-ideal solution	C
Second negative-ideal solution	C
Average solution	C
Euclidean distances from positive-ideal solution	P
Euclidean distances from positive-ideal solution	P
Euclidean distances from average solution	P
Determination of B (ratio between *RN* and *RP*)	P
Performance score	P
Total	$2(P \times C) + 5P + 5C$

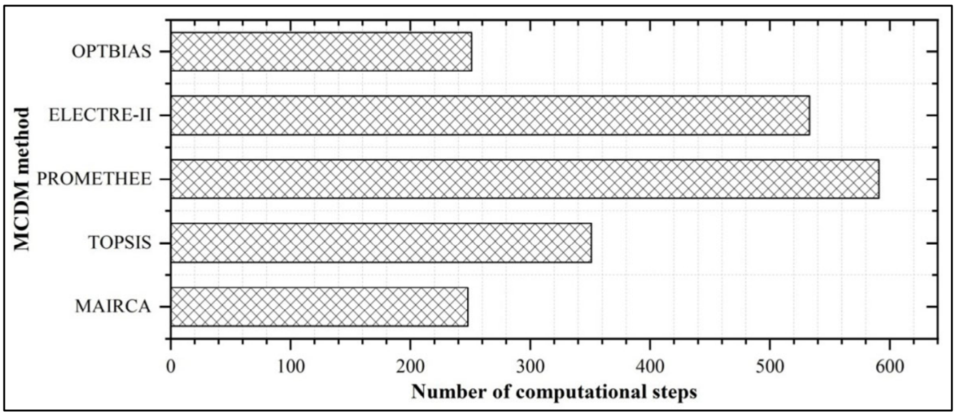
5.4 Based on number of computation steps

To compare performance of OPTBIAS method to that of other methods under consideration, the number of computations associated with its process is assessed, which is analogous to time complexity in its computation. Table 7 shows the number of computational steps involved in OPTBIAS for an MCDM problem with P alternatives and C criteria, whereas, Table 8 provides the numbers of computations required by other MCDM methods for the same MCDM problem (Chatterjee and Chakraborty, 2022). On the other hand, Figure 3 shows that for this assembly cobot selection problem having 13 alternatives and six criteria, OPTBIAS needs only 251 computations against 248, 351, 591 and 533 computations as required by MAIRCA, TOPSIS, PROMETHEE-II and ELECTRE-II methods respectively. Therefore, OPTBIAS almost outperforms the other MCDM techniques in terms of computational complexity.

Table 8 Number of computational steps for other MCDM techniques

MCDM	*Total computations required*
MAIRCA	$3PC + P + 1$
TOPSIS	$4PC + 3P$
PROMETHEE	$PC^2 + PC + 3P + C$
ELECTRE-II	$2P^2 + 2PC + 3P$

Figure 3 Computational complexity for different MCDM techniques



6 Sensitivity analysis

Detailed sensitivity analyses are conducted in this section in order to validate the ranking consistency and robustness of OPTBIAS approach with respect to gradual removal of the least important criterion, gradual removal of the least ranked alternative and different objective criteria weighting techniques.

6.1 *Based on gradual removal of the least important criterion*

Table 9 shows the set of LOPCOW weights of each criterion obtained after gradual removal of criterion which is least important from the decision matrix, and then again applying LOPCOW method to re-evaluate the corresponding criteria weights. This process is iterated till there are only two criteria left for analysis. For example, in set I, the criterion C_1 (least weighted) is first removed based on the actual LOPCOW weights, as mentioned in Table 3 and the remaining criteria weights are recalculated. Again in set II, criterion C_5 is removed from set I and the weights are reevaluated. This process continues till set IV as only two criteria are finally left for analysis. For each set, from Table 9, the corresponding ranks of the alternative assembly cobots are determined using OPTBIAS and are plotted in Figure 4. It can be observed that gradual removal of the least important criterion in the OPTBIAS method-based analysis has no effect on the best and worst ranked assembly cobots; nevertheless, slight changes are noticed in the ranks of the remaining cobots. The ranks of best (A_6) and worst (A_8) cobots thus remain unaffected, by changes in the criteria weights, proving the consistency and stability of the selected strategy.

Figure 4 Ranking of cobots after gradual removal of the least important criterion (see online version for colours)

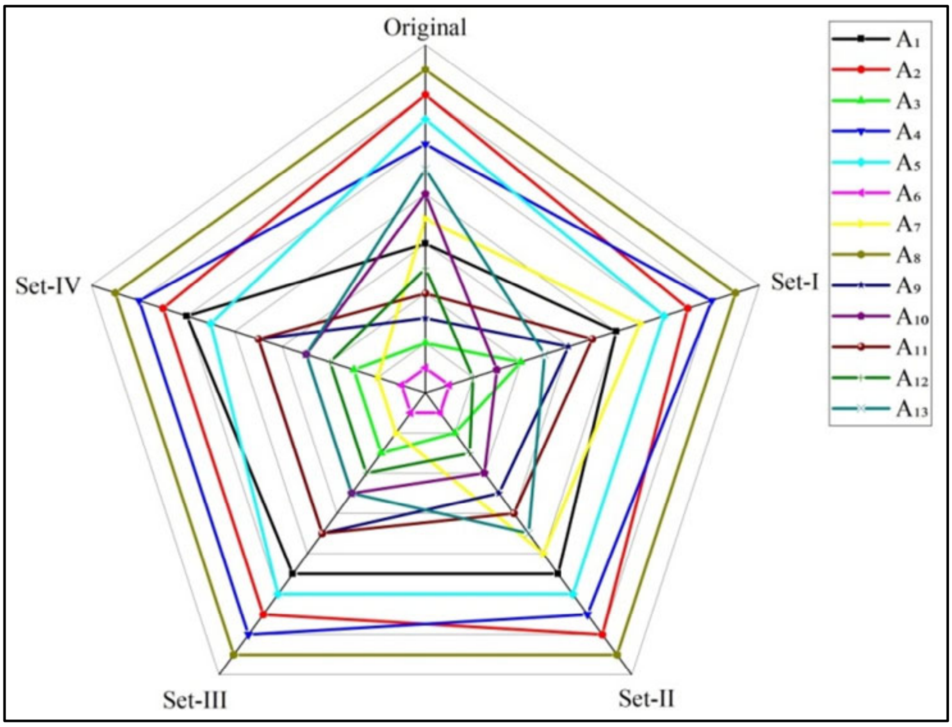
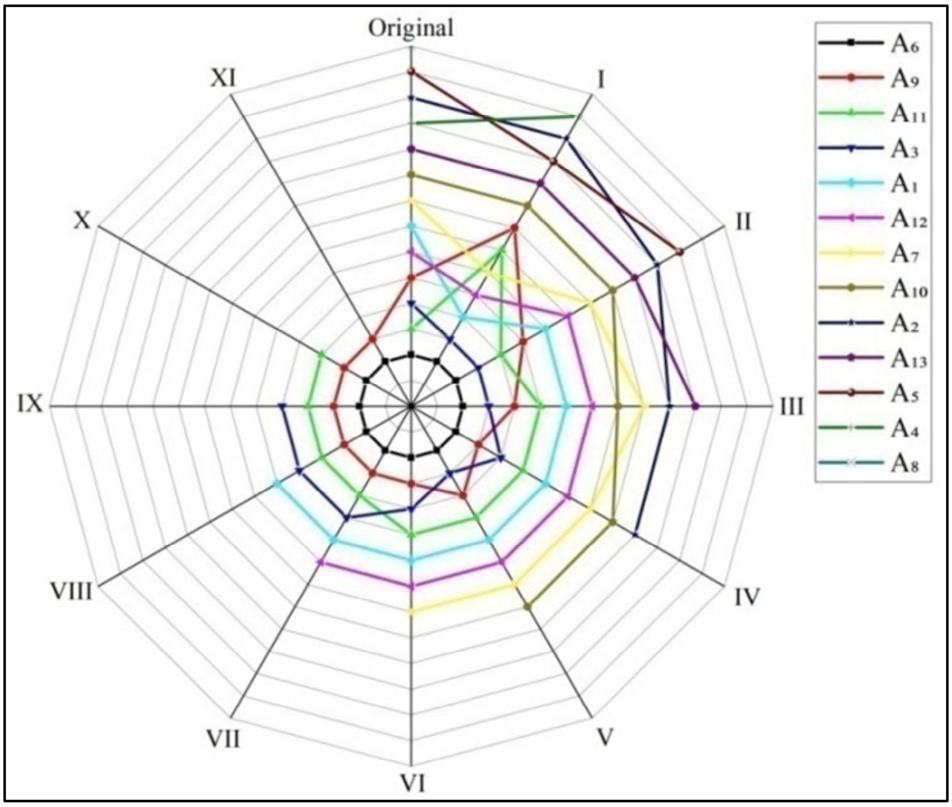


Table 9 Set of criteria weights after gradual removal of the least important criterion

LOPCOW weight	C_1	C_2	C_3	C_4	C_5	C_6
Actual weight	0.1023	0.1497	0.1994	0.1684	0.1442	0.2359
Set I	Removed	0.1668	0.2221	0.1876	0.1607	0.2628
Set II	-	0.1987	0.2646	0.2235	Removed	0.3131
Set III	-	Removed	0.3303	0.2790	-	0.3908
Set IV	-	-	0.4580	Removed	-	0.5420
Iteration stopped as only two criteria remains						

Figure 5 Ranking of cobots based on gradual removal of the least important alternative (see online version for colours)



6.2 *Based on gradual removal of the least important alternative*

Figure 5 shows cobot rankings in several cases, where each case takes into account a fresh set of criteria weights calculated after gradually removing the least preferred cobot alternative from further consideration. Table 5 reveals that LBR iisy 3 R760 (A_8) is the worst alternative for this problem. As a result, in case I, it is eliminated from the list and new criteria weights are computed using LOPCOW method based on the remaining 12 alternatives. Based on these newly estimated criteria weights, the ranks of the remaining

12 alternatives are again calculated using the OPTBIAS method. In case II, F&P Robotics F&P ILD (A_4) is removed based on the previous generated ranks, and the new set of criteria weights and associated ranks are determined. This procedure is repeated unitll case XI, at which point only two most desired cobot alternatives remains. Figure 5 clearly shows that Elfin-P (A_6) holds its top position in most of the cases. However, at the intermediate phases of the analysis there are minor variations in the ranks of A_3, A_9 and A_{11}. As a result, the position of the top-ranked cobot (A_6) is resistant to modifications while the least important alternative is gradually removed from analysis.

6.3 *Based on criteria weights using different methods*

To further carry out the sensitivity analysis, criteria weights of the considered evaluation criteria are computed using two other objective methods, i.e. entropy and CRITIC, as shown in Table 10. Based on these weights, Figure 6 is developed showing rankings of all the alternatives, while considering weights determined using entropy, CRITIC and LOPCOW methods, and the corresponding problems are solved using OPTBIAS method. It is important to note that alternative A_6 continues to perform well for all the objective criteria weighting techniques.

Figure 6 Rankings of cobots using different weighting methods along with OPTBIAS (see online version for colours)

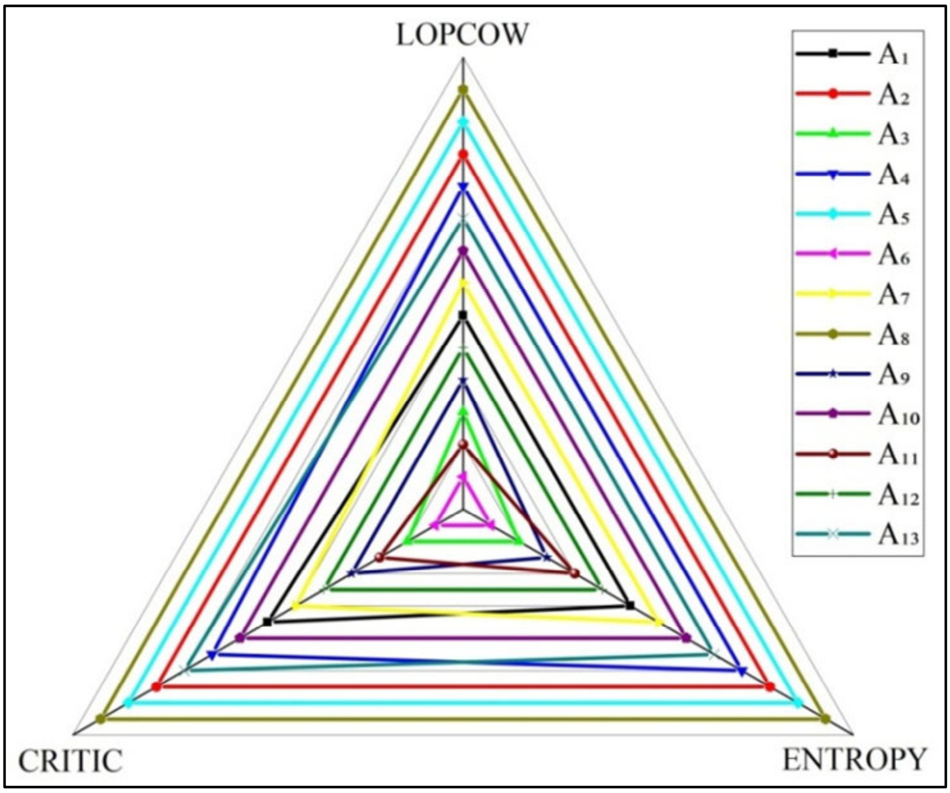


Table 10 Criteria weights using different objective techniques

Criteria	C_1	C_2	C_3	C_4	C_5	C_6
LOPCOW weight	0.1023	0.1497	0.1994	0.1684	0.1442	0.2359
Entropy weight	0.1108	0.0492	0.2928	0.1581	0.2462	0.1428
CRITIC weight	0.1600	0.1473	0.1664	0.1899	0.1855	0.1510

7 Managerial implications

The integrated technique which combines LOPCOW and OPTBIAS approaches has important practical applications in real-world production contexts. Industries confront with the challenging task of selecting appropriate assembly cobots based on several conflicting criteria. The proposed method can well address the problem to make better judgments. LOPCOW method identifies ‘cost’ as the most important criterion based on which a decision maker can efficiently prioritise cost over other criteria when selecting cobots for certain assembly procedures, particularly in industries, such as automotive manufacturing. This method is expected to result in significant cost reductions, increased productivity and improved operational efficiency.

This paper contributes to the knowledge and current literature by providing valuable insights into the fields of MCDM methods for selection of cobots. It presents an innovative and effective strategy for addressing the assembly cobot selection problem while successfully merging LOPCOW and OPTBIAS techniques. Furthermore, comparison with other common MCDM techniques supports the validation of the proposed method’s excellence and resilience. It thus strengthens understanding of MCDM methods and their applications in real-time manufacturing scenarios, giving academics and practitioners a firm platform for further study. The obtained results provide critical instruction for the decision makers and practitioners involved in cobot selection processes. The choice of ‘cost’ as the most important criterion highlights the importance of thoroughly evaluating and prioritising cost-related issues during the decision making process. However, the decision makers should also be aware of the limitations of LOPCOW and OPTBIAS methods. One of such drawbacks is their sensitivity. These limitations include sensitivity to data outliers, normal distribution assumptions and potential subjectivity in criteria weighting. Being aware of these constraints would permit more accurate decision making outcomes, ensuring that the chosen cobot align with the specific objectives and goals. The findings of this paper illustrate utility of the proposed methodology in addressing specific issues in selection of assembly cobots for real-time production processes. It allows industries, notably those in the automotive sector, to embrace and use the most recent breakthroughs in cobot technology, ultimately contributing to higher competitiveness and improved production quality. It would provide significant insights to the decision makers and researchers working in the relevant field, supporting them in making solid judgments for selection of assembly cobots for real-time production.

8 Conclusions

The paper proposes application of a new approach integrating LOPCOW and OPTBIAS methods for solving an assembly cobot selection problem in real-time manufacturing environment. LOPCOW is initially employed to evaluate objective weights of the evaluation criteria under consideration, which are subsequently utilised in OPTBIAS method to rank the alternative cobots. Based on LOPCOW, ‘cost’ is identified as the most important criterion, while OPTBIAS shortlists Elfin-P and LBR iisy 3 R760 models as the most and least preferred choices respectively for the specified assembly operation in an automobile industry. A comparative analysis of the ranking performance against other popular MCDM techniques is conducted along with detailed sensitivity analysis, which validates its consistency and robustness in accurately ranking the alternative assembly cobots. It is worthwhile to mention here that like other MCDM tools, both LOPCOW and OPTBIAS also have their own limitations. LOPCOW may not perform well while dealing with data containing outliers, and its assumption of normal distribution may not always hold in practice, leading to inaccurate weight estimations. Similarly, OPTBIAS heavily relies on criteria weights, which may introduce subjectivity and bias in the decision making process. Moreover, it may not be suitable for complex decision making problems due to its limited applicability and reliance on the Pareto-optimal solutions, which may not always accurately reflect the decision maker’s preferences and priorities. As such, it is important to carefully consider strengths and limitations of each of the MCDM methods before choosing a suitable approach for a specific decision problem. These methods can be applied for selection of both industrial and collaborative robots. The future scope of this paper may include contrasting its ranking performance against other MCDM tools, like ARAS, MABAC, CODAS and EDAS methods which are not considered here due to paucity of space. The future work may also be extended in estimating objective criteria weights based on randomness of the data in the initial decision matrix, and integrating OPTBIAS with fuzzy set, intuitionistic fuzzy set, neutrosophic fuzzy set etc. to more precisely deal with qualitative data in group decision making environment. The future research work can be further extended to include reaction of cobots to external inputs during handling, in terms of reaction speed and operator safety in particular. Considering solution of high-dimensional MCDM problems manually using this integrated approach impractical, development of a software prototype in the form of a decision support system is thus strongly recommend.

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Abbreviations

AHP	Analytic hierarchy process
ARAS	Additive ratio assessment
COCOSO	Combined compromise solution
CODAS	Combination distance-based assessment
COPRAS	complex proportional assessment
CRITIC	Criteria importance through intercriteria correlation
DEMATEL	Decision making trial and evaluation laboratory
EDAS	Evaluation based on distance from average solution
ELECTRE	Elimination et choice translating reality
LOPCOW	Logarithmic percentage change-driven objective weighting
MABAC	Multi-attributive border approximation area comparison
MAIRCA	Multi-attributive ideal-real comparative analysis
MCDM	Multi-criteria decision making
MOORA	Multi-objective optimization by ratio analysis
OPTBIAS	Ordering preference targeting at bi-ideal average solutions
PROMETHEE	Preference ranking organization method for enrichment of evaluations
QUALIFLEX	Qualitative flexible multi-criteria method
SCARA	Selective compliance assembly robot arm
SMART	simple multi-attribute rating technique
TARO	Technique of accurate ranking order
TOPSIS	Technique for order of preference by similarity to ideal solution
VIKOR	VIekriterijumsko KOmpromisno Rangiranje in Siberian
WASPAS	Weighted aggregated sum product assessment
WPM	Weighted product model
WSM	Weighted sum model

Saikat chatterjee
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