IMPLEMENTATION ISSUES IN SUPPLY CHAIN FOR LEAN TECHNOLOGY AND CIRCULAR ECONOMY IN OPERATIONS MANAGEMENT ENCOMPASSING ZED

THESIS SUBMITTED BY

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INDIA

2025

LIST OF PUBLICATIONS:

A. International Journals:

1. Dasgupta, R., Ghosh, S. K., & Mukhopadhyay, A. R. (2024). An approach to synergise the management of Lean, Green, Quality and Waste for achieving ZED emphasising SDG12. *The Journal of Solid Waste Technology and Management, 50*(4), 654–676. https://doi.org/10.5276/jswtm/iswmaw/50S1/2024.654

2. Dasgupta, R., Mukhopadhyay, A. R., & Ghosh, S. K. (2017). Reduction of lead time through curtailment of cycle time of a supplier: A case example. *International Journal of Engineering Trends and Technology (IJETT), 54*(4), 233–237. http://www.ijettjournal.org

3. Dasgupta, R., Ghosh, S. K., Mukhopadhyay, A. R., & Dolui, B. (2025). Integrated management of Scope 3 emissions in the steel supply chain. *Jurnal Presipitasi: Media Komunikasi dan Pengembangan Teknik Lingkungan, 22*(3), 1039-1050. https://doi.org/10.14710/presipitasi.v22i3.1039-1050

B. List of Presentations in International Conferences:

4. *Dasgupta, R., Sarkar, S., Dineshkumar, M., Ghosh, S. K., & Aich, A. (2025, July 5–8).* Carbon footprints in academic campus: Building a zero-waste city. *In Proceedings of the International Conference on Integrated Water Management Technologies* ***(ICWMT 2025)***, ***Beijing, China.***
5. *Dasgupta, R., Ghosh, S. K., Mukhopadhyay, A. R., & Saha, I. (2023). Monitoring the carbon footprint of manufacturing process: A methodological proposal. In Proceedings of the 13th International Conference of Sustainable Waste Management towards Circular Economy, K.J. Somaiya Management College, Mumbai, India.*
6. *Dasgupta, R., Ghosh, S. K., Mukhopadhyay, A. R., & Saha, I. (2023.). Sustainable production in the primary steel sector via resource efficiency. In Proceedings of the 13th International Conference of Sustainable Waste Management towards Circular Economy, K.J. Somaiya Management College, Mumbai, India.*
7. *Dasgupta, R., Ghosh, S. K., & Mukhopadhyay, A. R. (2024). Sustainable steel: Innovations and opportunities for reducing carbon footprint. In Proceedings of the 14th International Conference of Sustainable Waste Management towards Circular Economy, GITAM University, Visakhapatnam, India.*
8. *Dasgupta, R., Ghosh, S. K., & Mukhopadhyay, A. R. (2024). A comprehensive model for green supply chains: Leveraging circular economy and waste management for sustainable supplier selection. In Proceedings of the 14th International Conference of Sustainable Waste Management towards Circular Economy, GITAM University, Visakhapatnam, India.*
9. *Dasgupta, R., Saha, I., & Ghosh, S. K. (2020). Feasibility study of adoption of circular economy in SMEs across India. In Proceedings of the 10th International Conference of Sustainable Waste Management towards Circular Economy (pp. 1–10). Jadavpur University, India.*

10. *Dasgupta, R., Mukhopadhyay, A. R., & Ghosh, S. K. (2020). Exploring synergistic integration of ZED and waste management. In Proceedings of the 10th International Conference of Sustainable Waste Management towards Circular Economy (pp. 1–10). Jadavpur University, India.*
11. *Dasgupta, R., Mukhopadhyay, A. R., & Ghosh, S. K. (2019). Problems and prospects of tea industry in India. In Proceedings of the 9th International Conference of Sustainable Waste Management towards Circular Economy (pp. 3111–314). Kalinga Institute of Industrial Technology, India.*
12. *Dasgupta, R., Mukhopadhyay, A. R., & Ghosh, S. K. (2022). Sustainable manufacturing through recycling of wastes in primary sector like steel. In Proceedings of the 12th International Conference of Sustainable Waste Management towards Circular Economy (pp. 31–37). SVU University, Tirupati, India.*
13. *Dasgupta, R., Ghosh, S. K., Mukhopadhyay, A. R., & Saha, I. (2022). A strategy for integrating the management of lean, green, and quality to achieve ZED with a focus on SDG12. In Proceedings of the 12th International Conference of Sustainable Waste Management towards Circular Economy (pp. 51-58). SVU University, Tirupati, India.*

C. Accepted Paper Awaiting Publication:

Dasgupta, R., Mukhopadhyay, A. R., & Ghosh, S. K. (in press). Analysing emission trends and reduction strategies. Management of Environmental Quality: An International Journal.

D. Submitted and Under Review:

1. *Dasgupta, R., Mukhopadhyay, A. R., & Ghosh, S. K. (submitted).* Driving industrial sustainability: Circular economy metrics for SMEs. *Manuscript submitted for publication in the journal of Circular Economy and Sustainability.*

2. Dasgupta, R., Mukhopadhyay, A. R., & Ghosh, S. K. (submitted). *Material footprint analysis and recycling strategies for sustainable steel manufacturing*. Manuscript submitted for publication, *Resources, Conservation & Recycling*. [Submitted on 13th December 2025]

E. List of Patents: Nil

PROFORMA – 1

"Statement of Originality"

I Raktim Dasgupta registered on 21st June 2018 do hereby declare that this thesis entitled **"IMPLEMENTATION ISSUES IN SUPPLY CHAIN FOR LEAN TECHNOLOGY AND CIRCULAR ECONOMY IN OPERATIONS MANAGEMENT ENCOMPASSING ZED"** 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.

I also declare that I have checked this thesis as per the "Policy on Anti Plagiarism, Jadavpur University, 2019", and the level of similarity as checked by iThenticate software is 3 %.

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CERTIFICATE FROM THE SUPERVISORS

This is to certify that the thesis entitled "**IMPLEMENTATION ISSUES IN SUPPLY CHAIN FOR LEAN TECHNOLOGY AND CIRCULAR ECONOMY IN OPERATIONS MANAGEMENT ENCOMPASSING ZED**" submitted by Mr. **RAKTIM DASGUPTA**, who got his name registered on 18th June 2018 for the award of Ph.D. (Engg.) degree of Jadavpur University, is absolutely based upon his own work under the supervision of **PROF. SADHAN KUMAR GHOSH, PROF. ARUP RANJAN MUKHOPADHYAY** and **PROF. BISWANATH DOLOI** and neither this thesis nor any part of the thesis has been submitted for any degree/diploma or any other academic award anywhere before.

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ACKNOWLEDGEMENT

The insights and outcomes of this thesis are the result of the valuable contributions of several remarkable individuals. The author wishes to express his deepest gratitude to his Ph.D. (Engineering) thesis supervisors: **Prof. Sadhan Kumar Ghosh**, Retired Professor, Department of Mechanical Engineering; **Prof. Arup Ranjan Mukhopadhyay**, Professor, Indian Statistical Institute, India; and **Prof. Biswanath Doloi**, Professor, Department of Production Engineering, Jadavpur University, India. Their constant guidance, insightful suggestions, sustained support, encouragement, and invaluable advice from the initial conceptualization to the final stages of this research were instrumental. Without their constructive and timely mentorship, the progress and completion of this thesis would not have been possible. The author is deeply indebted to them for the time and effort they invested in this work.

The author gratefully acknowledges the cooperation and encouragement received from **Prof. Himadri Chattopadhyay, Prof. Prasanta Sahoo, Prof. Goutam Pohit, Prof. NipuModok**, the Head of the Department, and all other faculty members of the Department of Mechanical Engineering, Jadavpur University, during this research. Special thanks are extended to **Dr. Rahul Baidya**, Assistant Professor, Department of Mechanical Engineering, Institute of Engineering & Management, Kolkata, for his kind support and assistance.

The author also wishes to acknowledge **Mr. Saibal Mitra**, Quality Head, Tractor India Limited, and **Mr. Abhijit Ghosh**, Ex-Vice President, Electro steel Castings Limited, for their valuable insights and industry perspectives. Sincere thanks are extended to **FOSMI** (Federation of Small and Medium Industries) for their continuous industry support and assistance in facilitating contacts across various SMEs and steel sector enterprises throughout India. Their cooperation was vital for collecting and analysing real-world industry data and enriching the practical relevance of this research.

The author also sincerely appreciates the support and camaraderie of fellow colleagues and senior researchers, including **Dr. Ipshita Saha, Dr. Asit Aich, Dr. Sutripta Sarkar, Mrs. Sonali Roychowdhury, Mr. Dinesh Kumar**, and all other research scholars and postgraduate students whose cooperation and assistance significantly contributed to the smooth progress of this work. The author extends heartfelt thanks to his brothers and close friends—**Mr. Rittwik Sarkar, Mrs. Susmita Sarkar, Mr. Sudipto Ghosh, Mr. Arkaprabha Ghosh, Mr. Aniruddha Das, Mr. Anubhav Dey, Mr. Arhit Ghosh, Mr. Meghdoot Chakraborti, Mr. Sourjava Chakraborty, Mr. Udayan Deb, Mr. Arkajyoti Saha, Mr. Subhankar Saha, Mr. Aagnik Sengupta,**, and **Mr. Supantha Ghosh**—as well as to all family members for their unwavering belief in the value of education, their encouragement, and their moral support throughout the research journey. A special mention must be made of the author's mother, **Mrs. Matrika Dasgupta**, whose tireless support, sacrifices, and constant encouragement made this academic endeavour possible. Her unconditional love and strength have been the backbone of this journey.

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Date: 19/02/2026

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Dedication

With profound reverence and devotion,
I dedicate this thesis first and foremost to
Maa Durga,
the divine embodiment of strength, wisdom, and protection,
whose blessings have guided me through every challenge and triumph.

To my beloved mother, Mrs. Matrika Dasgupta,
whose boundless love, tireless sacrifices, and unwavering support have been the foundation of my life and learning,

To my father, Sri Tapas Bhusan Dasgupta,
whose values, encouragement, and quiet strength have always been a source of inspiration and motivation,

To my dear brothers,
Mr. Avik Dasgupta,Mr. Debroop Dasgupta, Mr. Soumyadeep Dasgupta, Mr. Souvik Dasgupta, Mr. Rittwik Sarkar, Mr. Sudipto Ghosh, Mr Arkaprabha Ghosh, Mr. Meghdoot Chakraborty,Arkajyoti Saha,Anubhav dey, Udayan Deb, Aagnik Sengupta, Subhankar Saha and Mr. Sourjava Chakraborty,
for their unconditional support, belief in me, and unwavering presence throughout this journey,

To Dr. Swarita Dasgupta,
a Ph.D. in Economics, a brilliant academic, and the wife of my brother Avik,
whose achievements, intellectual spirit, and dedication have been a true source of inspiration and pride,

To Mrs. Susmita Sarkar,

an academic content writer and the wife of my brother Rittwik,

whose thoughtful support, guidance, and valuable contributions have greatly helped me during this research,

And finally, to the youngest joy of our family,
Master Adidev Dasgupta,
whose innocent laughter and presence bring endless happiness and renewed purpose to my life.

This work is a humble offering of gratitude, love, and respect to each of you.

PREFACE

In the era of climate urgency and sustainable development, manufacturing industries face increasing pressure to reduce environmental impact while maintaining high standards of quality and operational efficiency. This thesis explores the integration of Lean, Green Technology, and the Circular Economy (CE) within the Zero Effect Zero Defect (ZED) framework, a national initiative introduced by the Government of India. The research aligns with the Sustainable Development Goals (SDGs), particularly SDG 12 (Responsible Consumption and Production), SDG 7 (Affordable and Clean Energy), and SDG 13 (Climate Action). The central aim is to develop an integrated and practical framework that supports sustainable industrial transformation, with particular focus on Indian micro, small, and medium enterprises (MSMEs).

The study begins by addressing the limitations of the traditional linear "take–make–dispose" model, which has led to resource depletion and pollution. It argues for a shift toward circular supply chains that promote reuse, recycling, and efficient resource use. Lean manufacturing contributes by reducing waste, Green technology offers environmentally sound practices, and CE ensures long-term resource circularity. When combined under ZED—which emphasizes producing defect-free goods with minimal environmental impact—these approaches strengthen India's industrial competitiveness.

The motivation for this study arises from five converging needs:

(i) addressing climate change and environmental pollution;
(ii) aligning industrial practices with India's ZED initiative;
(iii) overcoming inefficiencies in industrial waste management, particularly in the MSME sector;
(iv) enhancing quality through sustainability-focused strategies; and
(v) enabling industries to meet global ESG (Environmental, Social, Governance) standards.

A significant gap in current literature lies in the absence of a comprehensive and integrated decision-support framework that combines Lean, Green, and CE practices under ZED for practical implementation. This thesis addresses this gap by proposing a multi-criteria framework that supports systematic and informed decision-making for sustainable operations.

The work is structured around four core research objectives:

1. To develop a comprehensive ZED (Zero Effect Zero Defect) adoption framework by integrating waste management practices and Circular Economy principles validated through Lean- and Quality-driven models across multiple industrial case studies.
2. To implement a quantifiable, SME-specific Circular Economy assessment model by integrating key indicators such as eco-design, environmental footprints, and resource and energy efficiency, providing strategic insights for improving resource use and circularity.
3. To formulate mathematical models for quantifying Material and Carbon Footprints as emerging Circular Economy indicators, enabling sustainability performance evaluation through indices such as the Material Circularity Index (MCI), supported by real industrial data and optimization techniques.
4. To design a Scope 3 emission reduction strategy using Environmental Value Stream Mapping (EVSM) to identify carbon-intensive stages across supply chains and validate emission reduction measures within a circular manufacturing context.

Chapter 1 introduces the need to transition away from linear production and highlights the combined value of Lean, Green, and CE strategies under ZED.

Chapter 2 presents a detailed literature review and identifies gaps such as limited CE measurement systems, lack of integrated Lean–Green–CE models, and minimal research on Scope 3 emissions in resource-intensive industries.

Chapter 3 presents a mixed-method research methodology that combines industrial case studies with quantitative analytical techniques. This includes field investigations across seven MSMEs and two large steel plants, supported by statistical analysis and decision-making tools to evaluate sustainability performance and support improvement strategies.

Chapters 4–7 apply these methods to build and validate the ZED adoption model, SME CE assessment model, footprint-based optimization methods, and Scope 3 emission reduction strategies.

Key results show that integrating Lean (waste reduction), Green (energy and pollution control), and Quality tools (Six Sigma, TQM) with CE significantly improves sustainability performance. For example, optimizing scrap quality in an Electric Arc Furnace (EAF) plant reduced emissions by 10-14% and production costs by 10-12%. Circularity indicators such as Eco-design, Energy Resource Management, SQI, and MCI strongly predicted environmental performance.

From a policy standpoint, the findings highlight the need for stronger government interventions—such as Pollution Control Board–driven guidelines, CE-focused regulatory frameworks, mandatory Scope 1–3 reporting, and incentive-based schemes—to accelerate industrial adoption. Strengthened procurement policies and digital compliance systems can further support MSMEs in improving sustainability performance.

Future research should prioritize digitalization and AI-enabled tools. Real-time CE monitoring using IoT sensors, digital twins, and machine learning can help industries track resource use, scrap quality, emissions, and waste streams continuously. AI-driven CE dashboards and predictive analytics offer strong potential for optimizing circularity and supporting low-carbon, competitive manufacturing.

This research helps bridge the gap between Lean, Green, and Circular Economy concepts by providing practical frameworks, decision-support tools, and policy-level insights. It aligns with India's mission toward net-zero emissions, supports the *Make in India* initiative, and strengthens sustainable industrial growth through the ZED framework.

In conclusion, the thesis presents a holistic and integrated framework to guide Indian industries—particularly MSMEs—towards environmentally responsible, economically viable, and operationally efficient manufacturing systems.

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LIST OF ABBREVIATION

Chapter No	Symbol	Meaning
4	Q-P	Quality Performance
	E-P	Environment Performance
	W-P	Waste and Energy-related Performance
	S-P	Safety and Material Management Performance
	SR-P	Service-related Performance
5	$\boldsymbol{c_k}$	Critic Weight for kth Information
	W_k	Normalized Weight
	r_{ij}	Pearson Correlation Coefficient
	$P(X_A, X_B)$	Preference Function
	$\pi(A, B)$	Preference Index
	$\boldsymbol{\Phi^{+}(i)}$	Leaving Flow
	$\boldsymbol{\Phi^{-}(i)}$	Entering Flow
	$\boldsymbol{\Phi(i)}$	Net Flow
	α	Eco Design
	μ	Material Footprint
	γ	Carbon Footprint
	δ	Waste Management
	β	Resource & Energy Conservation
	w_j	Weight of indicator j
	L_{ij}	Loading of indicator j in principal component i
6	Y_{ij}	Emission (response variable) for the j-th observation in the i-th fuel type group
	μ	overall mean emission
	τ_i	τ_i is the effect of the i-th fuel type
	ϵ_{ij}	ϵ_{ij} is the random error term
	Y_{ij}'	Production cost for the j-th observation
	μ’	Overall mean production cost
	α_i'	Effect of the i-th fuel type
	ϵ_{ij}'	random error of the jth observation of ith fuel type
	d_i^+	Positive Ideal
	d_i^-	Negative Ideal
	S_1	Amount of high-quality scrap sold externally
	S_2	Amount of low-quality scrap sold externally
	M_1	Amount of high-quality scrap melted for production
	M_2	Amount of low-quality scrap melted for production
	P_1	Amount of high-quality scrap purchased from external dealer
	p_2	Amount of low-quality scrap purchased from external dealer
	A_1	Available high-quality scrap
	A_2	Available low-quality scrap
	$C_{s,i}$	Unit cost of onsite scrap of type i.
	$C_{p,i}$	Unit cost of purchase scrap of type i.
	$\boldsymbol{E_1}$	Emission factor for melting high-quality scrap (tons of CO_2 per ton).

LIST OF ABBREVIATION

Chapter No	Symbol	Meaning
6	E_2	Emission factor for melting low-quality scrap (tons of CO_2 per ton).
	D	Monthly production demand
	F_M	Emission Factor for melting process
	$E_{P;}$	Emission factor for purchased scrap
	P_m	Melting cost
	T	Carbon Tax
	c_p	Cost of purchased scrap
	Z_{max}	Maximum allowable emission
7	**M**	Mass of the finished product.
	m	Total waste used in the process.
	α	Fraction of recycled raw material.
	β	Fraction of reused raw material.
	γ	Fraction of scrap recycled.
	δ	Fraction of scrap reused.
	V(t)	Amount of virgin material being used at time t
	Λ	Proportionality constant
	M_0	Initial MCI
	S	SQI
	η_0	Initial melting efficiency
	s_0	Initial SQI
	E(t)	Emission at time t
	X	Fraction of recycled and reused raw material (raw materials recycled or reused in the process)
	y	Fraction of recycled and reused waste material (scrap or waste materials recycled or reused)
	R_{min}	Minimum fraction of virgin material.
	f	Maximum allowed fraction of recycled and reused materials (raw + waste), (dynamic input, typically $f \leq 1$)
	UP1	Iron ore/scrap transportation from supplier to plant
	UP2	Internal material handling and storage
	MS1	Electric Arc Furnace (EAF) steel production
	MS2	Rolling and finishing
	DS1	Packaging and warehousing
	DS2	Distribution to customer via road transport

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Introduction

1.1 Introduction:

The pursuit of sustainability and efficiency in operations management has led to the emergence of lean technology and circular economy as two complementary paradigms. Lean technology focuses on eliminating waste and maximizing value-added activities, while circular economy aims to reduce waste and promote the reuse and recycling of materials. However, implementing these paradigms in supply chain operations poses significant challenges. Achieving quality requires clearly understanding customer needs and ensuring that processes consistently meet defined quality standards. At the same time, organizations must minimize resource usage— such as time, energy, manpower, and materials— while maintaining product quality. This is a core principle of lean management, which aims to improve margins and ensure organizational growth and survival. Simultaneously, industries must reduce air, water, and soil pollution to improve their overall environmental performance.

Although conceptually synergistic, the integration of Lean, Green, and CE principles remains limited in practice. Industries—particularly MSMEs—face challenges such as fragmented supply chains, lack of standardized sustainability metrics, insufficient technological deployment, and limited workforce capability. The Zero Effect Zero Defect (ZED) framework of the Government of India seeks to overcome these issues by promoting high-quality, low-environmental-impact manufacturing. This thesis examines how combining Lean and Green practices within a CE-oriented ZED framework can minimize waste, reduce emissions, improve product quality, and strengthen industrial sustainability.

1.2 Background of Research:

Traditional supply chains have predominantly followed a linear ‘take-make-dispose’ model, contributing to excessive waste generation, resource depletion, and severe environmental impacts including greenhouse gas emissions and pollution. The limitations of linear models have become more evident as environmental degradation and climate concerns intensify. As a response, there is a growing emphasis on adopting circular economy (CE) frameworks that focus on resource recovery, reuse, and closed-loop production cycles (Geissdoerfer et al., 2017). Integrating circular approaches with lean methods allows industries to improve both efficiency and environmental outcomes. The **Zero Effect, Zero Defect (ZED)** framework, developed by the Government of India, further reinforces the dual goals of superior product quality and environmental sustainability. This framework supports the Sustainable

Development Goals (SDGs), particularly **SDG 12**: Responsible Consumption and Production; **SDG 7**: Affordable and Clean Energy; and **SDG 13**: Climate Action

Moreover, Indian industries often face resource inefficiencies, such as low material recovery, high scrap levels, poor waste segregation, and inefficient energy use. These inefficiencies contribute to air and water pollution, increased carbon emissions, and escalating waste management burdens. Overcoming these constraints is essential for advancing sustainable manufacturing ecosystems, enhancing global competitiveness, and ensuring compliance with evolving environmental regulations (Bressanelli et al., 2018). Addressing these challenges is essential for achieving regulatory compliance, sustainable growth, and global competitiveness.

1.3 Research Motivation:

The motivation for this research stems from the urgent need to transform industrial operations—particularly in emerging economies like India—toward sustainability while maintaining high product quality and operational efficiency. This study is driven by multiple interlinked factors:

1. **Environmental and Climate Concerns**: Industrial processes are major contributors to environmental degradation, carbon emissions, and energy overconsumption. Lean and circular practices provide a structured way to reduce environmental impacts and transition toward cleaner, more efficient production.
2. **National Push through ZED Initiative**: Launched by Prime Minister Narendra Modi, the Zero Effect Zero Defect (ZED) scheme aims to uplift Indian MSMEs by promoting energy efficiency, waste minimization, and product quality. The initiative offers a strategic opportunity for industries to align with sustainable development while enhancing market competitiveness.
3. **Industrial Waste Management in India**: India faces growing challenges in managing industrial waste, especially within the MSME sector. Poor segregation, limited recycling, and lack of technical capacity have led to resource inefficiencies and environmental damage. This research aims to design practical frameworks for sustainable waste management and material circularity.
4. **Sustainability-Driven Quality Enhancement**: Improving product quality through zero-defect approaches reduces waste, rework, and energy consumption, aligning operational efficiency with sustainability goals.
5. **Global Market Access and Compliance**: To remain competitive and attract investment, Indian industries must comply with global environmental regulations and meet ESG expectations.

6. **Need for Integrated Modelling and Decision Support**: There is a need for integrated models that combine lean, green, and circular principles to support better decision-making for sustainable operations.

1.4 Research Question:

This study aims to explore the following key research questions:

1. What is the current level of adoption and integration of Lean, Green, and Circular Economy practices in Indian manufacturing industries under the ZED (Zero Effect Zero Defect) framework?
2. How can supply chains be restructured to synergistically integrate Lean, Circular Economy, and Green Technologies to enhance quality, reduce waste, and improve environmental performance?
3. What type of mathematical or decision-support model can be developed to guide manufacturing industries in implementing Lean-Green-Circular strategies that minimize environmental footprint while ensuring product quality and process efficiency?
4. How can environmental value stream mapping (EVSM) be incorporated into process supply chains to identify hotspots of waste, energy loss, and emissions, thereby supporting sustainability-driven decision-making?

1.5 Research Focus and Innovation:

This study examines how lean methods, circular economy principles, and sustainability goals can work together to improve industrial performance. Key areas of study include the integration of lean and green technologies, circular economy performance assessment, material and carbon footprint management, and Scope 3 emission reduction strategies. A novel contribution of this study lies in its development of a comprehensive framework that synergises Lean, Green, and Circular Economy (LGCE) principles within the Zero Effect Zero Defect (ZED**)** paradigm—a relatively underexplored area in academic literature.

The study uses a combination of machine learning, statistical analysis, decision-making tools, and Six Sigma methods to support the framework. This approach connects operations management with sustainability and data analytics to support evidence-based improvements. The integration of ZED into the proposed model represents a significant innovation, providing a practical roadmap for industries—particularly MSMEs in India—to achieve high product quality with minimal environmental impact. Case studies validate the model and show practical ways to implement circular and ZED-aligned practices.

1.6 Fundamentals of Lean, Green Technology, Circular Economy and ZED:

In sustainable industrial practices, four key concepts—Lean Technology, Green Technology, Circular Economy (CE), and Zero Effect Zero Defect (ZED)—play crucial roles. Lean targets waste elimination, green focuses on environmental protection, CE promotes material reuse, and ZED integrates these for high-quality, low-impact production. Understanding their core definitions and traits is vital for building an integrated, sustainability-driven industrial model. To avoid conceptual redundancy, core principles are summarized concisely:

1.6A. Lean Technology

Focuses on systematic elimination of non-value-added activities, flow improvement, Just-in-Time (JIT), standardized work, and customer value enhancement. Table 1.1 presents the characteristics of Lean Technology.

Table 1.1 Characteristics of Lean Technology

Sl. No.	Characteristic	Description
1	Waste Elimination	Focuses on removing non-value-added activities (7 wastes: overproduction, waiting, transport, over-processing, inventory, motion, defects).
2	Continuous Improvement (Kaizen)	Encourages small, incremental improvements across all areas of production.
3	Value Stream Mapping	Analyses the flow of materials and information to identify bottlenecks and inefficiencies.
4	Just-in-Time (JIT) Production	Produces only what is needed, when it is needed, reducing inventory and lead times.
5	Pull System	Production is driven by actual customer demand rather than forecasted demand.
6	Standardized Work	Ensures consistency, efficiency, and quality by defining and maintaining best practices.
7	Visual Management	Uses tools like Kanban, 5S, and dashboards to create a clear, organized, and transparent work environment.
8	Employee Involvement	Empowers workers at all levels to identify problems and suggest improvements.
9	Process Optimization	Enhances workflows to increase productivity and reduce costs without compromising quality.
10	Focus on Customer Value	Prioritizes delivering maximum value to the customer at minimal resource input.

1.6B Green Technology

Green Technology emphasizes pollution prevention, energy efficiency, cleaner production, and life-cycle thinking. Table 1.2 presents the detailed characteristics of Green Technology.

Table 1.2 Characteristics of Green Technology

Sl. No.	Characteristic	Description
1	Environmental Protection	Minimizes pollution and harmful emissions to protect air, water, and soil quality.
2	Energy Efficiency	Reduces energy consumption through optimized processes, equipment, and renewable energy use.
3	Sustainable Resource Use	Promotes the use of renewable, biodegradable, or recyclable materials in manufacturing and operations.
4	Waste Reduction and Management	Encourages reduction, reuse, recycling, and safe disposal of industrial waste.
5	Cleaner Production	Adopts processes that minimize the use of toxic substances and reduce environmental risks.
6	Life Cycle Thinking	Considers the environmental impact of products from raw material extraction to end-of-life disposal (cradle-to-cradle).
7	Innovation and Eco-Design	Integrates environmental considerations into product design and innovation for reduced impact.
8	Compliance with Environmental Standards	Aligns with national and international environmental laws and regulations (e.g., ISO 14001).
9	Reduced Carbon Footprint	Targets reduction in greenhouse gas emissions through cleaner technologies and efficient operations.
10	Supports Circular Economy	Complements circular principles by promoting technologies that enable reuse, remanufacturing, and recycling.

1.6C Circular Economy

Circular economy is a systems-level approach to economic development and a paradigm shift from the traditional concept of linear economy model of extract-produce-consume-dispose deplete (epcd2) to an elevated echelon of achieving zero waste by resource conservation through changed concept of design of production processes and materials selection for higher life cycle, conservation of all kinds of resources, material and/or energy recovery all through the processes, and at the end of the life cycle for a specific use of the product will be still fit to be utilised as the input materials to a new production process in the value chain with a close loop materials cycles that improves resource efficiency, resource productivity, benefit businesses and the society, creates employment opportunities and provides environmental sustainability (Ghosh, S. K. 2019, ;Ghosh, S. K. & Ghosh., S K 2022) Promotes restorative industrial systems through resource efficiency, closed-loop cycles, eco-design, and long-product-life strategies.

Table 1.3 demonstrated the characteristics of Circular Economy.

Table 1.3 Characteristics of Circular Economy

Sl. No.	Characteristic	Description
1	Resource Efficiency	Maximizes the use of materials and energy across product life cycles.
2	Waste as a Resource	Treats waste not as an end, but as input for other processes (e.g., recycling, composting, remanufacturing).
3	Closed-Loop Systems	Ensures materials and products remain in use through reuse, repair, refurbishing, and recycling.
4	Product Life Extension	Encourages designing durable, upgradeable, and easy-to-repair products to extend service life.
5	Eco-Design and Innovation	Incorporates environmental considerations at the product design stage to reduce lifecycle impacts.
6	Systemic Thinking	Views the economy as an interconnected system of materials, processes, and stakeholders.
7	Regenerative Approach	Aims to restore natural ecosystems and biodiversity by minimizing extraction and pollution.
8	Business Model Transformation	Promotes service-based and product-as-a-service models (e.g., leasing instead of owning).
9	Stakeholder Collaboration	Involves supply chain partners, consumers, and governments in transitioning to circular practices.
10	Reduced Environmental Footprint	Minimizes material, water, energy use, and emissions across the entire value chain.

1.6D Zero Defect Zero Effect

ZED is a holistic certification scheme that aims to encourage manufacturers, especially MSMEs, to produce goods with zero defects and ensure that their production has zero adverse environmental and ecological effects."(Ministry of MSME, 2016. ZED Certification Guidelines).The ZED framework is a national initiative that integrates quality improvement with environmental sustainability by promoting waste minimization, process optimization, and compliance with environmental standards.

The detailed characteristics, enablers, and maturity model of ZED are presented in Tables 1.4, 1.5, and 1.6 respectively

Table 1.4 Characteristics of ZED Framework

Sl. No.	Characteristic	Management Practice	Enabler
1	Zero Defect (Quality Excellence)	Quality control, Continuous improvement (TQM, Six Sigma)	Quality management systems (ISO 9001)
2	Zero Effect (Environmental Sustainability)	Environmental management systems (ISO 14001)	Green technologies, eco-design, waste reduction
3	Lean and Green Integration	Lean principles (5S, JIT, Kaizen) + green initiatives	Eco-efficient machinery, renewable energy
4	SME Empowerment and Skill Development	Training programs and workshops	Government schemes, capacity building
5	Product and Process Innovation	R&D in cleaner production and sustainable practices	Collaboration with research institutions, adoption of new tech
6	Energy and Resource Efficiency	Energy audits, water and material optimization	Smart tech, energy-efficient equipment
7	Compliance with Environmental & Quality Standards	Regular audits, ISO/ZED certifications	Institutional support, certification bodies
8	Sustainability Audits and Certification	Third-party assessments	ZED certification framework
9	Supply Chain Sustainability	Supplier assessments, green procurement	Supplier engagement, sustainable sourcing
10	Circular Economy Mindset	Waste minimization, life-cycle management, closed-loop production	Recycling technologies, waste management partnerships

Figure1.1 ZED Maturity Assesment Model

Figure 1.2 Circular Economy Block Diagram

Table 1.5 ZED Adoption Enablers

Enabler Type	**Details**
Technological Enablers	IoT, AI, Machine Learning for predictive maintenance, automation, resource tracking
Process Enablers	Lean, Agile, and Green process implementation
Organizational Enablers	Leadership commitment, training, employee engagement
Financial Enablers	Investments in sustainable practices and clean technologies
Regulatory Enablers	Government incentives, environmental and quality compliance regulations

Table 1.6 ZED Maturity Assesment Model

Stage	Description
Stage 1: Initial	Basic awareness, early-stage adoption of ZED principles
Stage 2: Developing	Process-level integration with visible improvements in quality and environmental performance
Stage 3: Established	Full-scale implementation with measurable and consistent outcomes
Stage 4: Leading	Global benchmarking in quality and sustainability, continuous innovation and improvement

1.7 Supply Chain Linkage of Lean, Green and Circular Economy and ZED Framework:

Sustainability, quality, and environmental performance cannot be achieved through isolated improvements at the shop-floor level; rather, they are outcomes of coordinated actions across the entire supply chain. Each stage of the supply chain—raw material sourcing, manufacturing, logistics, distribution, product use, and end-of-life management—contributes directly to material consumption, energy use, emissions generation, and quality variation. Lean practices influence supply chain flow efficiency and inventory reduction, green technologies control energy and emission intensity across production and logistics, while circular economy principles restructure supply chains into closed-loop systems through reuse, recycling, and reverse logistics. The Zero Effect Zero Defect (ZED) framework further reinforces this integration by embedding quality excellence and environmental responsibility at every supply chain node. Consequently, the successful implementation of Lean, Green, Circular Economy, and ZED principles is inherently dependent on supply chain design, coordination, and governance, making a supply-chain-centric approach essential for achieving sustainable, low-emission, and high-quality industrial systems.

Table 1.7 Linkage of Lean, Green, Circular Economy and ZED across Supply Chain Stages

Supply Chain Stage	Lean Practices	Green Technology Practices	Circular Economy Practices	ZED (Zero Defect–Zero Effect) Linkage
Raw Material Sourcing	Supplier rationalization, reduced lead time, JIT procurement	Green sourcing, low-carbon materials, sustainable mining	Use of recycled/secondary raw materials	Supplier quality assurance, green procurement standards
Manufacturing / Processing	5S, Kaizen, JIT, waste elimination, defect reduction	Energy-efficient machinery, cleaner production, emission control	Scrap reuse, by-product utilization, closed-loop material flow	Zero defect production, zero discharge, energy and resource audits
Material Handling & Logistics	Lean layout, reduced handling systems, optimized transport	Fuel-efficient vehicles, route optimization	Reusable packaging, reverse logistics	Low-emission logistics, compliance with environmental norms
Distribution & Warehousing	Inventory reduction, pull-based distribution	Energy-efficient warehouses, renewable energy	Returnable pallets, packaging recovery	Quality preservation, reduced spoilage and Losses
Product Use Phase	Quality consistency, reduced warranty claims	Energy-efficient product design	Product life extension, modular design	Customer satisfaction, defect-free performance
End-of-Life / Reverse Flow	Elimination of disposal waste	Safe waste treatment, pollution prevention	Recycling, remanufacturing, refurbishing	Zero landfill target, environmental compliance
Supply Chain Governance	Value stream coordination, performance monitoring	Environmental reporting, carbon accounting	Closed-loop supply chain coordination	ZED maturity assessment and certification

1.8 Research Framework:

Figure 1.3 shows how lean, green, and quality practices interact to support eco-design, waste reduction, and recycling. This integration emphasizes carbon and material footprint reduction and energy efficiency, aligning with the Zero Effect Zero Defect (ZED) framework to support the achievement of SDGs 9, 12, and 13.

1.9 Summary:

This chapter explores how combining Lean, Green, and Circular Economy strategies within the Zero Effect Zero Defect (ZED) framework can support the shift toward more sustainable industrial practices. It outlines the research motivations, key questions, and the development of a data-centric model aimed at reducing environmental impact while improving process efficiency and product quality. By presenting the essential principles behind Lean, Green technologies, Circular Economy, and ZED, this chapter provides a strong conceptual foundation for researchers working to advance sustainable manufacturing systems.

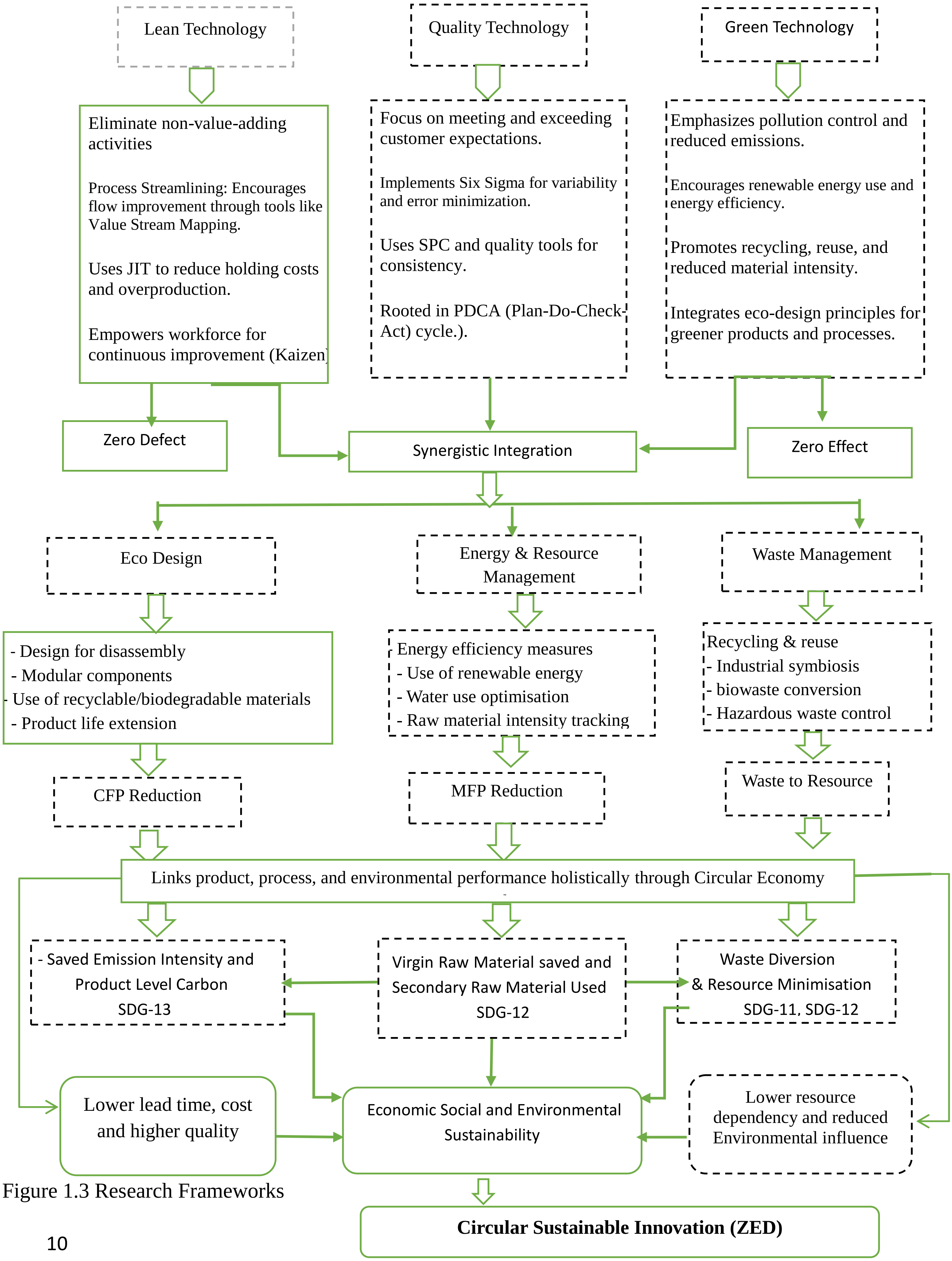

Figure 1.3 Research Frameworks

LITERATURE REVIEW& RESEARCH OBJECTIVE

2.1 Introduction:

Several past studies have explored the integration of Lean and Green practices to support sustainability transitions. Garza-Reyes (2015) conducted one of the earliest systematic reviews on lean-green integration, identifying synergies such as waste reduction, improved resource efficiency, and environmental performance. Similarly, Bai et al. (2023) proposed a Triple Bottom Line-oriented framework, emphasizing how Lean-Green integration designs can simultaneously improve economic, environmental, and social outcomes. These studies have been instrumental in establishing lean-green integration as a pathway toward sustainable operations.

Chiarini et al. (2023) and Li et al. (2023) provided further insights into how Lean practices such as value stream mapping and continuous improvement (Kaizen) align with green goals like energy efficiency, waste minimization, and pollution control. Liu et al. (2024) emphasized that the integration of Lean-Green strategies can be strengthened through process innovation, but their work focused more on large enterprises with established process maturity, neglecting the challenges faced by Small and Medium Enterprises (SMEs).

Research by De Sousa Jabbour et al. (2023) and Geng et al. (2022) attempted to link Lean-Green integration directly to circular strategies such as closed-loop manufacturing and extended producer responsibility. While these studies acknowledged the alignment between Lean principles (e.g., waste elimination) and CE strategies (e.g., reuse, remanufacturing), they often lacked empirical validation, especially across diverse industrial contexts and geographical regions.

Dora et al. (2013) and Fullerton et al. (2014) highlighted the operational benefits of Lean systems, but did not explore their potential integration with CE indicators such as Material Circularity Indicator (MCI), Water Footprint (WFP), and Carbon Footprint (CFP). Recent studies by Singh et al. (2020) and Wang et al. (2022) touched upon the role of green technologies in enhancing circularity, yet these contributions remained fragmented, and few offered a comprehensive model to quantify their collective impact on CE metrics.

Moreover, Zhang and Chen (2023) and Sadeghi et al. (2023) conducted bibliometric and systematic reviews on Lean evolution, yet they did not address how such evolutions are embedded within the circularity transition, particularly in manufacturing sectors with high material and energy intensity like steel, forging, and casting. Bevilacqua et al. (2017) pointed out the need for cultural and organizational shifts to embed circular thinking, but empirical work linking Lean and Green process improvements to measurable CE outcomes remains sparse.

2.2 Supply Chain Relevance of Lean–Green–Circular Economy Integration:

From a supply chain perspective, the integration of Lean, Green, and Circular Economy (CE) principles extends sustainability beyond firm-level operations to encompass upstream suppliers, logistics networks, and downstream recovery processes. Lean supply chain practices such as supplier integration, inventory synchronisation, and value stream coordination enhance material flow transparency and reduce non-value-adding activities across the chain (Christopher, 2016; Garza-Reyes et al., 2018). When combined with Green Supply Chain Management (GSCM), these practices enable emissions reduction through eco-friendly procurement, low-carbon logistics, and energy-efficient transportation systems (Srivastava, 2007; Hryhorak et al., 2023). Circular Economy further strengthens supply chain sustainability by promoting closed-loop configurations involving reverse logistics, scrap recovery, remanufacturing, and recycling, thereby reducing dependency on virgin materials and lowering Scope 3 emissions (Geissdoerfer et al., 2017; Wiedmann et al., 2021). However, empirical studies indicate that most supply chains lack integrated performance metrics linking Lean efficiency, environmental impact, and circularity indicators such as Material Footprint (MF), Carbon Footprint (CF), and Material Circularity Index (MCI) (Kirchherr et al., 2018; Jabbour et al., 2023). This gap is particularly evident in resource-intensive supply chains like steel, where supplier scrap quality, logistics emissions, and downstream product recovery critically influence overall sustainability performance. Consequently, a supply chain–oriented Lean–Green–CE framework—supported by tools such as Environmental Value Stream Mapping (EVSM)—is essential for identifying carbon and material inefficiencies across the value chain and enabling coordinated, data-driven sustainability interventions aligned with ZED and circular economy objectives.

2.3 Key Indicators of Lean, Green Technology and Circular Economy:

The integration of lean, green technologies with circular economy (CE) principles necessitates a comprehensive evaluation framework. Numerous scholars have contributed to the development of key performance indicators (KPIs) that evaluate environmental, operational, and resource-oriented performance. These indicators—such as carbon footprint, material footprint, eco-design, waste management, quality management, and resource optimization—have evolved into fundamental metrics for gauging sustainability in manufacturing systems. However, the fragmented nature of these studies, with limited integration across lean, green, and CE domains, presents a significant research gap. A unified framework that simultaneously incorporates operational efficiency (lean), environmental stewardship (green), and resource circularity (CE) remains underexplored. The following subsections provide a critical review of existing literature on key indicators, highlighting their contribution to sustainability and identifying existing gaps that motivate this research.

2.3.A. ***Eco Design***

Eco-design is a vital pillar of the circular economy, focusing on integrating environmental considerations into product development to reduce negative impacts across the entire life cycle. Within supply chains, it enables the creation of products that are easier to reuse, remanufacture, and recycle—supporting resource efficiency and minimising waste. This design approach aligns with circular economy goals by promoting product longevity and facilitating end-of-life recovery, thereby helping to close material loops. Recent studies have emphasised its strategic role in sustainable supply chain management. For example, Yang and Sun (2024) demonstrate how eco-design enhances resource efficiency in closed-loop supply chains involving outsourcing and remanufacturing. Similarly, the Ellen MacArthur Foundation (2024) highlights that embedding eco-design principles is essential for building circular supply chains capable of sustaining multiple product life cycles while reducing environmental footprints. Together, these insights reinforce that adopting eco-design from the outset is a key enabler of more sustainable production and consumption patterns.

2.3.B. ***Material Footprint***

The term **"material footprint"** (MF) acts as a global sustainability indicator that measures the allocation of used raw materials extraction to meet the final consumption of a particular economy (Cialani et al. 2025). Although, like the trade-based resources indicator, MF does not indicate the number of physical resources transferred from one country to another; instead, it highlights the connection between the beginning of the production chain and the final consumption (Cialani et al. 2025). MF also opened new perspectives on global supply chain materials, as they involve extracting, processing, and consuming environmental resources within the region (United Nations, 2019).

MF acts as a key indicator that assesses the effectiveness of the circular economy by tracking the need for raw materials to fulfil the consumption process (Cialani et al. 2025). As the primary aim of the circular economy is to reduce waste and maximise resource efficiency by using the products in the long term, assessing MF helps to analyse the resources (Blomsma, F. and Tennant, 2020; Moraga et al., 2022). In the year 2022, in the eighth environmental action programme, the EU focuses on reducing the

MF to safeguard natural resources and mitigate environmental impacts such as biodiversity and climate change (EEA, 2024). The EU's concern about the escalated MF highlights its importance in progressing towards a circular economy. However, Rosenboom et al. (2022) argued that lower MF does not always guarantee that the economy uses recycling products; it could also indicate reduced production. An economy should prioritise other indicators, such as waste management practices and recycling rates, for a more comprehensive view of achieving a circular economy.

2.3.C.***Carbon Footprint***

The concept of **carbon footprint** has become a crucial tool for comprehending how human activity affects the environment, especially when it comes to mitigating climate change (Cordero et al., 2020; Abbass et al., 2022; Holka et al., 2022). Usually, carbon footprint expressed in terms of CO_2 equivalent (CO_2 e) emissionsrefers to the entire amount of greenhouse gas (GHG) emissions that are created, either directly or indirectly, by a person, business, or product (Iannuzzi and Frankel, 2022). Hryhorak et al. (2023) argued that GSCM strategies focus on optimising material flow, reducing energy use, and selecting lower-carbon resources. Similarly, Elisha (2020) indicates that by shifting from a "take-make-dispose" model to a regenerative one, the circular economy reduces material consumption and emissions through recycling, remanufacturing, and extending product life. Integrating environmental criteria in procurement and supplier selection helps cut emissions linked to resource extraction (Münch et al, 2022; Bodendorf et al., 2022). These efforts significantly lower carbon footprints by reducing demand for virgin materials and minimising waste.

As organisations increasingly commit to net zero targets, accurately measuring and reporting emissions across the entire value chain has become essential to ensure accountability and transparency in global climate action, as emphasised by Hale et al. (2022) and Hernandez et al. (2025).Effectively addressing scope 3 emissions (indirect emissions from activities across the value chain, including raw material extraction, product use, and end-of-life disposal) is crucial for advancing circular economy goals, as it encourages resource efficiency, product longevity, and waste minimisation (Wiedmann et al., 2021).

GHG Protocol has classified this emission into 15 sub-categories, which are broadly classified as upstream emissions and downstream emissions. Upstream activities, such as transport and distribution, capital goods, purchased goods, and so forth, and Downstream activities, such as downstream transport and distribution, processing, use, and treatment of sold goods, and so forth are the primary sources of scope 3 emissions (GHG Protocol, 2013 cited in Emborg and Olsen, 2024). According to Ducoulombier (2021), Scope 1 and 2 emissions are associated with what companies directly buy or consume for their own operations and production; Scope 3, on the other hand, involves a complex and vast network of activities that occur outside of their entire value chain. Therefore, scope 3 emissions are essentially tough to manage as they occur outside the direct operational control of an organisation (Ducoulombier, 2021; Vieira et al., 2024). According to Zhang et al. (2021), the steel industry makes a significant contribution to annual CO_2 emissions, making it one of the key contributors to Scope 3 Emissions. According to the Environmental Protection Agency (2024), scope 3 emissions comprise a substantial portion of the carbon footprint in various industries. Scope 3 emissions typically account for 70-90% of an organisation's total emissions (Environmental Protection Agency, 2024).

2.3.D. Waste Management

Waste management is a key indicator of circular economy (CE) performance, aiming to minimise waste generation and maximise material recovery to close resource loops and enhance sustainability. Unlike linear systems, CE-driven waste strategies focus on reuse, remanufacturing, and recycling, significantly reducing environmental impact (Li et al., 2023; yang et al., 2024). Recent studies highlight the role of digital technologies in improving waste traceability and recycling efficiency within industrial systems (Zhang et al., 2024). Key performance indicators (KPIs) include waste generation rate, recovery and recycling efficiency, landfill diversion rate, hazardous waste reduction, and the material circularity indicator (MCI), which collectively measure the effectiveness of CE-orientated waste practices (WBCSD, 2023; Ellen MacArthur Foundation, 2024).

2.3.E. *Quality Management*

Quality management acts as a foundational enabler for circular economy adoption by ensuring product reliability, reducing rework, and supporting lifecycle extension. Modern quality practices, such as Taguchi’s Loss Function, Desirability Functions, and Distance Function Models, have been effectively deployed to optimize sustainability performance (Chiarini et al., 2023; Zhang & Li, 2024). These methods facilitate defect prevention, reduce variability, and enhance process stability, thereby aligning with CE principles. Advanced quality systems such as Lean Six Sigma and Total Quality Management (TQM) further extend circular benefits by enhancing product recyclability and enabling remanufacturing. Additionally, certifications like ISO 9001 and ISO 14001 reinforce environmental and quality commitments in supply chain operations, encouraging sustainable procurement, eco-friendly design, and process improvement (Geng et al., 2023).

2.4 ZED A Synergistic Lean, Green and Quality Management:

By combining lean, green, and quality management concepts, the Zero Defect Zero Effect (ZED) framework has become a key model for improving manufacturing operations. With an emphasis on reducing non-conformance, solid waste, air pollution, liquid discharge, and the waste of natural resources, ZED seeks to achieve "Zero Defects" in goods and services while guaranteeing "Zero Effect" on the environment (Hosseini & Farooq, 2019; Kumar & Gupta, 2023).

One of ZED's main goals is sustainable development, which benefits all parties involved—suppliers, workers, consumers, shareholders, and society at large. Achieving long-term sustainability requires this stakeholder-centric strategy (Singh et al., 2022). By identifying companies that are dedicated to environmental and quality stewardship, the framework also acts as a branding tool, improving their operational capabilities (Bhoganadam, 2017; Pérez-López & Díaz-Muñoz, 2023).

The ZED model encompasses 50 parameters that assess an organisation's maturity in implementing ZED principles across core and supporting processes, ensuring a holistic approach to business management (QCI Report, 2017-18; Zhang & Zhao, 2023). Furthermore, ZED can be compared with other business excellence frameworks, highlighting its unique enablers and management disciplines, which foster operational excellence (Singh, 2017; Mishra & Singh, 2022).

The ZED model covers all key aspects of business management functions practised in manufacturing. In order to improve organisational performance and lessen environmental effects, recent studies highlight the importance of integrating environmental management with lean manufacturing (Kumar & Gupta, 2023; Singh et al., 2022). The importance of ZED in modern industrial methods is further supported by this integration, which not only addresses quality and efficiency but also supports sustainable development goals. Effective **waste management** techniques are also essential to this integration since they help businesses reduce **waste production** and encourage resource efficiency, which supports **circular economy** efforts even more.

2.5 The Role of SMEs in Circular Economy Transition:

Small and Medium-sized Enterprises (SMEs) play a vital role in advancing sustainable development, not only because they make up over 90% of businesses worldwide and employ more than half of the global workforce but also due to their potential to implement impactful circular economy (CE) practices (OECD, 2023). By adopting strategies such as waste reduction, eco-design, efficient resource use, and closed-loop supply chains, SMEs contribute meaningfully to reducing environmental harm and improving sustainability outcomes (Rizos et al., 2016). Despite their potential, many SMEs face challenges related to scalability, technology adoption, and supply chain complexities (Agyemang et al., 2019). Fortunately, supportive policies, digital innovations, and collaborative ecosystems are helping more SMEs engage with CE principles (Jabbour et al., 2023). Initiatives like the European Green Deal and similar efforts in Asia and the Americas are easing financial and regulatory burdens, making CE adoption more feasible for smaller firms (European Commission, 2023). Yet, with only 7.2% of the global economy currently circular, there is a pressing need to scale up CE efforts and position SMEs as central players in the transition (Circle Economy, 2024). Looking ahead, research and policy must focus on developing tailored CE strategies for different sectors, encouraging digital tools, and building networks for knowledge exchange to fully harness the power of SMEs in creating a low-carbon, resource-efficient future.

Building on the vital role SMEs play in advancing circular practices, it's also essential to explore how circular economy indicators contribute to the broader goals of sustainable development. Indicators like waste reduction, eco-design, resource efficiency, and closed-loop supply chains not only drive more sustainable industrial practices but also support key SDGs, such as SDG 12 (responsible consumption and production), SDG 13 (climate action), and SDG 9 (industry, innovation, and infrastructure) by minimising environmental impact (Kirchherr et al., 2018; Jabbour et al., 2023; Rosa et al., 2019). These indicators match the goals of the circular economy, promoting a major change towards development that is low in carbon emissions, strong against challenges, and more inclusive. (Urbinati et al., 2017).

2.6 Integration of Lean, Green, and Quality Practices in the Steel Sector: A Circular Economy Perspective:

The global steel industry, while pivotal to economic development and industrial growth, remains one of the highest contributors to greenhouse gas (GHG) emissions. It is estimated that steel production alone accounts for nearly 7% of global CO_2 emissions, emphasizing the urgency of sustainable transformation in this sector (IRENA, 2023). In response to increasing regulatory pressure and the growing emphasis on climate commitments, a paradigm shift is being observed towards integrating Lean, Green, and Quality (LGQ) practices, particularly under the broader framework of the Circular Economy (CE).

Lean manufacturing has shown significant promise in steel production systems. The application of Lean principles—especially Lean Six Sigma—has contributed to the reduction of cycle times, rework, and inventory-related inefficiencies. In a recent case study from the Indian steel sector, Lean implementation improved the process cycle efficiency of a galvanizing line from 22% to over 60% by streamlining operations and removing non-value-adding activities (Srinivasan et al., 2024). Similarly, Lean-based improvements in procurement and supply chain management have enabled steel firms to minimize lead times and achieve cost efficiencies (Nugroho et al., 2021).

Green practices complement Lean by embedding environmental considerations into operational strategies. In steel manufacturing, this entails adopting energy-efficient technologies, reducing material usage, and minimizing emissions through pollution control. Recent empirical studies show that combining Lean and Green strategies enhances throughput and minimizes quality defects while simultaneously lowering environmental burdens (Abdelhadi et al., 2023). The integration of environmental performance metrics in production decision-making supports not only compliance but also market competitiveness, especially in regions with stringent carbon regulations.

Quality management systems serve as the third pillar in this triad, ensuring that process improvements and environmental initiatives maintain or enhance product integrity. The deployment of Total Quality Management (TQM) and ISO-based quality frameworks has proven effective in reducing variability and increasing customer satisfaction in the steel sector. Notably, quality enhancement efforts, when coupled with Lean and Green initiatives, create synergistic value—leading to superior performance in areas such as defect reduction, energy efficiency, and operational stability (Khoza, 2023).

The **integration of LGQ within a Circular Economy framework** adds further strategic depth. Circular Economy emphasizes resource recirculation, recycling, and reduction of raw material dependency. This aligns closely with Lean's waste minimization, Green's environmental stewardship, and Quality's consistency focus. The increasing adoption of Electric Arc Furnace (EAF) technology exemplifies Circular Economy (CE) principles by utilizing high proportions of steel scrap, thereby lowering Scope 1 and Scope 2 emissions compared to the traditional Blast Furnace–Basic Oxygen Furnace (BF–BOF) route (Klimek et al., 2024). However, the effectiveness of this transition depends heavily on overcoming challenges related to scrap quality, contamination, and material traceability—areas where rigorous quality control systems and Lean logistics processes are essential. Tools such as predictive maintenance, real-time monitoring, and data-driven decision-making are enabling smarter and more responsive steel manufacturing environments. Artificial Intelligence (AI)-enabled predictive models for maintenance and defect detection have been particularly effective in reducing unplanned downtime and waste, thereby supporting both Lean and Quality agendas while indirectly contributing to emissions reduction (Jakubowski et al., 2024).

2.7 Critical Analysis - Existing Model to Proposed Framework:

Although existing studies provide valuable insights into Lean, Green, and Circular Economy (CE) practices, most models remain **fragmented**, addressing only one or two dimensions at a time. For instance, Lean–Green frameworks (Garza-Reyes, 2015; Bai et al., 2023) improve waste reduction and resource efficiency, but do not incorporate CE performance metrics such as MCI, MF, WFP, or CFP. Similarly, studies linking Lean with CE strategies (Geng et al., 2022; De Sousa Jabbour et al., 2023) discuss conceptual alignment but lack **quantifiable indicators** or **decision-support models** for industrial implementation. Research on eco-design and green technologies (Yang & Sun, 2024; Singh et al., 2020) focuses primarily on environmental performance without integrating Lean efficiency tools or quality systems such as TQM or LSS. Table 2.1 describes the limitations of existing fragmented approaches.

Table 2.1 Limitations of Existing Approach

Existing Approaches	Limitations
Lean, VSM, Six Sigma	No carbon/CE indicators, no Scope 3 integration
Green/Environmental models	Weak operational alignment, limited optimization
Circular Economy indicators	Conceptual, not SME-centric, lack process data
Lean–Green or Lean–CE	Partial integration, no carbon–circularity linkage
Supplier sustainability models	No linkage to operational efficiency or CE metrics

The proposed Integrated LGC–Carbon Framework overcomes these limitations by merging Lean waste-reduction principles, Green environmental metrics, and CE indicators into a unified measurement and decision-support system. It incorporates Scope 1–2–3 emissions using Environmental Value Stream Mapping (EVSM), develops quantifiable indices such as the Material Circularity Index (MCI) and Scrap Quality Index (SQI), and uses advanced tools like CRITIC, PCA, TOPSIS, ANOVA, and optimization models for empirical validation. By linking supplier selection, carbon reduction, resource circularity, and operational efficiency within a single framework, the proposed model provides a holistic, data-driven approach—something absent in existing literature—making it more robust, industry-relevant, and capable of guiding both SMEs and steel industries toward circular, low-carbon, high-quality production systems.

2.8 Global Case Examples:

The global steel industry has emerged as a focal point for circular economy (CE) innovations due to its high material intensity, substantial carbon footprint, and extensive supply-chain dependencies. Recent international case studies demonstrate how leading steelmakers are adopting CE-aligned strategies such as scrap-based Electric Arc Furnace (EAF) production, hydrogen-based reduction, slag valorisation, and AI-driven process optimization. These initiatives highlight the transformative potential of integrating resource circularity, renewable energy, and digital technologies to reduce emissions and enhance operational efficiency. To contextualize the CE transition in heavy industries, Table 2.2 presents a synthesis of landmark CE case studies from major steel-producing regions across the world.

Table 2.2 Global Circular Economy Case Studies in Steel Sectors

Country /Region	Case Study / Industry	Key Circular Economy Actions Implemented	Outcomes / Impact	Reference
Sweden	HYBRIT (SSAB, LKAB, Vattenfall) – Fossil-free steel	Hydrogen-based reduction, 100% renewable energy	90–95% CO_2 reduction compared to BF-BOF; first fossil-free steel prototype delivered	HYBRIT. (2021). HYBRIT: Fossil-free steel – Milestone report.
European Union	Arcelor Mittal Europe	Scrap recycling loops, slag valorisation, biomass injection, carbon capture pilots	7–15% CO_2 intensity reduction; increased circular material recovery	ArcelorMittal Europe. (2022). Circular economy and low-carbon steelmaking.
USA	Nucor Steel	100% EAF steelmaking, high-purity scrap systems	Steel with 70–80% lower carbon footprint; nearly closed-loop scrap cycle	Nucor Corporation. (2023). Sustainability report.
South Korea	POSCO	Smart scrap management, waste-heat recovery, AI-integrated production	Lower energy consumption; improved scrap purity; reduced CO_2 emissions	POSCO. (2023). POSCO Green Tomorrow.
Poland	EAF Circular Steelmaking – CE Analysis	High scrap utilisation in EAF; optimization of circular loops	Reduction of Scope 1 & 2 emissions; resource savings	Klimek et al. (2024). Resources, Conservation and Recycling.
India	Lean Transformation in Galvanizing Line	Lean–CE integration through cycle time optimization, defect reduction	Cycle efficiency improved from 22% to 60%; reduced waste	Srinivasan et al. (2024). Production Planning & Control.

Small and Medium-sized Enterprises (SMEs) are increasingly recognized as critical actors in the circular economy transition, given their dominance in global industrial ecosystems and their capacity for rapid innovation. However, despite their potential, SMEs face unique constraints—technological, financial, and infrastructural—that often hinder large-scale CE adoption. Global case studies demonstrate how targeted policies, digital tools, eco-design principles, and closed-loop systems are helping SMEs overcome these challenges and implement CE practices effectively across diverse sectors such as textiles, metal fabrication, furniture, and electronics. Table 2.3 provides a consolidated overview of notable CE-focused SME case studies from multiple countries, illustrating the breadth of circular approaches and their measurable outcomes.

Table 2.3 Global Circular Economy Case Studies in SME Sectors

Country /Region	Case Study / Industry	Key Circular Economy Actions Implemented	Outcomes / Impact	Reference
Netherlands	Circular Textiles SMEs	Closed-loop textile recycling; waste sorting automation	Higher recycling rates; lower MF and CF	PBL Netherlands. (2023). Circular textiles monitoring report.
Finland	Finnish Metal Fabrication SMEs	Product-life extension, scrap reuse, eco-design	Better material efficiency; reduced waste and costs	Finland Ministry of Economic Affairs. (2023). CE Case Report.
Italy	Furniture Manufacturing SMEs	CE-driven eco-design, modular design, waste recovery	20–40% reduction in waste; improved recyclability	Italian Ministry for Ecological Transition. (2023). CE in Furniture.
Europe (multi-country)	Multi-Sector SMEs	Large empirical survey of CE adoption barriers/enablers	Identified digitalization as key CE accelerator	Jabbour et al. (2023). Business Strategy and the Environment.
Ghana–China–Brazil	SMEs in Manufacturing	Drivers & challenges of CE adoption	Financial and knowledge barriers remain dominant	Agyemang et al. (2019). Journal of Cleaner Production.
China	Digital CE Technologies in SMEs	AI-based waste sorting, predictive recovery	Higher recycling efficiency; reduced landfill	Zhang & Chen. (2024). Journal of Industrial Ecology.
Global	CE Barriers and Enablers in SMEs	Systematic review of CE adoption obstacles	Identifies lack of KPIs, financial support barriers	Rizos et al. (2016). CEPS Research Report.

2.9 Summary of Literature Review:

The literature review reveals that although Lean, Green, and Circular Economy (CE) practices each contribute to operational efficiency, environmental protection, and resource circularity, their integration remains fragmented in both SMEs and resource-intensive sectors such as steel. Existing studies largely examine these domains independently, with limited empirical evidence on combined Lean–Green–CE frameworks, insufficient incorporation of circularity metrics such as the Material Circularity Index (MCI) and Scrap Quality Index (SQI), and minimal attention to Scope 3 emissions. Research further indicates a lack of sector-specific, data-driven models capable of linking process efficiency with environmental and circularity outcomes under frameworks like ZED. These gaps collectively justify the need for a unified, quantifiable, and industry-validated model—directly shaping the research objectives of this study.

Global case studies—such as SSAB's HYBRIT hydrogen-based steelmaking in Sweden, ArcelorMittal's Smart Carbon pathway in Europe, and Nippon Steel's high-scrap EAF transition in Japan, along with SME-focused CE programmes like the EU Circularity Initiative, Japan's Eco-Town model, and Dutch industrial symbiosis networks—demonstrate practical, data-driven approaches to circularity and decarbonisation. These benchmarks highlight the gap in India, where integrated Lean–

Green–CE systems, digital monitoring, and measurable CE indicators remain limited, reinforcing the need for the unified, quantitative framework proposed in this study.

2.10 Research Gap-Research Objective:

An in-depth literature review has revealed several research gaps aligned with the formulated research questions, as summarized in Table 2.4.

Table 2.4 Research Gap and Research Objective

Research Question	Research Gap	Research Objective
RQ1: What is the current level of adoption and integration of Lean, Green, and Circular Economy practices in Indian manufacturing industries under the ZED framework?	1. Empirical studies on Lean-Green-CE integration in Indian SMEs are limited, especially under the ZED framework (Geng et al., 2022; Bai et al., 2023). 2. The application of Lean tools to CE performance indicators like MCI and waste-to-product ratio is underexplored in heavy industries such as steel (Platon et al., 2023; Hertwich, 2021).	RO-1: To develop and validate a comprehensive model for Zero Effect Zero Defect (ZED) adoption through the strategic integration of Lean, Green, Quality, and Waste Management practices across manufacturing industries, using empirical evidence from multiple industrial case studies.
RQ2: How can supply chains be restructured to synergistically integrate Lean, Circular Economy, and Green technologies to enhance quality, reduce waste, and improve environmental performance?	1. Limited integration of Material Footprint (MFP) with CE metrics and process efficiency in supply chains (Singh & Wang, 2023; Kumar et al., 2024). 2. Lack of sector-specific strategies combining CE, lean, and quality tools for CFP reduction (Arora et al., 2022; Ren et al., 2023).	RO-2: To develop a carbon footprint reduction strategy for the steel sector by integrating circular economy principles with Lean and Quality Management practices, supported by industry-specific case studies and validated through statistical analysis and optimization modelling.

Continued Table:

RQ3: What type of mathematical or decision-support model can be developed to guide manufacturing industries in implementing Lean-Green-Circular strategies that minimize environmental footprint while ensuring product quality and process efficiency?	1. Existing models address CF, MF, or Eco-design individually, but integrated, quantifiable models for unified CE performance are lacking (Cialani et al., 2025; Moraga et al., 2022; Holka et al., 2022). 2. There is a gap in decision-support models that align circular and quality metrics with process optimization in high-impact industries.	RO-3: To develop a quantifiable, SME-specific Circular Economy (CE) assessment model that integrates key performance indicators such as eco-design, environmental footprints, and resource and energy management, enabling a comprehensive evaluation of CE maturity and guiding strategic improvements in sustainability performance.
RQ4: How can environmental value stream mapping (EVSM) be incorporated into process supply chains to identify hotspots of waste, energy loss, and emissions, thereby supporting sustainability-driven decision-making?	1. Use of EVSM for mapping Scope 3 emissions (especially upstream/ downstream processes) is rare in resource-intensive sectors like steel (Zhao et al., 2024; Ramaswamy et al., 2023). 2.Sector-specific emission hotspot identification using EVSM is missing in CE integration studies.	RO-4: To develop an integrated circularity-emission evaluation framework by first formulating a quantifiable Material Circularity Index (MCI) and Scrap Quality Index (SQI) to assess material reuse efficiency and input quality, and then applying Environmental Value Stream Mapping (EVSM) to identify carbon-intensive upstream and downstream activities across supply chains. This dual approach aims to reduce Scope 3 emissions and support data-driven, circular economy-aligned sustainability interventions in resource-intensive industries.

2.11 Objectives of the Present Work:

This chapter has critically reviewed the literature on the integration of Lean and Green technologies and their contribution to Circular Economy (CE) principles. It established that Lean initiatives, focusing on waste minimization and process efficiency, and green technologies, emphasizing environmental sustainability and resource optimization, complement each other in advancing CE goals such as reuse, remanufacturing, recycling, and reduction of resource dependency.

The literature also revealed that although Lean and Green are widely adopted individually, their combined application within the CE framework remains underexplored in many manufacturing sectors, especially in the context of Indian industries operating under the ZED (Zero Effect Zero Defect) framework. Gaps identified include the lack of integrated decision-making models, absence of sector-specific implementation roadmaps, and inadequate performance metrics that link Lean-Green practices to CE outcomes.

In conclusion, the strategic integration of Lean, Green, and Quality practices offers a powerful pathway for the steel industry to transition toward a circular and sustainable future. This holistic approach supports operational excellence, resource efficiency, and environmental responsibility—key pillars of a decarbonised and resilient steel sector. In response to these gaps, this chapter has helped shape the research direction by identifying the following key research objectives:

Research Objective 1: To develop a comprehensive ZED (Zero Effect Zero Defect) adoption framework through the integration of waste management practices and Circular Economy principles validated via Lean and Quality-driven models across multiple industrial case studies.

Research Objective 2: To develop a carbon footprint reduction strategy for the steel sector by integrating circular economy principles with Lean and Quality Management practices, supported by industry-specific case studies and validated through statistical analysis and optimization modelling.

Research Objective 3: To develop a quantifiable, SME-specific Circular Economy (CE) assessment model that integrates key performance indicators such as eco-design, environmental footprints, and resource and energy management, enabling a comprehensive evaluation of CE maturity and guiding strategic improvements in sustainability performance.

Research Objective 4: To develop an integrated circularity-emission evaluation framework by first formulating a quantifiable Material Circularity Index (MCI) and Scrap Quality Index (SQI) to assess material reuse efficiency and input quality, and then applying Environmental Value Stream Mapping (EVSM) to identify carbon-intensive upstream and downstream activities across supply chains. This dual approach aims to reduce Scope 3 emissions and support data-driven, circular economy-aligned sustainability interventions in resource-intensive industries.

Overall, this chapter lays a strong foundation for the rest of the study by connecting theoretical concepts, policy developments, and industrial realities. The next chapter, **Chapter 3: Research Methodology**, presents the research design, research approach, analytical tools, and modelling techniques that will be employed to address these objectives. It outlines the methodological roadmap for validating the integrated framework and proposed models using case studies, statistical analysis, and multi-criteria decision-making tools.

Research Methodology

3.1 Introduction:

This chapter presents the research methodology designed to achieve the four main research objectives (ROs) aimed at enhancing sustainability in manufacturing industries through the integration of Circular Economy (CE) principles. The study addresses **four Research Questions (RQs),** identifies **eight Research Gaps**, and is structured around **25 Work Packages (WPs**) distributed across the **four Research objectives**. For **Research Objective 1 (RO-1)**, the study comprises six work packages, designated as **WP-1 to WP-6**.For **Research Objective 2 (RO-2)**, the work is structured across **WP-7 to WP-11**.**Research Objective 3 (RO-3)** is addressed through **WP-12 to WP-17**, while **Research Objective 4 (RO-4)** encompasses **WP-18 to WP-25**.

To accomplish these objectives, a range of advanced techniques will be used. These include statistical decision-making tools such as Analytical Hierarchy Process (AHP), TOPSIS, PROMETHEE, and Critic Method for evaluating trade-offs and making data-driven decisions. Additionally, machine learning algorithms will be applied to enhance model accuracy and validate results. Optimization techniques, such as Genetic Algorithms (GA) and Linear Programming (LPP), will help streamline processes and achieve cost-effective solutions. Lean tools like Kanban, SMED, and JIT will be employed to reduce waste and improve efficiency, while Six Sigma quality tools will be used for performance improvement.

The methodology also incorporates statistical methods like regression analysis, ANOVA, and multivariate techniques such as Principal Component Analysis (PCA) and clustering to analyse and quantify CE indicators. Python programming will be used for model development, data analysis, and validation, ensuring robust and scalable outcomes.

Game Theory will be integrated to model stakeholder behaviour and strategic decision-making for Scope 3 emission reduction, ensuring collaborative and competitive strategies are aligned with sustainability and economic goals. Figure 3.1 presents the overall research design, illustrating how each research objective is decomposed into structured work packages and methodological blocks, collectively forming the integrated research framework and guiding the progression toward future research directions. The table 3.1 elaborates the individual work packages in detail, providing a clear and systematic structure for the research process and supporting its effective execution.

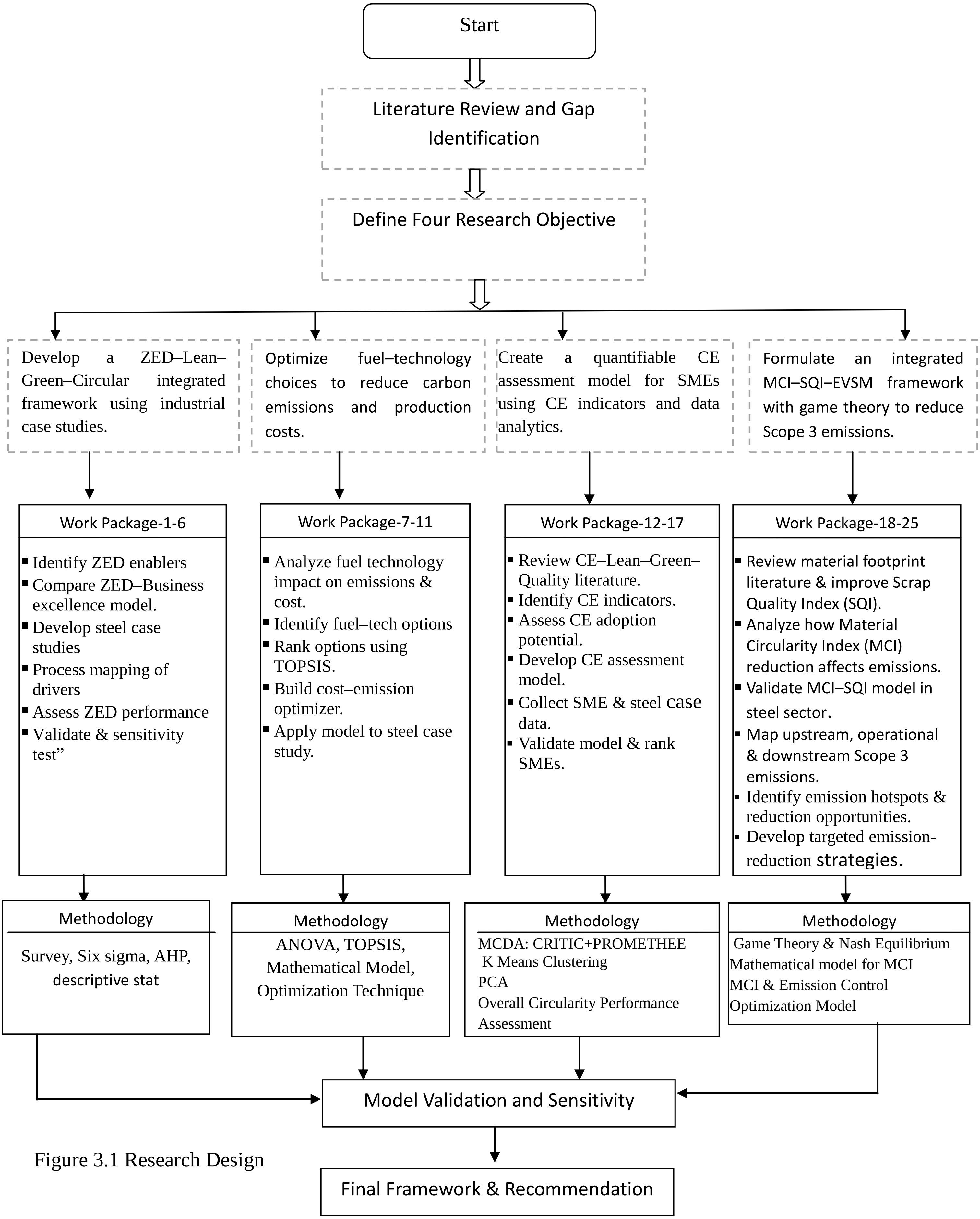

Figure 3.1 Research Design

Table 3.1 Research Objective- Work Packages

Research Objective	Work Packages	Description
Research Objective 1: (RO-1) To develop a comprehensive ZED (Zero Effect Zero Defect) adoption framework through the integration of waste management practices and Circular Economy principles, validated via Lean and Quality-driven models across multiple industrial case studies.	WP-01	Conduct a literature review on Zero Defect Zero Effect (ZED) to identify key enablers.
	WP-02	Compare the ZED Maturity Model with Business Excellence Model to highlight common principles.
	WP-03	Develop three case examples from the steel sector to demonstrate CE adoption and its impact on ZED.
	WP-04	Identify constructs and drivers through Process Map.
	WP-05	Evaluate overall ZED performance through quantitative modelling and quality assessment.
	WP-06	Validate the model parameters for applicability in similar industries, and perform a sensitivity analysis to assess the robustness of the model.
Research Objective 2: (RO-2) To develop a carbon footprint reduction strategy for the steel sector by integrating circular economy principles with Lean and Quality Management practices, supported by industry-specific case studies and validated through statistical analysis and optimization modelling.	WP-07	Analyse the effect of fuel and technology on carbon emissions and production costs in the steel sector using statistical methods.
	WP-08	Identify existing fuel-technology combinations in the Indian steel sector.
	WP-09	Determine the best possible combination using TOPSIS (Technique for Order Preference by Similarity to Ideal Solution).
	WP-10	Develop an optimization model to minimize emissions and production costs.
	WP-11	Apply the model to a case example in the Indian steel industry.
Research Objective 3: (RO-3) To develop a quantifiable, SME-specific Circular Economy (CE) assessment model that integrates key performance indicators such as eco-design, environmental footprints, and resource and energy management, enabling a comprehensive evaluation of CE maturity and guiding strategic improvements in sustainability performance.	WP-12	Literature review on CE, lean, green and quality technology.
	WP-13	Identification of indicators for Circularity Assessment.
	WP-14	Scope of adoption of CE in SME
	WP-15	A comprehensive model is developed to integrate key indicators of Circular Economy adoption. A case example of the steel industry is used to demonstrate the practical application of CE principles.
	WP-16	Data collection from steel industry and 15 SMEs.

Continued Table

	WP-17	This WP involves validating the developed model using real-world case data to assess its accuracy and identify potential over- or under-fitting issues. Furthermore, the research aims to: 1. Identify the top 10 SMEs with respect to Circular Economy (CE) adoption. 2. Develop remedial measures for improvement and cost-effectiveness in these industries. 3. Conduct an overall circularity performance analysis to provide insights into the effectiveness of CE strategies.
Research Objective 4: (RO-4) To develop an integrated circularity-emission evaluation framework by first formulating a quantifiable Material Circularity Index (MCI) and Scrap Quality Index (SQI) to assess material reuse efficiency and input quality, and then applying Environmental Value Stream Mapping (EVSM) to identify carbon-intensive upstream and downstream activities across supply chains. This dual approach aims to reduce Scope 3 emissions and support data-driven, circular economy-aligned sustainability interventions in resource-intensive industries.	WP-18	Improve Scrap Quality Index and increase the percentage of reused and recycled material.
	WP-19	Analyse the impact of reduced MCI on emissions.
	WP-20	Validate the model in the Indian steel sector.
	WP-21	1. Upstream activities: Analysing emissions from raw material extraction, processing, and transportation. 2. Operational activities: Examining emissions from energy consumption, production processes, and waste management. 3. Downstream activities: Assessing emissions from product use, end-of-life, and waste disposal.
	WP-22	Gathering and consolidating data from various sources to create a comprehensive emissions profile.
	WP-23	Calculating and examining emissions from different activities to understand their environmental impact.
	WP-24	Pinpointing areas with the highest emissions and identifying opportunities for reduction.
	WP-25	Creating targeted plans to minimize emissions and improve sustainability.

3.2 Research Methodology for RO-1 to RO-4:

The consolidated research methodology brings together all four research objectives (RO-1 to RO-4) into one clear and connected design, ensuring that the work packages, analytical steps, and validation activities follow a structured and coordinated approach instead of appearing as separate or scattered components. This integrated approach combines literature review, indicator identification, statistical analysis, multi-criteria decision-making, optimization modelling, machine-learning techniques, circularity metrics, and game-theoretic modelling into a single methodological pathway. Each research objective contributes a specific layer—ZED framework development (RO-1), emission–cost optimization (RO-2), SME-focused CE maturity assessment (RO-3), and circularity–emission integration with Scope 3 modelling (RO-4)—but all are executed through common tools and analytical platforms such as Python, Minitab, PROMETHEE, TOPSIS, PCA, clustering, MCI/SQI computation, and EVSM. Together, these interconnected methods establish a comprehensive and rigorous research design that systematically links all work packages into one cohesive methodological structure.

Table 3.2 Consolidated Research Methodologies for All Research Objectives

Category	Techniques / Methods Used	Purpose / Application Across All Research Objectives (RO-1 to RO-4)
Literature Review & Conceptual Analysis	• ZED Framework Review • CE, Lean, Green Technology Review • Material & Carbon Footprint Review	• Identify key enablers, indicators, and research gaps. • Establish theoretical foundation for ZED–Lean–Green–CE integration.
Statistical Techniques	• Descriptive Statistics • ANOVA • Tukey HSD • Regression Analysis	• Assess impact of fuel–technology combinations on emissions and cost (RO-2). • Analyze CE indicators, environmental footprints, and waste measures (RO-3).
Quality & Lean Tools	• Six Sigma • Process Mapping • VSM/EVSM • Lean Tools (5S, JIT, Kanban, SMED)	• Benchmark waste, defects, and cycle-time improvements (RO-1). • Map emissions hotspots for Scope 3 reduction (RO-4).
Multi-Criteria Decision Making (MCDM)	• AHP • TOPSIS • PROMETHEE • CRITIC Weighting	• Prioritize ZED factors (RO-1). • Rank optimal fuel–technology combinations (RO-2). • Assess and rank SMEs based on CE maturity (RO-3).
Machine Learning & Data-Driven Modeling	• K-Means Clustering • PCA • Predictive Modelling (Python)	• Classify SMEs into CE performance groups (RO-3). • Identify dominant CE indicators and factor loadings (RO-3).
Circularity & Sustainability Metrics	• Material Circularity Index (MCI) • Scrap Quality Index (SQI) • Carbon Footprint (CFP)	• Quantify material reuse efficiency (RO-4). • Link scrap quality to emissions and cost optimisation (RO-2 & RO-4).
Optimization Techniques	• Linear Programming (LP) • Goal Programming • Differential Equation Models • Genetic Algorithm (GA)	• Optimize emission–cost trade-offs for fuel–technology selection (RO-2). • Model circularity–emission interactions (RO-4).
Game Theory Modeling	• Non-Cooperative Game • Cooperative Game • Nash Equilibrium • Payoff & Utility Functions	• Model stakeholder collaboration for Scope 3 emission reduction (RO-4).
Data Collection & Case Studies	• Steel Plant Case Studies (BF-BOF, EAF) • 15 SME Case Data • Field Visits, Interviews, and Operational Data	• Validate models across real industrial environments (RO-1 to RO-4).
Software Tools	• Python • Minitab • Microsoft Excel	• Statistical analysis, optimization, clustering, PCA, modeling, and visualization for all research objectives.

3.3 Data Sources and Validation Procedures:

This research is grounded entirely on original primary data collected directly from manufacturing industries. The data sources and validation procedures used across both the SME survey and steel-sector case studies are described below to ensure methodological transparency and authenticity.

3.3.1 **Data Collection for Objective 1**

The data collection process for Objective 1 was designed to capture a multi-dimensional view of **Zero Defect Zero Effect (ZED)** performance across three diverse manufacturing units: ductile iron pipe, cylinder, and aircraft components. The data were gathered through a structured, three-phased approach:

Phase I: Qualitative Process Mapping and Construct Identification Initial data were collected via **SIPOC-based process mapping** to define the operational boundaries of each industry. This involved conducting on-site observations and semi-structured interviews with functional heads across production, quality, maintenance, logistics, and EHS departments. These qualitative insights facilitated the identification of **20 constructs** and **50 ZED enablers**, which were further refined into a set of measurable performance indicators.

Phase II: Quantitative Binary Diagnostic and Sigma Benchmarking To establish baseline and improved performance levels, primary data were extracted from production logs, quality records, maintenance histories, and waste registers. For each of the 20 constructs, data were recorded for **4 to 5 key drivers** using a **binary variable system**. A value of **1** was assigned for active implementation and **0** for operational gaps. This binary dataset provided the empirical foundation for calculating both **baseline and post-improvement sigma ratings**, allowing for a statistical comparison of functional efficiency before and after targeted interventions.

Phase III: Expert Judgment for Strategic weighting The final data collection phase involved gathering subjective expert judgments from managers and domain specialists. Utilizing **pair wise comparison questionnaires**, data were collected to satisfy the requirements of the **Analytic Hierarchy Process (AHP)**. These data points allowed for the quantification of the relative importance of each cluster—Quality, Environment, Waste/Energy/5R, Safety, and Serviceability—thereby enabling the prioritization of ZED performance metrics across the case industries.

3.3.2 Data Collection for Research Objective 2

The data used for evaluating circular economy performance in SMEs were collected through a carefully planned field-based approach that evolved progressively during the course of the study, rather than being imposed through a rigid, pre-defined theoretical structure. The study initially engaged with **fifteen SMEs** to ensure broad sectoral representation and to capture variability in circular economy adoption across different manufacturing contexts. At the outset, informal discussions were conducted with plant managers, quality heads, and production supervisors to understand how circular economy practices are perceived and implemented at both shop-floor and managerial levels. These interactions, supported by preliminary site observations, informed the refinement of the data collection strategy. Following this exploratory phase, a structured questionnaire was developed iteratively. An initial version of the questionnaire was prepared based on insights from existing literature and field interactions and was subsequently pilot-tested in two SMEs. Feedback from the pilot study enabled simplification of technical language, elimination of ambiguous items, and alignment of questions with actual operational practices rather than sustainability goals. The finalized questionnaire captured five core circular economy dimensions—eco-design, material footprint, carbon footprint, waste management, and resource and energy conservation—using a five-point rating scale reflecting the extent of implementation. Data were primarily collected through on-site interviews and guided questionnaire administration, allowing clarification of responses and minimizing respondent bias. PROMETHEE-based preliminary analysis was applied to the full set of fifteen SMEs, after which detailed ranking was restricted to the top ten SMEs to retain meaningful discrimination, as the remaining firms exhibited very low and closely clustered net flow values. Among these, **seven SMEs showing positive net flow values ($\Phi > 0$)** were shortlisted for detailed analysis, as they demonstrated relatively stronger circular economy orientation. For these seven SMEs, questionnaire responses were systematically validated using available secondary evidence, including material purchase records, scrap generation logs, energy consumption bills, waste disposal invoices, and internal audit reports. In instances where complete numerical data were unavailable, relative performance assessments were finalized through cross-functional managerial consensus. Consistency and reliability were further ensured by comparing responses across different functional roles within each organization and resolving discrepancies through follow-up discussions. Ethical considerations were strictly observed, including informed consent, confidentiality, and anonymization of company identities. This phased and iterative data collection process ensured that the final dataset was grounded in real industrial practices and constraints, thereby providing a robust and credible foundation for subsequent circular economy performance evaluation and decision-support analysis.

3.3.3 **Data Collection for Research Objective 3**

The data used in this chapter were collected through a structured industrial case-based approach aimed at capturing realistic production, cost, and emission characteristics of steel manufacturing under different technology–fuel combinations. The study focused on operational steel plants in India where both conventional and emerging production routes coexist, enabling comparative analysis under real industrial constraints. Initial engagement involved detailed discussions with plant management, production engineers, and energy and environment personnel to understand existing process configurations, fuel usage patterns, and decision-making criteria related to cost and emissions. Based on these interactions, data collection was planned in two stages: technology–fuel performance assessment and scrap-based Electric Arc Furnace (EAF) optimization analysis. Primary operational data were obtained from plant production records covering a continuous multi-month period, ensuring that the dataset reflected routine operating conditions rather than short-term experimental trials. The collected data included fuel-wise production costs, electricity and auxiliary fuel consumption, process-level emission data, scrap consumption rates, melting yields, and quality-related losses. Emission data were derived from plant-level energy consumption records using standard emission factors consistent with national and international reporting practices, while production cost data were compiled from accounting records covering raw materials, energy, consumables, labor, and maintenance. To ensure comparability across fuel types and technologies, all data were normalized to a common functional unit of steel production. Prior to analysis, the dataset was screened for consistency, and outliers arising from abnormal shutdowns or maintenance periods were excluded following consultation with plant personnel. Statistical adequacy of the data for inferential analysis was verified before applying ANOVA to examine the significance of fuel type on production cost and emissions. Only technology–fuel combinations that were either operationally feasible or already implemented in Indian steel plants were retained for subsequent multi-criteria decision analysis using TOPSIS, ensuring practical relevance of the results. For the optimization segment, detailed scrap-related data were collected from an operating EAF unit, including quantities of high- and low-quality scrap, procurement costs, melting efficiencies, quality loss rates, and emission factors. These data were obtained from daily production logs, scrap yard records, and energy monitoring systems and were further validated through cross-checks with monthly summary reports. Where variability existed due to scrap quality fluctuations, averaged values over the data collection period were used to represent stable operating conditions. Ethical considerations were maintained throughout the study, with plant identities anonymized and data used solely for academic purposes. This carefully planned, plant-driven data collection process ensured that the analyses presented in this chapter are grounded in actual industrial performance, thereby enhancing the credibility and applicability of the cost–emission trade-offs and optimization outcomes derived from the study.

3.3.4 **Data Collection for Research Objective 4**

The data used in this chapter were collected through a case-based, supply-chain-oriented field study designed to capture material circularity and Scope-3 emission behaviour across upstream, internal, and downstream stages of steel manufacturing. The study was conducted in collaboration with an operating steel production system where both material flow and supply-chain interactions could be observed over time. Initial planning involved multiple rounds of interaction with plant management, procurement personnel, logistics coordinators, and environmental officers to understand the structure of the supply chain, material sourcing practices, scrap usage patterns, and emission reporting mechanisms. Based on these discussions, the supply chain was segmented into upstream, manufacturing, and downstream stages, and a clear system boundary was defined to ensure consistency in data capture. Data collection was carried out in two complementary phases: material circularity assessment and Scope-3 emission mapping. For material circularity analysis, primary data were obtained from production and scrap management records, including quantities of virgin raw material consumed, recycled and reused material inputs, scrap generation rates, recovery efficiencies, and waste reuse practices. These data were collected over a continuous operational period to capture normal production variability and were used to compute baseline values of the Material Circularity Index (MCI) and Scrap Quality Index (SQI). Scrap quality data, including contamination levels, recovery rates, and melting efficiency, were collected from scrap yard logs, laboratory reports, and furnace operation records and were cross-validated with monthly production summaries.

For Scope-3 emission analysis, data were collected across identified upstream and downstream activities, including raw material and scrap transportation, internal material handling, distribution logistics, and post-production processing stages. Activity data such as transport distances, fuel consumption, material throughput, and handling frequencies were obtained from logistics records, vendor invoices, and dispatch documentation, while emission estimates were derived using standard emission factors consistent with GHG Protocol classifications. Environmental Value Stream Mapping (EVSM) was employed as the primary tool to integrate material flow, energy use, and emission data across supply-chain stages, enabling identification of emission hotspots and high-impact stakeholders. To enhance data reliability, emission and material flow estimates were discussed and validated with responsible functional managers, and extreme values caused by abnormal operational conditions were excluded from analysis. Following baseline assessment (Phase I), data were recollected after implementation of selected circular and collaborative interventions, enabling Phase II comparison and evaluation of improvement effects on MCI and Scope-3 emissions. For the cooperative game-theoretic analysis, stakeholder-level emission reduction potentials and cost estimates were compiled through a combination of operational records and managerial estimates, reflecting realistic abatement capabilities. Ethical considerations were strictly maintained, with confidentiality agreements, anonymization of company and stakeholder identities, and exclusive academic use of data. This longitudinal, multi-source data collection approach ensured that the analysis presented in this chapter is grounded in actual supply-chain behaviour and material flow dynamics, thereby providing a robust foundation for optimized material circularity modeling and credible Scope-3 emission reduction strategies.

3.4 Summary:

This chapter has systematically outlined the research methodology tailored to each objective, ensuring a structured approach to integrating Circular Economy with Lean, Green, and Quality practices. By employing tools such as six sigma, AHP, TOPSIS, PROMETHEE, optimization models, and Game Theory, the study ensures that outcomes are measurable, achievable, and relevant to real-world industrial challenges. The methodologies are designed to be replicable and implementable within defined timeframes, ensuring practical applicability and strategic impact in sustainable manufacturing. Detailed, objective-specific data collection for all four research objectives was carried out through phased field studies, on-site industrial investigations, guided surveys, operational records, and supply-chain–level validation, ensuring that the empirical foundation of the research is grounded in actual industrial practices rather than theoretical assumptions. The objective-wise data collection strategies, sources, and validation approaches adopted across Chapters 4 to 7 are summarized in Table 3.3, which provides a consolidated reference linking each research objective to its corresponding empirical data and section locations within the thesis.

Table 3.3 Summary of Data Collection and Reference Location for All Research Objectives

Research Objective	Case / Study Context	Data Source	Nature of Data Collected	Data Collection Approach	Validation Strategy
Objective 1: ZED performance assessment	Ductile iron pipe, cylinder, and aircraft component manufacturing units	Plant operations, functional departments	Process-level qualitative data, binary implementation data, expert judgment	SIPOC-based process mapping, on-site observations, semi-structured interviews, binary diagnostic survey, AHP pairwise comparison	Cross-functional verification, baseline vs post-improvement comparison, expert consistency checks
Objective 2: Circular Economy performance of SMEs	15 SMEs (shortlisted to 10; final 7) across manufacturing sectors	SME management and operational records	Likert-scale CE indicator scores, qualitative validation evidence	Guided questionnaire survey, on-site interviews, pilot testing, PROMETHEE-based screening	Cross-source triangulation, managerial consensus, normalization and consistency checks
Objective 3: Cost–emission optimization in steel production	Operating steel plants (BF–BOF and EAF routes)	Plant production, energy, and cost records	Fuel-wise production cost, energy use, emission data, scrap quality parameters	Extraction from production logs, energy bills, accounting records, engineer consultations	Outlier screening, functional unit normalization, statistical adequacy checks, NSGA II.
Objective 4: Material circularity and Scope 3 emission reduction	Integrated steel supply chain (upstream–internal–downstream)	Supply chain stakeholders and logistics records	Material flow data, scrap recovery, transport activity data, stakeholder emission estimates	Longitudinal case study, EVSM-based data mapping, stakeholder interactions	Multi-source triangulation, Phase I–Phase II comparison, stakeholder validation

Holistic Integration of Lean Green ZED and Circular Economy with Quality Management toward ZED Excellence

Work Packages		
Research Objective	**Work Packages**	**Description**
Research Objective 1: (RO-1) To develop a comprehensive ZED (Zero Effect Zero Defect) adoption framework through the integration of waste management practices and Circular Economy principles, validated via Lean and Quality-driven models across multiple industrial case studies.	WP-1	Conduct a literature review on Zero Defect Zero Effect (ZED) to identify key enablers.
	WP-2	Compare the ZED Maturity Model with Business Excellence Model to highlight common principles.
	WP-3	Develop three case examples from the steel sector to demonstrate CE adoption and its impact on ZED.
	WP-4	Identify constructs and drivers through Process Map.
	WP-5	Evaluate overall ZED performance through quantitative modelling and quality assessment.
	WP-6	Validate the model parameters for applicability in similar industries, and perform a sensitivity analysis to assess the robustness of the model.

4.1 Introduction:

The advent of the Zero Defect and Zero Effect (ZED) concept has thrown a significant challenge in integrating quality management, lean philosophy and green management within industrial operations. Achieving quality outcomes requires fulfilling both external and internal customer expectations through effective requirement analysis and meeting specific quality dimensions. At the same time, organizations must minimize resource usage—such as time, energy, manpower, and materials—while maintaining product quality. This is a core principle of lean management, which aims to improve margins and ensure organizational growth and survival. Simultaneously, environmental sustainability must be prioritized by minimizing air, water, and soil pollution, in line with green management principles.

To enhance this integration, the **Circular Economy (CE)** perspective is increasingly relevant. CE focuses on designing waste out of the system, extending product life cycles, and promoting the reuse, recycling, and remanufacturing of materials, thereby reducing reliance on virgin resources. Integrating CE principles strengthens the ZED framework by promoting material efficiency, reducing environmental footprints, and enabling closed-loop industrial practices—essential for achieving long-term sustainability.

This study highlights a mutually beneficial relationship between lean and green , circular economy and offers a thorough methodology for businesses to improve operational effectiveness and advance environmental sustainability. In order to evaluate overall ZED performance in the manufacturing sector, the study also outlines the key parameters of a ZED Maturity Model. The study demonstrates a model for prioritising the parameters using the Fuzzy Analytical Hierarchy Process (FAHP). Along with offering organisations useful approaches to improve their sustainability efforts while attaining operational excellence, the study also provides actionable plans for enhancing the performance of vital few parameters using the Six Sigma metric. Through a blend of theoretical frameworks and real-world examples, this article illustrates how supply chain environmental initiatives can align with overall organisational performance to minimise industrial solid waste and contribute to Sustainable Development Goal 12 (SDG 12). The alignment of ZED principles with SDG 12 is illustrated in **Figure 4.1**, which demonstrates how the integration of lean, green, quality practices enables responsible resource use and production efficiency.

This study investigates the adoption of ZED practices in three distinct Indian manufacturing sectors: a ductile iron pipe manufacturer, a cylinder production company, and an aircraft component supplier. These industries were selected due to their similar SIPOC (Suppliers, Inputs, Process, Outputs, and Customers) structures, which enable a comparative analysis while accounting for varying environmental impacts. The objective is to identify key ZED enablers and evaluate each industry's contribution toward Sustainable Development Goal 12: Responsible Consumption and Production.

The ductile iron pipe industry, located in eastern India, has integrated production facilities—from Blast Furnace-based metal production to pipe casting and finishing—along with a BF gas-based captive power plant and a 3.6 L TPA sinter plant. The cylinder manufacturing firm in southern India produces a range of high-pressure cylinders and tanks, serving major public sector clients like IOCL, HPCL, and BPCL, and follows global manufacturing standards. Meanwhile, the aircraft component manufacturer, also based in the south, supplies critical aerospace components including titanium fittings, GRE systems, and heavy wall forgings for aero engines and piping systems. Although the three manufacturing products (DI Pipe, Cylinder, and Aircraft Components) exhibit a similar high-level SIPOC structure**,** this similarity is intentional and methodologically justified. The SIPOC framework is used in this study not to replicate identical processes, but to establish a common structural interface for comparative assessment across heterogeneous manufacturing systems.

Figure: 4.1 Responsible Consumption and Production (12th SD Goal) through ZED

The detailed process flows for these three industries are illustrated in Figures 4.2, 4.3, and 4.4 respectively.

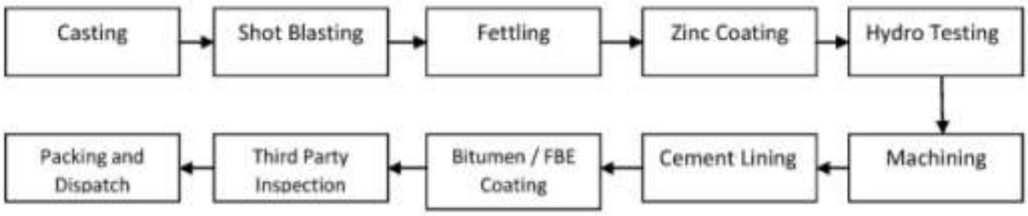

Figure 4.2 Process Map of Production of Di Pipe

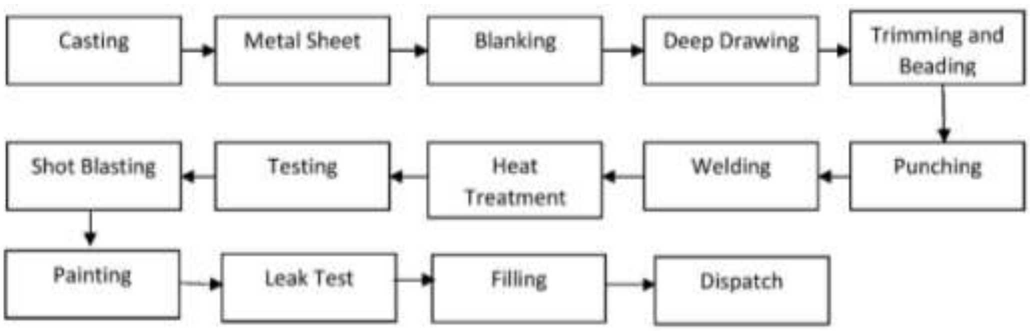

Figure 4.3 Process Map of Production of Cylinder Manufacturing

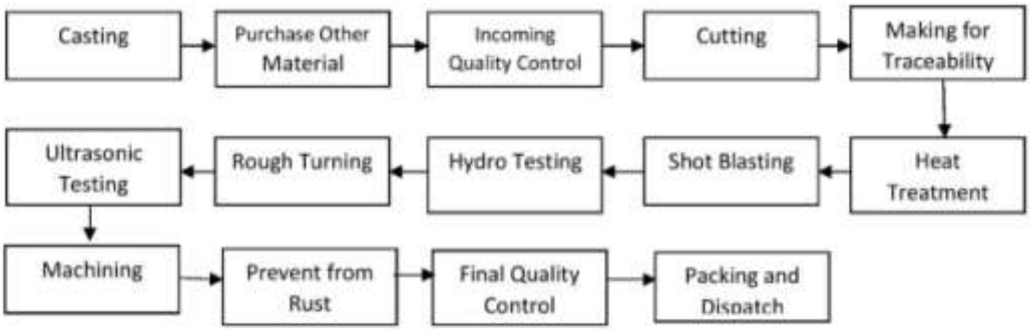

Figure 4.4 Process Map of Pipe Fittings and Aircraft Component Manufacturing

4.2 Research Frame:

Considering 12 management practices and 50 enablers of ZED (Appendix -1) as well as circular SIPOC interfaces, 20 Constructs have been identified. Our main objective is to measure the functional efficiency of the three industries with respect to identified Constructs to achieve social, environmental, and economic sustainability. The identified constructs considering the SIPOC interface and ZED management practices with detailed functional areas of three industries are described respectively in Figure 4.5 in Table 4.1.

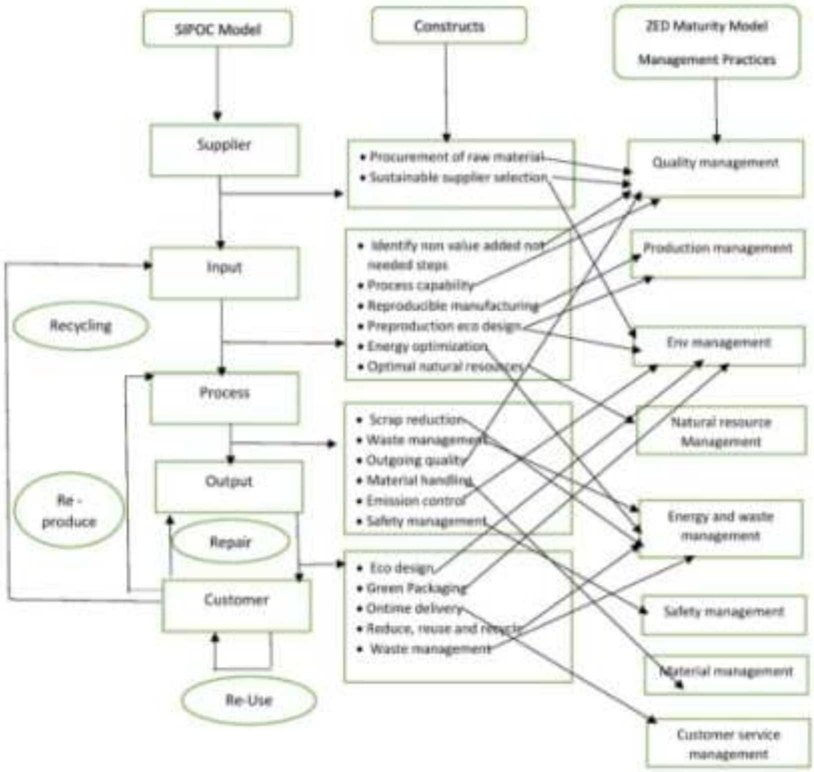

Figure4.5 Derived Constructs from Circular SIPOC Interface Encompassing ZED Management Practices

Table 4.1 Description of Constructs with SIPOC Interface and Functional Area

SL No.	Constructs	Functional Area		
		DI Pipe	Cylinder	Aircraft Component
1	Procurement of raw material	Casting, Cement Lining, Zinc Coating	Casting, Paint job	Casting, Purchase Material
2	Sustainable supplier selection	Casting, Machining	Casting, Paint job	Casting, Purchasing material
3	Identifying non-value-added not needed steps	All Processes	All Processes	All Processes
4	Optimal use of natural resources	Casing, Hydro testing, Cement lining	Casing, Leak test, Heat treatment, Welding	Casing, Hydro testing
5	Reproducible manufacturing	Machining, Hydro testing, Third-party inspection (TPI)	Trimming, Punching, Heat treatment, Leak test	Income quality control, Heat treatment, Shot blasting, Rough turning
6	Pre-production eco-design	Casting	Casting	Casting, Purchase Material
7	Energy optimisation	Casting, Fettling, Bitumen Coating	Casting, Heat treatment, Shot blasting	Heat treatment, Machining, Ultrasonic testing
8	Process capability and in-house quality	Casting, Shot blasting, Machining	Punching, Trimming, Heat treatment, Leak test, Painting	Heat treatment, Shot blasting Machining, Ultrasonic testing
9	Scrap reduction	Shot blasting, Fettling, Machining, TPI	Punching, Trimming, Test, Shot blasting	Rough turning, Shot blasting, Machining, Final quality control
10	Waste management	Casting, Fettling, Hydro testing, Machining	Casting, Heat treatment, Painting, Testing	Casting, Heat treatment, Machining
11	Outgoing quality	TIP	Testing, Leak test, Filling	Final quality control, Prevent from rust
12	Material Handling	Cement lining, Machining, Packing	Testing, Shot blasting	Machining, Preventing rust, Final quality control
13	Emission control	Casting, Coating	Casting, Painting	Casting, Heat treatment
14	Safety management	All Processes	All Processes	All Processes
15	Green packaging	Packing	Non-existent	Packing
16	On-time delivery	All inter-mediatory processes	All inter-mediatory processes	All inter-mediatory processes
17	Reuse	Water in hydro testing, Bitumen coating paint sludge	Water in leak test, Heat treatment, Welding	Water in hydro testing
18	Repair	Defect detected in Shot blasting hydro testing, Machining,	Defect detected in Shot blasting Leak test, Testing	Defect detected in Rough Turning, Machining, Ultrasonic testing
19	Remanufacture	Casting defect, Fettling defect	Casting defect, Trimming and punching defect	Casting, Shot blasting, Rough turning defect
20	Recycling	Scrap generated in all processes	Paint sludge and scrap generated in all processes	Scrap generated in Shot blasting, Machining and Final quality control

At the macro level, the SIPOC elements—Supplier, Input, Process, Output, and Customer—remain consistent across industries, as these represent universal manufacturing stages. However, at the micro and functional level, the processes, activities, and control mechanisms differ significantly**,** which are explicitly captured and clarified in Table 4.1**.**

4.3 Root Cause Analysis:

Root cause analysis, as outlined by Sarkar et al. (2013), provides a structured approach for continuous improvement across the selected case industries. Its primary objective is to identify core issues and implement corrective actions that directly address the root causes, thereby preventing their recurrence. For each construct, 4 to 5 key drivers were identified through a combination of literature review and brainstorming sessions with engineers and technicians from the three industries under study.

Each driver was treated as a binary variable—assigned a value of 1 if actively implemented in the industry and 0 if not. This binary approach enabled a precise diagnosis of implementation gaps and problem areas. A detailed description of the drivers associated with each construct is presented in Appendix 1. The drivers were also evaluated for implementation feasibility, ensuring practical relevance in industrial settings.

4.4. **Data Analysis**:

Following data collection, the 20 identified constructs were grouped into five independent clusters, based on expert input obtained during brainstorming sessions. This clustering helped streamline the analysis and align related constructs for comparative evaluation. The resulting cluster–construct mapping is presented in Table 4.2

Table 4.2 Cluster Construct Interface

Cluster Serial No.	Name Of Cluster	Constructs Merged in the Cluster
Cluster-1	Quality performance	a) Procurement of raw material b) Identifying non-value-added not needed steps c) Process capability and in-house quality d) Outgoing quality e) Sustainable supplier selection
Cluster-2	Environment and Natural Resource Performance	a) Green packaging b) Pre-production eco-design c) Emission control d) Optimal use of natural resources
Cluster-3	Waste, energy performance and 5R	a) Scrap reduction b) Waste management c) Energy optimisation d) 5R Strategy
Cluster-4	Safety and material handling performance	a) Safety management b) Material Handling
Cluster-5	Serviceability	a) On-time delivery

4.5 Comparison of Clusters through Sigma Rating:

In this endeavour of ours, the drivers that have been marked as 0 refer to the weak area of that particular industry. In keeping with the nomenclature of the Six Sigma philosophy; henceforth, they will be operationally defined and termed as Defects in this paper. The Sigma Rating (Mukhopadhyay, Ghosh, 2007) thus computed for each of the industries with respect to the constructs and functional area has been demonstrated in Table 4.3

Table 4.3 Comparative Sigma Rating of Three Industries

	Di Pipe Industry	Cylinder Industry	Pipe Fittings and Aircraft Component Industry
No. of units checked in Different Functional areas	97	95	96
Sigma Value	2.24	1.63	1.96

From Table 3.3, it has been seen that the overall sigma value for the cylinder manufacturing industry is 1.63 and for the aircraft manufacturing industry is 1.96, whereas, for the ductile iron pipe manufacturing industry, the computed sigma value is 2.24. Now, we need to prioritise the recommended root causes/ drivers of Six Sigma metrics for unravelling the corresponding actionable causes to enhance the overall performance of ZED in the aforementioned industries. It is to be noted that a sigma level of 4 is considered to be an average-performing industry in the USA (Harry, 2006)

4.6. **Action Plans for Improvement**:

To tide over the problems related to the cluster performances, some action plans have been suggested and implemented by the company. The cluster-wise action plans on this behalf are described in a nutshell for three case examples.

4.6A. **Quality-Related Performance**

Quality performance across the three industries—cylinder manufacturing, DI pipe production, and aircraft components—was assessed using rejection rates from January to May 2021. The sigma level in cylinder manufacturing is lowest at **2.9** (80,000 defective ppm), while the DI pipe industry reports a higher sigma of **3.5** (20,000 defective ppm) but with an elevated **rework ppm of 50,000**, adversely affecting its rolled throughput yield. The aircraft component industry exhibits a sigma level of **3.2** with approximately 40,000 defective ppm.

Root causes of high rejection were identified each industry: punching, trimming, and hydro-testing in cylinder manufacturing; shot blasting and machining in DI pipe production; and inappropriate heat treatment in aircraft manufacturing. Targeted quality improvement initiatives for each operation are recommended. Additionally, material rejections during in-process testing cause delays due to the need for reproduction. To mitigate this, **implementation of a Kanban system** (Rahman et al., 2013) is advised for streamlined replenishment. Other quality enhancement measures proposed include:

- Establishing systems to correlate field performance quality with in-house and outgoing quality.
- For cylinder manufacturing, improving low sigma performance by identifying critical processes and implementing process-specific quality plans and controls.
- Training across all industries in Six Sigma and Statistical Process Control (SPC).
- Developing a supplier selection model considering quality, price, delivery, service, and environmental performance, especially for the aircraft and cylinder sectors.
- Improving order forecasting accuracy to reduce material overstocking and stock-outs.

4.6B. Environmental Performance

Steel production significantly impacts environmental parameters such as air emissions, wastewater generation, and hazardous waste. Improving environmental performance requires each industry to adopt, implement, and continually improve an Environmental Management System (EMS).

I. Heat Recovery

Heat-intensive steelmaking operations generate substantial waste heat. In aircraft component manufacturing, heat treatment issues such as oxidation and decarburisation result in high rejection rates. Integrating waste heat recovery systems enhances energy efficiency and reduces thermal degradation.

Recommended technologies include:

- Heat exchangers for utilizing exhaust heat (Mohseni et al., 2023),
- Heat Recovery Steam Generators (HRSGs) for process steam generation (Zhang et al., 2023),
- Combined Heat and Power (CHP) systems to produce electricity and usable heat (Kumar et al., 2024).

These systems reduce heat-related defects and improve product quality in heat treatment processes.

II. Water Recycling

Cooling operations post-heat treatment in cylinder and aircraft production requires substantial water use. Establishing water reuse systems for cooling, hydro-testing, and leak testing is crucial. Treated water should be stored and reused to minimize freshwater demand and operating costs (Zhou et al., 2022; Singh et al., 2023).

In the aircraft sector, initiatives for rainwater harvesting have begun; however, proper treatment infrastructure is needed to use collected rainwater in processes like hydro-testing and zinc plating (Kumar et al., 2023).

III. Emission Control

With approximately 1.85 tonnes of CO_2 emitted per tonne of steel, the industry must adopt decarbonisation strategies. Carbon Capture, Utilization, and Storage (CCUS) technologies offer viable solutions, particularly in blast furnace operations, where captured CO_2 can be repurposed into construction materials (Kumar et al., 2022; Carbon Clean, 2023).

Key recommendations include:

1. **Mapping industrial pollutants** and integrating them with environmental monitoring systems (Smith et al., 2023).
2. **Adopting ISO 14064** for GHG accounting and **ISO 19011** for auditing EMS performance (ISO, 2022).

4.6 D. Waste and Energy-related Performance (Circular Economy Approach)

Steel's recyclability makes it central to a Circular Economy. In India, enhancing scrap processing and by-product utilization (e.g., slag) can significantly improve energy efficiency and sustainability. Recycling 1 tonne of scrap saves ~0.7 tonnes of coal, ~1.1 tonnes of iron ore, cuts GHG emissions by 58%, and reduces water use by 40% (Kumar et al., 2023).

Figure 4.6 shows projected scrap supply-demand (2022–2030) indicating a growing gap due to limited domestic recovery systems . A CE-based policy framework is needed to bridge this gap through improved collection, segregation, and reuse.

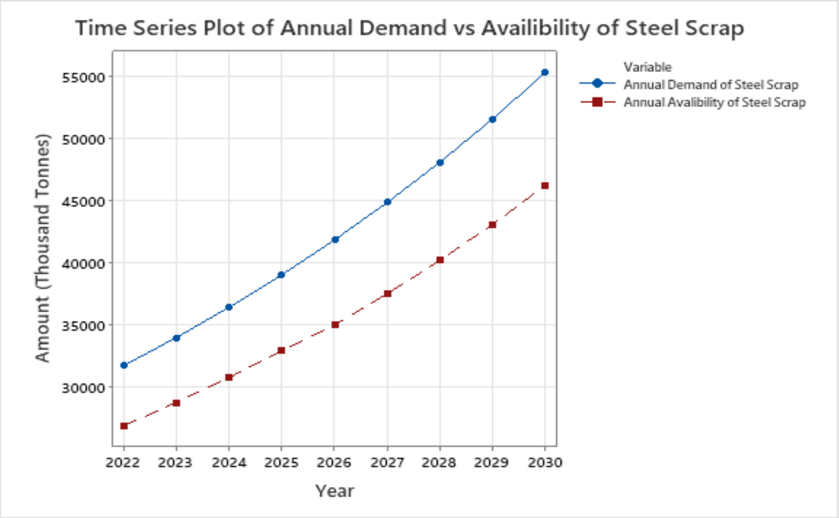

Figure 4.6 Time series Plot of Steel Scrap

Effective scrap management is critical to achieving circularity in the Indian metals sector. However, current practices across the DI Pipe, Cylinder, and Aircraft Component industries remain largely informal. The DI Pipe industry generates approximately 15–18 tonnes of scrap annually, the Cylinder industry about 10 tonnes, and the Aircraft Component industry around 8 tonnes. This scrap is typically sold to informal dealers at low prices (Rs 15–25/kg) without quality-based segregation.

Key limitations include the absence of organised scrap collection systems, lack of integration between producers and recyclers, and an inadequate regulatory framework. Despite high import duties, India continues to rely on scrap imports to meet demand, highlighting inefficiencies in domestic recovery.

To enhance circularity and resource efficiency, the following measures are recommended:

1. **Implement COPQ (Cost of Poor Quality) assessments** to identify and reduce scrap generation at source.
2. **Promote the adoption of Electric Arc Furnace (EAF) technology**, which is scrap-intensive and environmentally favourable.
3. **Establish linkages with certified scrap dealers**, enabling segregation based on quality, chemical composition, and hazard level.
4. **Regular scrap analysis** and key performance indicators (KPIs) were implemented to track scrap quality and identify areas for improvement. Moreover, scrap material that met quality standards was explored for potential resale or reuse in new products.

These steps, supported by the proposed 3R-based scrap management framework (Figure 4.7), are essential for advancing toward a circular steel production system.

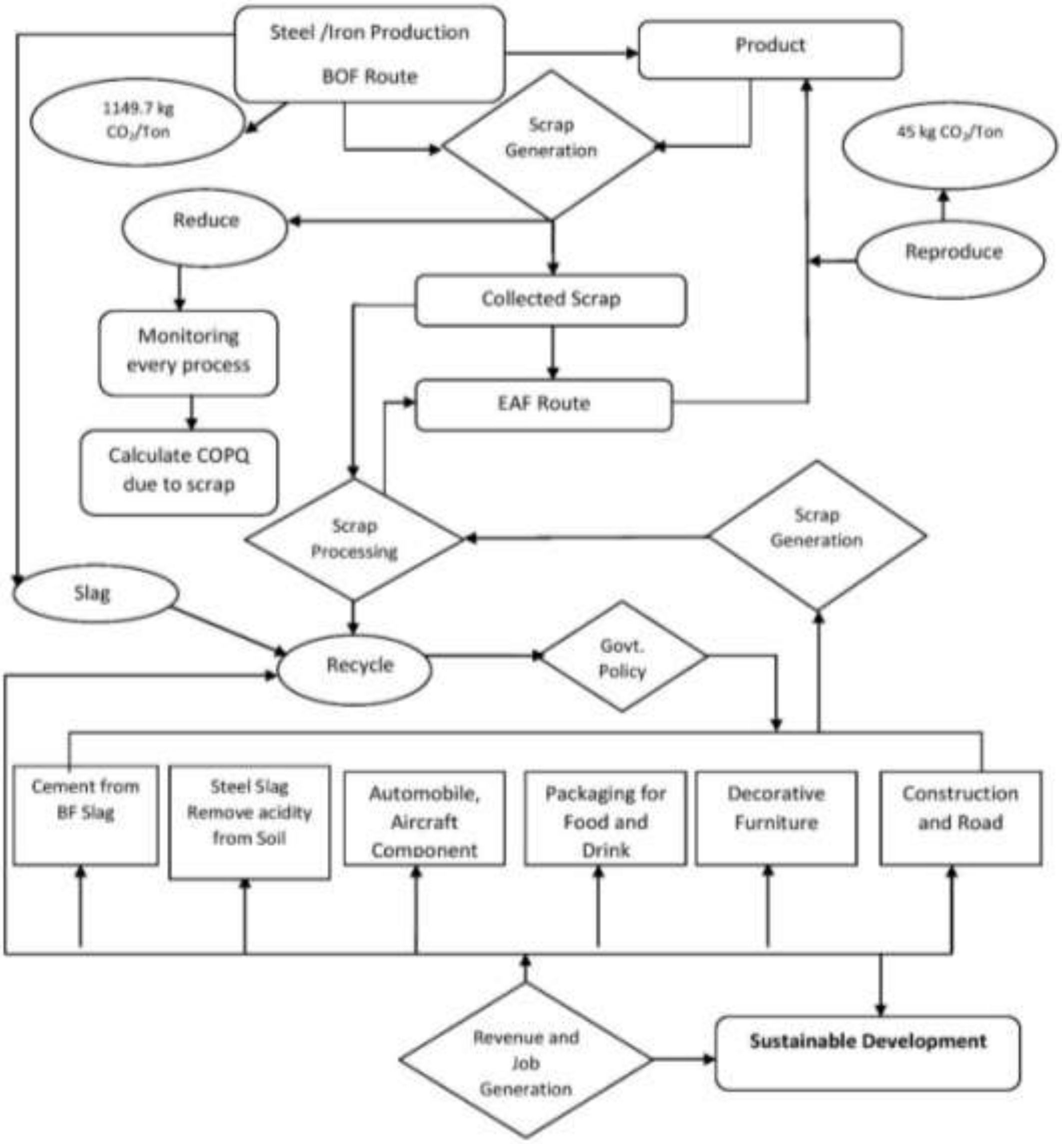

Figure 4.7 Proposed flow chart of iron/steel scrap life cycle

4.6E. Safety, Material Handling and Serviceability Performance

The following action plans are imperative to improve the cluster's performance.

I. Measure and Monitor OTIF (on time in full) (Morales, 2021) for all orders to assess the delivery performance.

II. Improve the system to ensure on-time delivery by adopting just-in-time, Kanban and different lean techniques.

III. Measure Customer satisfaction and respond to the query of the customer within the set deadline.

IV. Automation of material handling system.

V. Adoption of HIRA (hazardous identification and risk assessment)

4.7. **The Extent of Improvement:**

Subsequent to adopting the appropriate remedial measures for the three industries with respect to all 5 clusters, the extent of improvement has been worked out from the data collected during the post-improvement period.

For **quality-related performance,** we have recommended two projects – one on improper heat recovery and the other on understanding the reasons for punching, trimming, shot blasting and machining defects. After successful completion of projects, data on rejection have been collected for about 5 months for the post-improvement period, and the performance in terms of sigma rating has been compared with that of before improvement. Table 4.4 portrays this comparison.

Table 4.4 Comparative Sigma Rating on Rejection

Name of Industry	Sigma Rating Before Improvement	Sigma Rating After Improvement
DI Pipe Manufacturing Industry	3.5	4.7
Cylinder Manufacturing Industry	2.9	3.9
Air Craft Component Manufacturing Industry	3.2	4.2

For **Environmental Performance**, we have recommended a project on heat recovery for the aircraft component manufacturing industry, which is ongoing. The guidelines for ISO 14064 (on emission control) and ISO 19011 (on environmental management systems) have also been implemented and documented for all three industries. The re-use of treated water for the leak test has started for all three industries. Table 4.5 describes different technologies adopted by the three industries for reducing emissions and implementing ISO 14064

Table 4.5 Technology Adoption to Reduce Carbon Footprints

Name of Industry	Technology Adopted
DI Pipe Manufacturing Industry	Maximise secondary flow through recycling scrap in an electric arc furnace
Cylinder Manufacturing Industry	usage of DRI (Direct reduced iron) in combination with EAF.
Air Craft Component Manufacturing Industry	Introduce hydrogen-based DRI (Direct reduced iron) and scrap in combination with EAFs

For **Waste and energy-related performance**, all three industries have integrated their supply chain with government-authorised scrap dealers so that all manufacturing units can recycle their scrap through scrap dealers and use it in electric arc furnaces (secondary raw material for their own process) and also reuse the remaining scrap for purchasers beyond the company for different beneficial usages, mentioned earlier in this article. The use of scrap as a secondary raw material has increased the resource efficiency practices encompassing ZED as well as SDG12. Table 4.6 describes material footprint efficiency for all three industries in the post-improvement period.

Table 4.6 Post-improvement Material Footprint

Industry	$\% U_{SRM}$	$\%U_{SCRAP}$	Revenue Generation (Rs)
	$\frac{ScrapusedinEAF\ \ (kg)}{Scrapgenerated\ \ (kg)}*100$	$\frac{\text{Scrap used for steel production}}{Quantumoftotalproduction}*100$	
DI Pipe Manufacturing Industry	67%	6%	700000
Cylinder Manufacturing Industry	42%	11%	4,50,000
Air Craft Component Manufacturing Industry	56%	9%	5,60,000

Note: $\%U_{SRM}$ implies the extent of utilisation of secondary raw material in overall scrap used

$\%U_{scrap}$ implies the extent of utilisation of scrap in production

4.8 Post-improvement Sigma Rating:

In the post-improvement phase, the Sigma rating has been done for the overall performance of the three industries consisting of the 5 clusters of performance on quality, environment, waste & energy, safety & material handling and serviceability and the associated drivers described in Appendix 1. The sigma rating thus found is compared with the pre-improvement sigma rating arrived in an analogous manner. Table 4.7 compares the post-improvement sigma rating with that of the pre-improvement sigma rating.

Table 4.7 Comparative Sigma Rating on Overall Performance

	Di Pipe Industry	Cylinder Industry	Aircraft Component Industry
Sigma Value (Pre-Improvement)	2.24	1.63	1.96
Sigma Value (Post-Improvement)	4.22	3.58	4.07

4.9 Cluster Weight age Determination for Assessing ZED:

Apart from the improvements measured through sigma rating, for understanding the importance of individual clusters, the weight age of each cluster has been determined through the Analytical Hierarchy Process (Appendix 2). Tables 3.8 and 3.9 describe the calculation of Fuzzy AHP and the normalised weight age calculation of the clusters. It is to be noted that the value of the consistency index and consistency ratio are 0.10 and 0.09, respectively, which is acceptable (Liu et al., 2020). The overall ZED performance, thus, computed from Tables 8 and 9, is given below.

$$\textbf{Overall ZED Performance} = (\mathbf{0.50}) * \boldsymbol{QP} + (\mathbf{0.20}) * \boldsymbol{EP} + (\mathbf{0.09}) * (\boldsymbol{WP}) + (\mathbf{0.04}) * \boldsymbol{SP} + (\mathbf{0.17}) * \boldsymbol{SRP}$$

[Where QP= Quality Performance, EP= Environmental Performance, WP= Waste and energy-related performance, SP= Safety and material management performance, and SRP=Service-related Performance.]

Table 4.8 Fuzzy AHP for Pair-wise Cluster Comparison Matrix

	Q-P	E-P	W-P	S-P	SR-P
Q-P	(1,1,1)	(4,5,6)	(4,5,6)	(7,8,9)	(2,3,4)
E-P	(1/6, 1/5, 1/4)	(1,1,1)	(2,3,4)	(4,5,6)	(1,2,3)
W-P	(1/6, 1/5, 1/4)	(1/4,1/3,1/2)	(1,1,1)	(4,5,6)	(1/4,1/3,1/2)
S-P	(1/9, 1/8, 1/7)	(1/6,1/5,1/4)	(1/6,1/5,1/4)	(1,1,1)	(1/5,1/4,1/3)
SR-P	(1/4,1/3,1/2)	(1/3, 1/2,1)	(2,3,4)	(3,4,5)	(1,1,1)

Table 4.9 Normalised Weight age of Clusters

Cluster	fuzzy weight	Weights	Normalised Weight
Q-P	(0.34,0.508,0.743)	0.53	0.50
E-P	(0.122,0.202,0.316)	0.21	0.20
W-P	(0.061,0.091,0.146)	0.10	0.09
S-P	(0.026,0.037,0.055)	0.04	0.04
SR-P	(0.100,0.163,0.281)	0.18	0.17
Consistency Index=0.10		Random Index (n=5) =1.12	
Consistency Ratio=0.09<0.1 (Weight ages are acceptable)			

4.9 Overall ZED Performance of the Three Industries:

The overall ZED performance of the three concerned industries in this study has been assessed by making use of equation 1. Table 4.10 depicts both the cluster performance and the overall ZED performance subsequent to conversion to percentage.

Table 4.10 Overall performance of ZED in three Industries

Cluster Performance	DI Pipe Industry	Cylinder Industry	Aircraft Component Industry
Q-P	88	76	90
E-P	85	90	80
W-P	93.3	86.6	80
S-P	100	80	100
SR-P	87.5	62.5	75
ZED Performance	**88.27**	**77.62**	**84.95**
	$(\mathbf{0.50}) * \boldsymbol{QP} + (\mathbf{0.20}) * \boldsymbol{EP} + (\mathbf{0.09}) * (\boldsymbol{WP}) + (\mathbf{0.04}) * \boldsymbol{SP} + (\mathbf{0.17}) * \boldsymbol{SRP}$		

It is clear from Table 10 that despite getting an edge over Quality Performance (Q-P), the aircraft component manufacturing industry lags behind the DI pipe industry for overall ZED performance that considers in a composite manner the contribution of performance of other clusters in addition to quality.

4.10 Sensitivity Analysis of ZED Performance:

Sensitivity analysis was conducted to examine how variations in criterion weightages affect the overall ZED performance scores of the three industries. This analysis provides insights into which criteria exert the most influence and supports more informed decision-making for strategic improvements. Although criterion weights are systematically derived using Fuzzy AHP, sensitivity analysis is essential to test the robustness and stability of the ZED performance rankings under possible variations in expert judgment. Fuzzy AHP captures uncertainty in human perception at a given point in time; however, in practical decision-making, policy priorities and managerial emphasis may change**,** especially in sustainability-oriented frameworks such as ZED.

Therefore, sensitivity analysis is conducted not to re-estimate weights, but to:

1. Examine how small, plausible variations in criterion weight ages influence overall ZED performance scores, and
2. Identify dominant performance dimension**s** that have the greatest impact on industry rankings.

4.10.1 Scenario 1: Varying Environmental Performance (EP) Weight

Increasing the weight of EP slightly improves the ZED score of the DI Pipe industry due to its relatively stronger environmental practices. The Cylinder and Aircraft Component industries exhibit minimal change, indicating lesser influence of EP on their overall performance (Figure 4.8).

4.10.2 Scenario 2: Varying Service Performance (SP) Weight

Industries with higher service performance, such as the Aircraft Component and DI Pipe industries, show a noticeable increase in ZED scores when SP weight is raised. The Cylinder industry, with weaker service performance, displays limited sensitivity (Figure 4.9).

4.10.3 Scenario 3: Varying Quality Performance (QP) Weight

The Aircraft Component industry, having strong QP, shows the most pronounced increase in ZED score as QP weight increases. The Cylinder industry, with lower QP, remains less sensitive to such changes (Figure 4.10). Overall, Quality and Service performances emerged as more influential in determining ZED outcomes. These findings help prioritize criteria for performance enhancement and supplier evaluation.

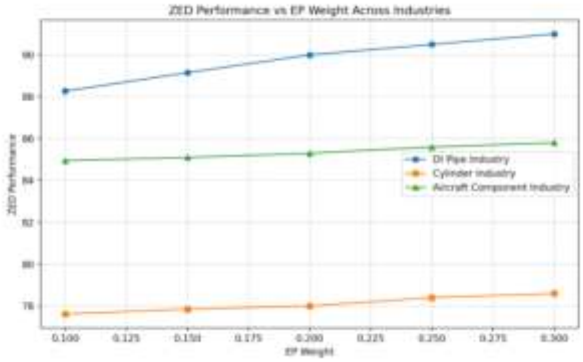

Figure 4.8 Sensitivity Study of ZED Performance by Changing Ep Weightage

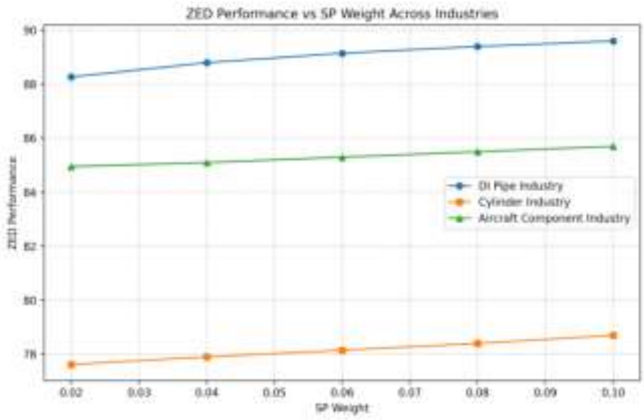

Figure 4.9 Sensitivity Study of ZED Performance by Changing Sp Weightage

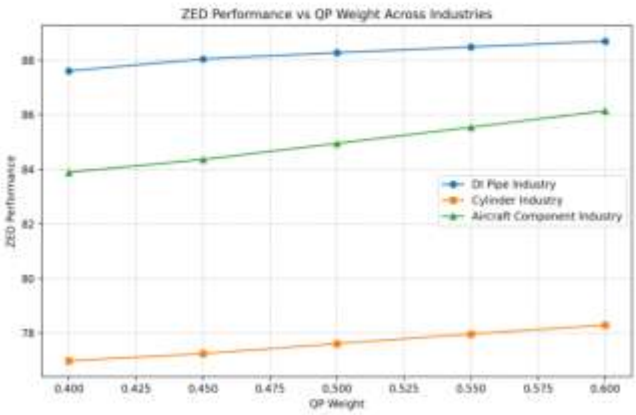

Figure 4.10 Sensitivity Study of ZED Performance By Changing QP Weightage

4.11. Outcomes of the Present Research:

This study highlights the relevance and applicability of the ZED Maturity Assessment Model in evaluating and enhancing the operational, environmental, and quality performance of selected Indian manufacturing industries. The DI Pipe industry showed strength in environmental practices, while the Aircraft Component industry excelled in quality performance. However, all three sectors exhibited gaps in systematic scrap management and supply chain integration, impacting circularity and sustainability.

The findings also emphasize that ZED performance is most influenced by environmental and quality parameters, as shown in the sensitivity analysis. The adoption of circular economy practices such as the 3R approach and greater use of EAF technology can significantly improve material efficiency and reduce carbon footprints. Overall, the ZED model supports India's manufacturing competitiveness and contributes toward achieving SDG 12 by promoting sustainable production and resource efficiency.

In terms of future work, further validation of the ZED Maturity Model across different sectors, beyond those considered in this study, is necessary. Surveys and empirical testing will be critical in extending the model's applicability and robustness. Additionally, the study would continue to support industries through awareness building, certification, and guidance, to help attain edge over competitors for global acceptance through illustrious contributions towards India's "Make in India" initiative. This ZED model has the potential to serve as a benchmark across various sectors, including public sector units (PSUs) and defence industries, contributing to the sustainable growth and modernization of India's manufacturing landscape

Chapter-5

Driving Industrial Sustainability: Circular Economy Metrics for SMEs

Work Packages		
Research Objective 3: (RO-3) To implement a quantifiable, SME-specific Circular Economy assessment model by integrating key performance indicators such as eco-design, environmental footprints, and resource and energy efficiency, providing strategic insights for resource minimization and circularity enhancement.	WP-12	Literature review on CE, lean, green and quality technology.
	WP-13	Identification of indicators for Circularity Assessment.
	WP-14	Scope of adoption of CE in SME
	WP-15	A comprehensive model is developed to integrate key indicators of Circular Economy adoption. A case example of the steel industry is used to demonstrate the practical application of CE principles.
	WP-16	Data collection from steel industry and 15 SMEs.
	WP-17	This WP involves validating the developed model using real-world case data to assess its accuracy and identify potential over- or under-fitting issues. Furthermore, the research aims to: 1. Identify the top 10 SMEs with respect to Circular Economy (CE) adoption. 2. Develop remedial measures for improvement and cost-effectiveness in these industries. 3. Conduct an overall circularity performance analysis to provide insights into the effectiveness of CE strategies.

5.1 Introduction:

Circular Economy (CE) has emerged as a key strategy for sustainable development, ensuring that waste is minimised and the efficient use of resources is enhanced. Unlike the conventional "take-make-dispose" economy, CE focuses on the reuse and recycling of products. SMEs have a crucial role to play during the CE transition because they account for a large share of global industrial activity, resource consumption, and employment, thus making their sustainable transition necessary to create a broad impact. This research proposes a new method to assess CE performance of SMEs on five key indicators: eco-design, material footprint, carbon footprint, waste management, and resource &energy conservation. Drawing on information gathered from 15 SMEs in various industries, this research aims to provide insights into CE adoption patterns and points of improvement.

A mixed-methods approach is employed using statistical analysis, cluster techniques, and principal component analysis (PCA) to yield informative information concerning CE adoption trends. The research analyses 15 SMEs operating in various industrial sectors in India and determines specific performance clusters from the context of sustainability efficiency. The uniqueness of this research is in its integrated analytical strategy through the combination of clustering and PCA, allowing the systematic quantification of CE performance with a data-driven, flexible technique specifically designed for SMEs in various industrial sectors.

The study advances both academics and industry by providing a scalable, methodical approach to assessing CE performance in SMEs. Through an understanding of sectoral distinctions, barriers, and drivers, the research provides SMEs with strategic knowledge to promote circularity. In order to promote the transition to a low-carbon, resource-efficient economy, the study also highlights the need for legislative actions, financial incentives, and technological advancements.

5.2. Unlocking Sustainable Growth: The Vital Role of SMEs in India's Industrial Development through Circular Economy Principles:

Indian small and medium enterprises (SMEs) are a driving force behind the country's economic growth, accounting for 48% of exports, 45% of industrial output, and about 30% of GDP. With more than 63 million MSMEs functioning in a variety of industries, they are essential to the creation of jobs, industrial growth, and economic stability. However, these businesses often struggle with environmental sustainability due to high resource consumption and waste generation. Embracing Circular Economy (CE) principles can help Indian SMEs overcome these challenges and achieve sustainable growth. By adopting a circular business model, SMEs can reduce waste, optimise resource use, and minimise environmental impact.A review of existing literature on CE and SDG linkages in SMEs highlights the need for such performance indicators to effectively assess each enterprise's progress toward circularity.

Key benefits of CE adoption in Indian SMEs include:

- Enhanced resource efficiency and cost savings
- Improved environmental sustainability and reduced carbon footprint
- Increased competitiveness and business resilience
- Better compliance with environmental regulations and standards

By integrating CE strategies into their operations, Indian SMEs can contribute to the country's sustainable development goals, drive economic growth, and create a more environmentally conscious business ecosystem.In order to effectively move Indian SMEs towards a circular economy, quantifiable metrics that monitor waste management, carbon footprint reduction, and resource efficiency must be established. A review of existing literature on CE and SDG linkages in SMEs highlights the need for such performance indicators to effectively assess each enterprise's progress toward circularity.

5.3 Adoption of Circular Economy in SMEs Across India (Step-1):

This study examines the adoption of circular economy (CE) principles among 15 Indian Small and Medium-sized Enterprises (SMEs) across diverse industries, including aircraft component manufacturing, steel casting, textiles, galvanising, waste management, printed circuit board (PCB) manufacturing, food processing, and pipe production. 25 key drivers, with 5 drivers for each of the 5 CE indicators, have been identified and evaluated for their practical implement ability within the respective industries using a 5-point Likert scale. The compiled data provides a comprehensive overview of the findings, offering insights into the CE practices of these SMEs. Table 5.1 presents the detailed drivers associated with each of the five Circular Economy (CE) indicators.

Table 5.1 Drivers of Circular Economy Indicators

Sl No	Indicators	Drivers
1	Eco Design	A. To what extent does your company use recycled, biodegradable, or renewable materials in product design? B. How well has your company optimised energy consumption through low-energy production techniques, automation, or renewable energy sources? C. To what extent are your products designed for easy disassembly, allowing components to be reused or recycled? D. How effectively does your company integrate Lean, Six Sigma, or Circular Manufacturing techniques to reduce material waste & emissions? E. How frequently does your company conduct Life Cycle Assessments (LCA) to evaluate and minimize environmental impact from production to disposal?
2	Material Foot Print	A. To what extent does your company utilize recycled, recovered, or secondary raw materials in production? B. To what extent has the company optimized its material usage to minimize scrap, defects, or excess consumption? C. How well does the company integrate sustainability criteria when selecting material suppliers (e.g., certified sustainable sources, local sourcing, closed-loop supply chains)? D. To what extent are materials selected based on durability, recyclability, and low environmental impact across the product life cycle? E. How effectively does the company collaborate with other

		industries to use by-products, scrap materials, or industrial waste as inputs?
3	Carbon Foot Print	A. To what extent has the company reduced direct emissions (fuel combustion, manufacturing processes, on-site energy use) through efficiency improvements or cleaner technologies? B. What percentage of total energy consumption comes from renewable energy sources (solar, wind, hydro, biomass, etc.) instead of fossil fuels? C. How actively does the company engage with suppliers and logistics partners to reduce upstream and downstream carbon emissions? D. To what extent does the company have real-time monitoring, reporting, and reduction strategies for its total carbon footprint across all operations? E. How well does the company implement carbon offset mechanisms, such as afforestation, carbon credits, or circular economy-based carbon reduction strategies?
4	Waste Management	A. To what extent does your company **segregate and minimise waste** at the source before disposal? B. What percentage of total waste generated is **recycled or reused within the supply chain** instead of being landfilled or incinerated? C. Does your company **exchange waste as raw materials** with other industries to promote circularity? D. How well does your company **identify, treat, and dispose of hazardous waste** in compliance with environmental laws? E. What level of implementation does your company have for **waste-to-energy (WTE) or zero-waste-to-landfill** policies?
5	Resource and Energy Conservation	A. To what extent has your company adopted**energy-efficient technologies, such as LED lighting, VFDs, or automated energy monitoring?** B. What percentage of total energy consumption is **sourced from renewables (solar, wind, bioenergy, etc.)?** C. How effectively does your company **reuse, recycle, or minimise water consumption** in production processes? D. To what extent does your company **source raw materials from recycled or sustainable sources**? E. How well has your company **optimized production processes** to minimise material waste and maximise resource efficiency?

Table 5.2 presents CE performance across the 15 industries. The average scores for each indicator—derived from the driver ratings—provide a data-driven snapshot of each SME's CE engagement. This comparison highlights top-performing sectors and those requiring targeted improvement.

Table 5.2 Industry-Wise CE Performance Scores Based on Average Ratings of Across Five Key Indicators

Industry	Eco Design	Material Foot Print	Carbon Foot Print	Waste Management	Resource and Energy Conservation
S-01	3.8	4.2	3.6	4.0	3.4
S-02	2.6	3.4	2.8	3.2	3.0
S-03	4.0	3.8	3.4	4.2	3.8
S-04	2.4	2.8	3.0	3.6	3.2
S-05	3.6	3.2	3.8	4.0	3.4
S-06	2.9	4.4	3.8	3.5	2.4
S-07	2.4	2.1	4.2	3.5	3.8
S-08	2.1	4.4	4.1	2.5	2.5
S-09	2.5	2.8	3.3	3.1	2.7
S-10	3.5	2.3	2.7	2.9	3.1
S-11	3.1	4.9	4.2	3.8	3.1
S-12	2.5	2.2	4.6	3.8	4.1
S-13	2.1	4.9	4.5	2.6	2.5
S-14	2.6	2.9	3.6	3.3	2.9
S-15	3.8	2.4	2.9	3.1	3.4

5.4 Weight Determination (CRITIC Method) Step-2:

The CRITIC (Criteria Importance Through Inter Criteria Correlation) method is a fair way to assign importance to different criteria by looking at how much they differ from each other and how they relate to one another. Unlike subjective MCDA methods (like AHP), CRITIC removes human bias by automatically giving more importance to indicators that show more variation and are less related to others, making the evaluation based on data and free from personal opinions. Steps included in a CRITIC approach are

1. Compute standard deviation (σ_k) for each criterion k to measure variability.

2. Calculate the Pearson correlation coefficient (r_{ij}) between each pair of criteria i,j

3. Determine the information content (C_k) for each criterion using:

$$c_k = \sigma_k \sum_{j=1}^{n} (1 - |r_{k,j}|)$$

4. Normalise weights by computing: $W_k = \frac{C_k}{\sum_{k=1}^{n} c_k}$

Table 5.3 illustrates the result of CRITIC method and determines the weightage of all indicators to evaluate CI score.

Table 5.3 CRITIC Method Outcomes

Criteria	Standard Deviation	$\sum_{j=1}^{n} (1 - \lvert r_{k,j} \rvert)$	c_k	W_k
Eco Design	0.654	2.571	1.687	0.186
Material Foot Print	0.987	2.991	2.953	0.325
Carbon Foot Print	0.614	3.098	1.901	0.209
Waste Management	0.512	2.661	1.362	0.149
Resource and Energy Conservation	0.510	2.320	1.183	0.130

The CRITIC method assigns the highest weight (0.3250) to **material footprint**, highlighting its strong influence on circular economy performance, while **resource and energy conservation** has the lowest weight (0.1302). This weighting ensures that highly fluctuating and independent criteria contribute more significantly to the Circularity Index (CI).

5.5 Industry Ranking (PROMETHEE Method) Step-3:

The PROMETHEE (Preference Ranking Organisation Method for Enrichment Evaluations**)** approach is utilised to systematically rank the 15 SMEs based on their circular economy performance. By incorporating the **CRITIC-determined weights**, this method ensures an objective and data-driven evaluation, facilitating a comprehensive assessment of sustainability performance across industries. The steps included in a PROMETHEE approach are:

1. Normalisation: Convert the raw indicator values into a comparable scale (0 to 1) by Max-Min transformation.
2. Preference Function Calculation: Determine the preference difference between industries for each criterion.For each pair of industries **(A & B)**, the preference function is computed as:

$$P(X_A, X_B) = 0 \qquad If\ X_A \leq X_B$$
$$= X_A - X_B \quad If\ X_A > X_B$$

where $P(X_A, X_B)$represents how much Industry A is preferred over B.

3. Weighted Preference Calculation: Multiply preference values by CRITIC weights.
   The **preference index** for each pair **(A, B)** is computed as:

$$\pi(A,B) = \sum_{J=1}^{5} W_J P(X_{A,J}, X_{B,J})$$

4. Positive & Negative Flow Calculation: Compute the net flow for each industry.
   Leaving Flow (Φ^+)(how much industry i outranks others):

$$\boldsymbol{\Phi^+(i) = \frac{1}{n-1} \sum_{k=1}^{n} \pi(i,k)}$$

   Entering Flow (Φ^-) (how much industry i is outranked by others):

$$\boldsymbol{\Phi^-(i) = \frac{1}{n-1} \sum_{k=1}^{n} \pi(k,i)}$$

5. Ranking: Assign final rankings based on net flow values. The **final ranking score** also known as net flow score for each industry is:

$$\boldsymbol{\Phi(i) = \Phi^+(i) - \Phi^-(i)}$$

Higher values of Φ(i) indicate better performance. Table 5.4 Illustrates the outcome of PROMETHEE.

Table 5.4 PROMETHEE Result:

RANK	Industry	Positive Flow	Negative Flow	Net Flow
1	S-11	0.092182	0.008472	0.083710
2	S-01	0.073219	0.012931	0.060289
3	S-03	0.070133	0.019977	0.050156
4	S-13	0.083111	0.034702	0.048409
5	S-06	0.061043	0.022949	0.038093
6	S-05	0.047936	0.027040	0.020896
7	S-08	0.057293	0.040344	0.016949
8	S-12	0.041714	0.058333	-0.016619
9	S-02	0.022859	0.053475	-0.030616
10	S-14	0.018677	0.049462	-0.030785

Due to the computational complexity of PROMETHEE calculations for 15 industries, the detailed step-by-step calculations are not included here. Instead, a Python-based implementation was developed, and the complete code is provided in the Appendix3. Table 5.4 summarises the top industries identified through the PROMETHEE analysis, along with their respective positive, negative, and net flow values.

The PROMETHEE analysis ranks ten SMEs based on their Circular Economy (CE) performance, using weights determined by the CRITIC method. The results indicate that Industry S-11 exhibits the highest net flow score, positioning it as the most favourable in terms of CE performance, while Industry S-14 ranks lowest among the top ten. The initial set of 15 SMEs ensured broad representation. PROMETHEE ranking was limited to the **top 10 SMEs** to retain meaningful discrimination, as the remaining SMEs showed very low and closely clustered net flow values. Following the identification of the top ten industries through PROMETHEE, it was observed that seven of them demonstrated positive net flow values. Consequently, a detailed process map analysis was undertaken for these seven industries to identify potential areas for enhanced CE adoption. The comprehensive descriptions of these process maps, along with profiles of the top seven industries, are provided in Appendix 4.

5.6 Recommendation for Circular Economy Adoption in Top Industries: (Step 4)

The potential for improving Circular Economy (CE) practices in the chosen industries is shown through specific suggestions based on careful process mapping. This analysis identified material flow inefficiencies, waste hotspots, and energy-intensive operations, guiding targeted sustainability interventions. Table 5.5 presents industry-specific recommendations based on process analysis, surveys, and interviews with quality and management personnel, supporting the shift toward resource-efficient and environmentally responsible supply chains.

Table 5.5 Recommendation for Leading SMEs

Industry	Description	Eco-Design	Material Footprint	Carbon Footprint	Waste Management	Resource & Energy Conservation
S-11 (Precision Manufacturing)	Produces metal components for automotive and aerospace applications.	Introduce modular designs for reusability.	Increase recycled metal alloy usage.	Implement energy-efficient furnaces & optimise heat treatment cycles.	Develop an internal scrap segregation system.	Adopt renewable energy sources like solar/wind.
S-01 (Chemical Processing)	Specialises in specialty chemicals and coatings.	Develop biodegradable & low-VOC coatings.	Enhance solvent recovery to reduce virgin material usage.	Shift to low-emission reactors & adopt heat integration strategies.	Implement closed-loop wastewater treatment.	Improve heat exchanger efficiency & optimise reaction temperatures.
S-03 (Steel Casting & Forging)	Manufactures heavy machinery and construction components.	Develop a remanufacturing program for end-of-life components.	Increase scrap-based steel production.	Optimise EAF energy consumption & improve slag utilisation.	Enhance slag valorisation for construction applications.	Utilise waste heat recovery in refining operations.
S-13 (Plastics & Polymers)	Produces automotive interiors and packaging materials.	Increase biodegradable & recyclable polymer usage.	Implement post-consumer plastic recycling.	Optimise moulding temperatures for energy efficiency.	Set up a waste polymer collection & reprocessing unit.	Utilise energy-efficient extrusion machines.
S-06 (Paper & Pulp)	Manufactures packaging-grade & speciality papers.	Develop alternative fibre-based papers (bamboo/agricultural waste).	Increase recycled paper input.	Optimise boiler efficiency & transition to biomass energy.	Implement closed-loop water recycling.	Adopt energy-efficient drying technologies.
S-05 (Metal Fabrication)	Supplies components for electronics & construction.	Make sure your components are easily disassembled and modular.	Utilise remanufactured aluminium & stainless steel.	Introduce low-energy anodising & electroplating processes.	Set up an industrial symbiosis network for scrap reuse.	Implement AI-driven process optimisation.
S-08 (Glass Manufacturing)	Produces architectural and automotive glass.	Use recyclable glass formulations with extended durability.	Increase cullet (recycled glass) proportion in production.	Optimise melting furnace temperature profiles.	Develop a glass take-back programme for recycling.	Implement waste heat recovery from kilns.

To ensure economic feasibility, only the most cost-effective and impactful recommendations have been selected for implementation. The following outlines the industry-wise phased implementation plan over five-months (Feb 23 to June 23) period.

For **Precision Manufacturing** (S-11), optimising component design using CAD and advanced materials can enable lightweight, upgradable parts, while on-site metal scrap reprocessing reduces waste and raw material dependency. In **Chemical Processing** (S-01), solvent recovery and process optimisation minimise waste and raw material costs. **Steel Casting & Forging** (S-03) should adopt waste heat recovery and use secondary raw materials to enhance energy and material efficiency. **Plastics & Polymers** (S-13) can benefit from post-consumer plastic recycling partnerships and improved separation processes. **Paper & Pulp** (S-06) should implement closed-loop water systems and advanced filtration to reduce freshwater use and discharge. For **Metal Fabrication** (S-05), lean practices and basic monitoring can minimise scrap and improve efficiency. Lastly, **Glass Manufacturing (S-08)** should increase cullet usage and improve sorting to lower energy demand and virgin material use.

5.7 **Formulation of each Indicator - Step 5**:

After implementing targeted remedial strategies, the Circular Economy (CE) performance of the top seven industries—identified by their positive net flow scores—was quantified using industry-specific mathematical formulations. Each of the five key CE indicators—eco-design, material footprint, carbon footprint, waste management, and resource &energy conservation—was represented through equations tailored to reflect the operational realities of the respective industries. These formulations enabled a structured, data-driven evaluation of CE performance, ensuring both relevance and accuracy. The complete set of indicator formulations is presented in Table 5.6.

Table 5.6: Formulation of CE indicators:

Indicator	Mathematical Formulation	Description
Eco Design	$\alpha = \frac{N_{Sustainable}}{N_{Total}}$	Ratio of sustainable design elements implemented to total design components.
Material Footprint	$\mu = \frac{m_{recycled}}{m_{total}}$	Ratio of recycled material usage to total material consumption.
Carbon Footprint	$\gamma = \sum_{i=1}^{n} E_i * EF_i$	Sum of energy consumption multiplied by emission factors for different processes.
Waste Management	$\delta = \frac{w_{recycled} + w_{reused}}{w_{total}}$	Percentage of waste that is either reused or recycled out of total waste generated.
Resource & Energy Conservation	$\beta = \frac{E_{efficiency} + R_{reduction}}{E_{Total} + R_{Total}}$	Efficiency gains and raw material reductions relative to total resource and energy use.

5.8 **Data Collection Protocol for Circular Economy Performance Evaluation:**

A structured data collection plan was designed to assess circular economy (CE) performance across seven industries over six months. The focus was on five key indicators: eco-design (α), material footprint (μ), carbon footprint (γ), waste management (δ), and resource &energy conservation (β). The selected industries were chosen for their significance in CE adoption, material use diversity, and potential for integrating circular strategies. Monthly data tracking ensured consistency and provided insights into performance trends.

A mixed-methods approach was used, combining primary and secondary data sources. Primary data came from manufacturing process reports, industry surveys, plant visits, and interviews with sustainability officers. Environmental reports, life cycle assessments (LCAs), carbon footprint audits, and sustainability reports provided the secondary data. Each CE indicator had a tailored data collection approach, specific to the industry's operations:

1. **Eco-Design (α)**: Product lifecycle assessments, design process documentation, and sustainability certifications helped evaluate sustainable design elements.
2. **Material Footprint (μ)**: Procurement records, bills of materials, and waste stream analysis were used to measure recycled material usage.
3. **Carbon Footprint (γ)**: Energy consumption logs, emission factor calculations, and process-level carbon assessments estimated CO_2 emissions per production unit.
4. **Waste Management (δ)**: Waste audit reports, recycling facility data, and production waste logs assessed the proportion of waste reused or recycled.
5. **Resource & Energy Conservation (β)**: Utility reports, energy efficiency metrics, and raw material optimisation studies measured efficiency improvements and resource reductions. The process involved:

- **Monthly Data Logging**: Industries maintained tracking sheets updated with real-time production data.
- **Cross-Validation & Verification**: Data was validated through site inspections, stakeholder interviews, and third-party environmental reports.
- **Data Normalisation & Pre processing**: Z-score normalisation was applied to standardise all indicators, ensuring comparability without introducing biases from other scaling methods.

Monthly scores were averaged over the six-month period for each indicator to provide a comprehensive performance assessment. Tables 5.7 and 5.8 present the raw and normalised scores, enabling standardised industry comparisons.

Table 5.7 Circular Economy Indicator Performance Score

Industry	Eco Design (α)	Material Footprint (μ)	Carbon Footprint (γ) (kg CO_2/unit)	Waste Management (δ)	Resource & Energy Conservation (β)
S-11 (Precision Manufacturing)	0.687	0.820	110.91	0.470	0.796
S-01 (Chemical Processing)	0.975	0.661	111.18	0.546	0.523
S-03 (Steel Casting & Forging)	0.866	0.725	131.72	0.583	0.804
S-13 (Plastics & Polymers)	0.799	0.312	169.21	0.628	0.585
S-06 (Paper & Pulp)	0.578	0.882	153.43	0.793	0.533
S-05 (Metal Fabrication)	0.578	0.799	129.51	0.500	0.974
S-08 (Glass Manufacturing)	0.529	0.427	184.01	0.657	0.983

Table 5.8 Normalized Circular Economy Indicator Performance

Industry	Eco Design (α)	Material Footprint (μ)	Carbon Footprint (γ)	Waste Management (δ)	Resource & Energy Conservation (β)
S-11 (Precision Manufacturing)	-0.172	0.745	-1.078	-1.162	0.270
S-01 (Chemical Processing)	1.537	0.001	-1.068	-0.465	-1.110
S-03 (Steel Casting & Forging)	0.890	0.300	-0.343	-0.126	0.310
S-13 (Plastics & Polymers)	0.493	-1.633	0.981	0.287	-0.796
S-06 (Paper & Pulp)	-0.819	1.035	0.424	1.800	-1.059
S-05 (Metal Fabrication)	-0.819	0.647	-0.421	-0.887	1.170
S-08 (Glass Manufacturing)	-1.1097	-1.0947	1.5038	0.5530	1.2150

5.9 **Multivariate Analysis for Circular Economy Performance-Step-6**:

To evaluate the Circular Economy (CE) performance of seven industries, a combination of clustering analysis and principal component analysis (PCA**)** was employed. **Clustering analysis** was used to identify industries with similar sustainability performance patterns, while **PCA** helped reduce dimensionality, highlight dominant performance factors, and reveal underlying trends. Clustering was performed to **group industries based on their CE indicator similarities,** enabling targeted recommendations for sustainability improvement. The python program of clustering and PCA was described in Appendix 5. Using k-means clustering, industries were categorised into three distinct groups:

- Cluster 0: Moderate CE adoption (S-01, S-03, S-13**)** – Industries with mixed sustainability efforts, requiring improvements in waste management and carbon footprint reduction.
- Cluster 1: Strong CE performance (S-11, S-05, S-08) – Industries demonstrating strong resource and energy conservation with comparatively lower material circularity and eco-design integration. These industries show potential for improvement through enhanced circular material strategies and eco-design adoption.
- Cluster 2: Waste-Centric Circularity Leaders *(S-06)*-Industries excelling in waste recycling and recovery practices, but facing challenges related to higher carbon emissions and energy intensity.

Table 5.9 Clustering Results of Seven Industries:

Cluster	Eco Design (α)	Material Footprint (μ)	Carbon Footprint (γ)	Waste Management (δ)	Resource & Energy Conservation (β)
Cluster 0	0.9733	-0.444	-0.1433	-0.1013	-0.532
Cluster 1	-0.4955	0.696	-0.7495	-1.0245	0.720
Cluster 2	-0.8190	1.035	0.4240	1.8000	-1.059

Principal Component Analysis (PCA) was used to identify the key factors driving variations in circular economy (CE) performance. Eigenvalues represent the proportion of variance explained by each component, with higher values indicating greater data retention. Table 5.10 shows the cumulative explained variance, illustrating the contribution of each principal component to the overall data structure.

Table 5.10 Result of PCA

Principal Component (PC)	Eigen value	Explained Variance (%)	Cumulative Variance (%)
PC1	2.914	58.28%	58.28%
PC2	1.158	23.16%	81.44%
PC3	0.665	13.30%	94.74%
PC4	0.218	4.36%	99.10%
PC5	0.045	0.90%	100%

The component loadings indicate the strength and direction of correlations between original variables and principal components, highlighting the key indicators that most influence each component. Detailed values are presented in Table 5.11.

Table 5.11 Principal Component Loadings (Factor Contributions)

Indicator	PC1	PC2	PC3	PC4	PC5
Eco Design (α)	0.542	-0.135	0.212	0.781	0.167
Material Footprint (μ)	0.612	0.493	-0.228	-0.298	-0.474
Carbon Footprint (γ)	-0.421	0.608	0.599	0.011	-0.125
Waste Management (δ)	0.378	-0.576	0.624	-0.190	-0.115
Resource & Energy Conservation (β)	0.314	0.206	-0.374	0.495	0.699

PCA identified two key factors influencing CE performance: PC1 (58.28% variance) and PC2 (23.16% variance). PC1, or the Circular Material Efficiency Factor, indicates that industries with high scores excel in eco-design, recycled material use, and resource efficiency. PC2, the Emission & Waste Management Trade-Off Factor, reflects a balance between carbon footprint reduction and waste management efficiency. The PCA revealed that industries in Cluster 1 had high PC1 scores, while Cluster 3 industries had negative PC1 scores, suggesting poor circularity adoption. Detailed interpretations and recommendations are provided in Table 5.12.

Table 5.12 Combined Interpretations and Recommendation

Cluster	CE Performance Characterisation	Key Issues Identified	Recommendations for Improvement
Cluster 0	Moderate CE Adoption (Balanced Profile)	Moderate eco-design and material circularity with scope for improvement in waste management and emission control	Strengthen waste segregation and recovery systems; integrate low-carbon process technologies
Cluster 1	Resource & Energy-Efficient CE Profile	Strong resource and energy conservation but limited eco-design integration and material circularity	Enhance closed-loop recycling; invest in next-generation eco-design and secondary material optimization
Cluster 2	Waste-Driven Circularity Profile	High waste recovery efficiency accompanied by higher carbon and energy intensity	Introduce energy-efficient waste processing; adopt carbon mitigation strategies such as process optimisation and cleaner fuel substitution

5.10: Specific Action Plans based on PCA Result:

For SMEs, prioritising material circularity (PC1) through improvements in material footprint and resource & energy conservation is key to driving sustainability. Simultaneously, focusing on waste management and carbon footprint (PC2) is essential for balanced environmental stewardship. Investing in eco-design strategies (PC3) will foster long-term success. Aligning SME strategies with these indicators enhances sustainability, cost efficiency, and regulatory compliance.

The PCA validation confirmed the clustering outcomes, showing a strong link between high PC1 scores and high-performing clusters, thus effectively identifying areas for improvement in CE adoption

5.11 Determination of Circular Economy Performance Weights Using PCA:

The weights of Circular Economy (CE) performance indicators were derived using Principal Component Analysis (PCA), with absolute loadings weighted by the explained variance of each component. Material Footprint (24.10%) emerged as the most influential indicator, followed by Carbon Footprint (21.73%), Waste Management (20.73%), Eco-Design (19.10%), and Resource & Energy Conservation (14.33%). These weights highlight the key drivers of CE performance and inform targeted improvement strategies.

PCA and cluster analysis serve complementary, not redundant, purposes in this study. PCA is used for dimensionality reduction and to identify the dominant CE performance drivers, thereby removing multi-co linearity and noise from the dataset. Cluster analysis is then applied on the PCA-informed data to group SMEs with similar CE performance patterns, enabling meaningful segmentation and interpretation. Using PCA alone does not provide group classification, while clustering without PCA would be sensitive to noise and correlated variables; therefore, their combined use ensures robust, interpretable, and statistically sound clustering outcomes.

The weight of each indicator is computed using absolute loading values weighted by the explained variance of each principal component.

The formula used:

$$W_j = \sum_{i=1}^{k} \left| L_{ij} \right| * EV_i$$

where:

- w_j = Weight of indicator j
- L_{ij} = Loading of indicator j in principal component i
- EV_i = Explained variance of principal component i(normalised)

The Python code for calculating W_j is presented in Appendix 3. Computed weight for each indicator are-

- Eco Design weight (W_1) : 0.19
- Material Footprint weight (W_2): 0.24
- Carbon Footprint weight (W_3): 0.22
- Waste Management weight (W_4): 0.21
- Resource & Energy Conservation weight (W_5): 0.14

The overall performance of the CE in seven Industries is mentioned in Table 5.13.

Table 5.13 Overall CE Performances

INDUSTRY	Overall Score	Recommendation
Paper and Pulp (S-06)	0.713	Excelling in material footprint and waste management.
Steel Casting and Forging (S-03)	0.480	Benefits from better material circularity.
Glass Manufacturing (S-08)	0.307	Showing potential for sustainability improvement.
Metal Fabrication (S-05)	0.182	Implements lean manufacturing to minimise waste generation. Enhance material recovery through closed-loop production.
Plastic and Polymer (S-13)	0.164	Improve waste management strategies to reduce environmental impact. Explore bio-based and recyclable polymer alternatives.
Chemical Processing (S-01)	0.101	Introduce carbon capture & storage (CCS) to lower emissions. Shift to greener chemical alternatives and circular feed stocks.
Precision Manufacturing (S-11)	0.000	**Scores** the lowest**,** indicating challenges in wast management and carbon footprint control.

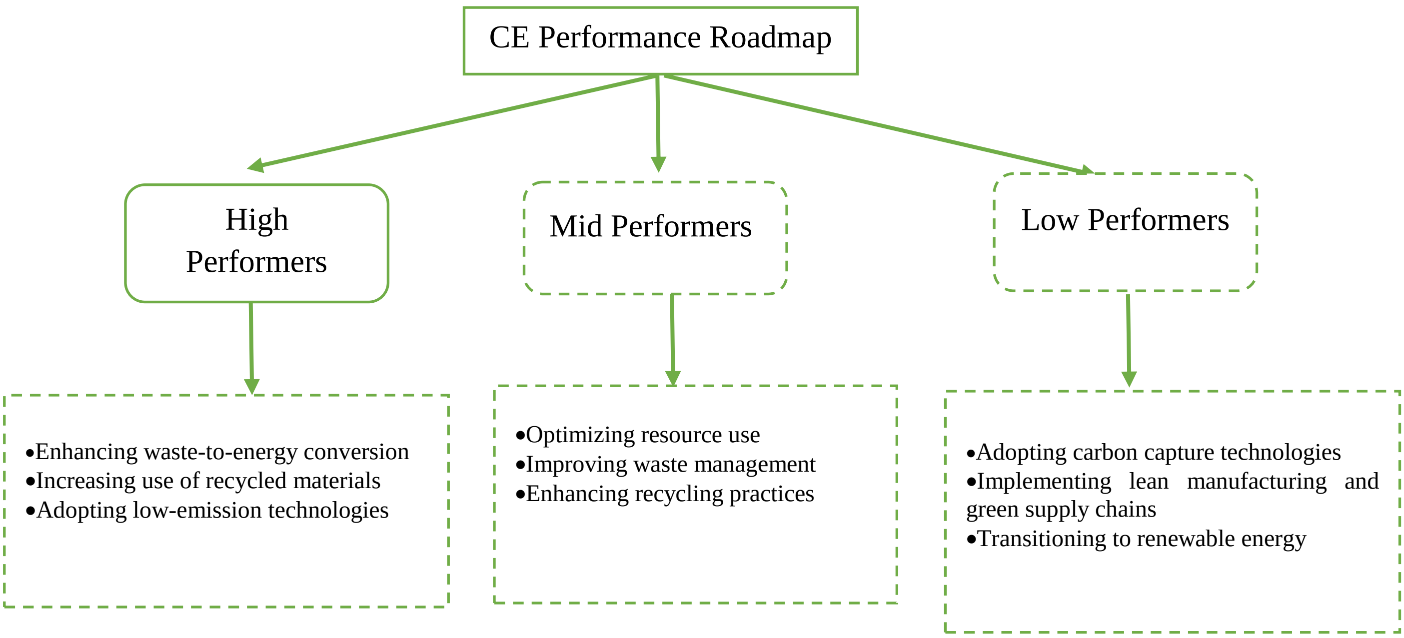

Figure 5.1 Circular Economy Road Map

5.12 Economic Sustainability of the Model-Step-7:

Adoption of Circular Economy (CE) practices has the potential to generate measurable economic benefits by improving resource efficiency and reducing operational expenditures. Strategies such as eco-design integration, material footprint reduction, and resource and energy conservation enable industries to lower costs associated with raw material procurement, energy consumption, waste treatment, and

emissions management. Increased recycling rates and improved material utilisation directly reduce material input costs, while energy efficiency initiatives and enhanced waste management practices further decrease operational overheads. In addition, reduced carbon emissions may help industries mitigate future compliance costs associated with increasingly stringent environmental regulations.
However, the present analysis is based on a six-month observation period, which limits the ability to fully quantify long-term economic benefits. Many CE-related investments—particularly eco-design and process re-engineering—tend to deliver financial returns over extended time horizons. Within this limitation, Table 5.14 summarises the relative economic sustainability characteristics observed across the identified industry clusters.

Table 5.14 Economic Sustainability of the Clusters

Cluster	Industries	Key Economic Driver	Cost-Saving Characteristics	Economic Sustainability Potential
Cluster 1	S-11, S-05, S-08	Material & Energy Efficiency	Strong focus on optimized material usage and energy conservation results in noticeable short-term reductions in operational costs	High (Short-term)
Cluster 0	S-01, S-03, S-13	Eco-Design & Material Optimization	Cost savings are strategic and gradual, emerging over time through improved product design, reduced material intensity, and lower waste generation	Moderate (Long-term)
Cluster 2	S-06	Waste & Material Circularity	Effective waste reduction contributes to cost savings; however, higher energy intensity limits overall economic gains	Moderate (Mixed)

From an economic sustainability perspective, industries in Cluster 1 demonstrate stronger short-term cost-saving potential due to their emphasis on material efficiency and energy conservation, which are closely aligned with PC1 (Circular Material Efficiency Factor)**.** Cluster 0 industries exhibit moderate but strategically important economic benefits, as eco-design-driven improvements typically yield financial returns over longer periods. Cluster 2 industries show mixed economic outcomes, with strengths in waste reduction offset by challenges in energy efficiency, highlighting the need for integrated energy optimisation strategies.

Overall, the economic analysis reinforces the complementary role of clustering and PCA in identifying not only environmental performance patterns but also the nature and timing of economic benefits arising from CE adoption. This provides decision-makers with clearer insights into short-term versus long-term economic implications of circular economy strategies in SMEs.

5.13 Outcome of the Present Work:

This study offers a practical and well-rounded framework to assess Circular Economy (CE) performance in SMEs by integrating PROMETHEE, CRITIC, clustering, and PCA methods. By analysing diverse industrial sectors across India, the research not only maps the current standing of SMEs on their CE journey but also systematically identifies critical areas where strategic interventions are required. The use of multi-criteria decision-making techniques alongside unsupervised learning enables a robust and nuanced classification of industries based on sustainability indicators. It empowers decision-makers to develop targeted action plans tailored to the unique strengths and challenges of each cluster, thereby promoting resource optimization, cost efficiency, and environmental stewardship. The framework's scalability and adaptability make it suitable for broader implementation, both nationally and globally, especially in emerging economies where SMEs play a vital role in industrial growth and sustainability.

Looking ahead, there is considerable scope to build on this foundation. Future research could explore real-time CE performance tracking, apply machine learning techniques to refine clustering further, and work towards developing a standardized CE performance index. There is also potential to examine how policy support, financial incentives, and digital technologies can accelerate CE adoption, particularly in resource-constrained SMEs. Expanding the study to include more industries and longer timeframes would offer a more comprehensive picture and support informed, sustainable decision-making that aligns with global circular economy goals.

Integrated Process and Optimization Strategies for Low-Carbon, Cost-Efficient Steel Production

Work Packages		
Research Objective 2: (RO-2) To develop a carbon footprint reduction strategy for the steel sector by integrating circular economy principles with Lean and Quality Management practices, supported by industry-specific case studies and validated through statistical analysis and optimization modelling.	WP-07	Analyse the effect of fuel and technology on carbon emissions and production costs in the steel sector using statistical methods.
	WP-08	Identify existing fuel-technology combinations in the Indian steel sector.
	WP-09	Determine the best possible combination using TOPSIS (Technique for Order Preference by Similarity to Ideal Solution).
	WP-10	Develop an optimization model to minimize emissions and production costs.
	WP-11	Apply the model to a case example in the Indian steel industry.

6.1 Introduction:

The steel industry is pivotal to the global economy, providing a strong, durable, and endlessly recyclable material. However, it’s significant environmental footprint—accounting for nearly 7–9% of global carbon dioxide emissions—makes it a crucial sector in the fight against climate change. While advanced economies have started making progress toward greener steel production, emerging economies like India face a more complex challenge. As the world's second-largest steel producer, India's booming construction, automotive, and infrastructure sectors are pushing demand even higher. Simultaneously, India has pledged to reach net-zero emissions by 2070 and to cut carbon intensity by 33–35% by 2030. These dual pressures—industrial growth and climate responsibility—make India a particularly important and globally relevant case for understanding how the steel sector can transition to low-carbon pathways.

Although many studies have explored energy efficiency and decarbonisation strategies for steel, most focus either on broad policy frameworks or individual technologies. There is a demonstrable lack of detailed analysis that integrates real production data, evaluates multiple energy and technology options together, and balances both economic and environmental outcomes. Furthermore, while Electric Arc Furnaces (EAFs) and scrap recycling is recognised as lower-carbon options, few studies have systematically modelled how scrap quality, energy sourcing, and production costs interact in practice. This study addresses these gaps by offering three main contributions to the literature:

Methodological Integration: It is the first to use a combined statistical and optimisation approach, utilizing ANOVA, TOPSIS, and a mathematical model, to identify the best production pathways for minimizing both cost and emissions.

Process Optimization: It introduces an optimization model for EAF operations that incorporates scrap quality as a decision variable—a critical but often overlooked factor in steel sustainability.

Policy Relevance: It provides India-specific insights that can guide both policymakers and industry leaders in designing practical strategies for greener growth.

Based on these contributions, the key objectives of this study are to:

- Analyze the effects of different fuel types and production technologies on both costs and Scope 1 and Scope 2 emissions in Indian steel production.
- Apply a multi-criteria decision-making approach (TOPSIS) for selecting the most sustainable fuel-technology combination.
- Develop a new optimization model for EAF processes that improves scrap management and energy efficiency.
- Propose actionable strategies for making India's steel sector more sustainable and circular.

The study’s novelty lies in combining statistical analysis, multi-criteria decision-making, and optimization modelling, specifically tailored to the Indian steel industry context. By introducing a Scrap Quality Index and optimizing the EAF pathway, it offers a unique, practical framework for balancing economic and environmental goals in emerging economies.

6.2 Data Collection for Analysis:

In this study, data were collected directly through primary fieldwork, without relying on any secondary sources or previously published materials. The research team conducted extensive factory visits, closely observed manufacturing processes, and carried out on-site measurements at steel plants located in Eastern India. Primary data were gathered from a major steel plant where production is mainly based on the BF-BOF (coal-based) and EAF (electricity-based) routes. Through direct observation and real-time data recording during the site visits, the team documented fuel usage patterns, emission points, and production cost structures. While coke remained the primary fuel for the Blast Furnace (BF), the plant had begun trials to reduce carbon emissions through natural gas injection and biomass-based energy generation using rice husk and other agricultural residues. Operational data from these trials were recorded first-hand during the visits.

In Eastern India, collaboration with a leading steel producer allowed for systematic on-site data collection between December 2023 and May 2024. Daily production costs (INR per tonne) and CO_2 emissions (tonne per tonne of crude steel) were recorded for operations utilizing coal, natural gas, and biomass. While coal is the main fuels during standard operations, natural gas and biomass were introduced experimentally during pilot phases. During these trials, the research team collected data directly from control room systems and operational logs, ensuring the dataset's accuracy and authenticity.

6.3 **Core Statistical Analysis:**

Primary data were collected from a steel factory located in Eastern India during the period from December 2023 to May 2024 to analyse the impact of different fuels—coal, natural gas, and biomass—on CO_2 emissions (tonnes per tonne of crude steel) and production costs (INR per tonne). Electricity was excluded from the emission dataset as it is not a combustion fuel in the BF–BOF process and therefore does not generate measurable point-source CO_2 emissions. Prior to conducting ANOVA, the assumptions of homoscedasticity and normality—which are prerequisites for valid ANOVA analysis—were verified. Levene’s Test for equality of variances yielded a p-value of 0.317, indicating no significant difference in variances across groups. Additionally, the Anderson-Darling Test for normality produced a p-value of 0.0713, confirming that the residuals were normally distributed. These results validated the suitability of the data for proceeding with the ANOVA. The ANOVA model applied can be expressed as: $Y_{ij} = \mu + \tau_i + \epsilon_{ij}$

Where, Y_{ij} is the emission (response variable) for the j-th observation in the i-th fuel type group. μ is the overall mean emission. τ_i is the effect of the i-th fuel type. ϵ_{ij} is the random error term. The results of the ANOVA, as summarized in Table 6.1, indicate a statistically significant effect of fuel type on emissions.

Table 6.1 ANOVA Table Effect of emission on Production Cost

Source	Df	SS	MS	F-value	p-value
Fuel Type	2	4.484	1.495	225.52	0.000
Error	12	0.080	0.007		
Total	14	4.563			

Following the results of ANOVA, which indicated a significant effect of fuel type on emissions ($p < 0.001$), a post-hoc analysis using Tukey's HSD test was conducted. The test revealed that biomass exhibited significantly lower emissions compared to both natural gas and coal, while no significant difference was observed between natural gas and coal.

Table 6.2 Tukey's Method for Significant Emission Differences

Fuel Type	N	Mean	Group
Biomass	4	0.8275	A
Natural Gas	4	1.6150	B
Coal	4	1.9225	B

As shown in Table 2, biomass (Mean = 0.8275) differs significantly from both natural gas (Mean = 1.6150) and coal (Mean = 1.9225), while natural gas and coal do not differ significantly from each other, as indicated by their belonging to the same group.

These findings highlight the environmental advantage of biomass as a cleaner fuel alternative compared to coal and natural gas. It is notable that the emissions impact of coal and natural gas is statistically similar. However, to make biomass a viable alternative for large-scale steel production, further investigation into its cost-effectiveness is warranted, given potential trade-offs between environmental benefits and production economics.

6.4 Effect of Fuel Type on Production Costs (ANOVA):

The influence of different fuel types, including biomass and electricity, on production cost was assessed using the one-way ANOVA model. In the earlier ANOVA analysis the focus was strictly on fuel-based variations within the BF–BOF route because the primary field data were collected from a plant where steelmaking was predominantly coal-based, with trial injections of natural gas and biomass. Electricity was not included in the emission ANOVA analysis, as it is not a primary fuel in the BF–BOF process and does not undergo combustion to produce measurable furnace-level CO_2 emissions. The EAF route—where electricity serves as the main energy source—was not part of the direct emission measurement dataset used in this study. Consequently, electricity could not be represented in the emission dataset expressed in tonnes of CO_2 per tonne of steel. However, electricity is still consumed extensively across the plant for auxiliary operations such as blowers, pumps, cooling systems, motors, material handling, and process-control activities. These uses, although not generating direct emissions, contribute substantially to the daily operational expenditure. Therefore, electricity appropriately appears in the production-cost dataset while remaining absent from the emission-based ANOVA. This distinction reflects the different functional roles of electricity in cost versus emission generation within the BF–BOF system. The model is written as follows: $Y_{ij}{}' = \mu' + \alpha_i{}' + \epsilon_{ij}{}'$

Where: Y_{ij}' Production cost for the j-th observation in the i-th fuel type group. μ' is the overall mean production cost. $\alpha_i^{'}$ is the effect of the i-th fuel type. $\epsilon_{ij}{}'$ is the random error of the jth observation of ith fuel type. Before conducting ANOVA, assumptions of homoscedasticity and normality were verified and satisfied. Levene's Test for equality of variances yielded a p-value of 0.321, indicating homoscedasticity. Normality of residuals was checked using the Anderson-Darling Test, which gave a p-value of 0.752, confirming that the residuals are normally distributed. The detailed result of ANOVA is shown in Table 6.3

Table 6.3: ANOVA Table for Production Cost in Different Fuel Type

Source	Df	SS	MS	F-value	p-value
Fuel Type	3	1.23×10^{9}	4.11×10^{8}	35.67	<0.001
Error	12	1.38×10^{8}	1.15×10^{7}		
Total	15	1.37×10^{9}			

Fuel type has a statistically significant impact on production costs, as indicated by the F-value of 35.67 and p-value less than 0.001. Following the ANOVA results, a post-hoc analysis using the Least Significant Difference (LSD) method was performed. The LSD value was calculated as LSD = $t_{\frac{\alpha}{2}}, df\ error \times \sqrt{\frac{\sqrt{(2 \times MSE\ )}}{n}}$ = 5225.06

Based on a Mean Square Error (MSE) of 1.15×10^{7}, degrees of freedom for error = 12, and significance level of 0.05. The pair wise comparisons of production cost differences between fuels are summarized in Table 6.4.

Table 6.4 Significant Production Cost Differences between Fuels

Fuel Type-1	Fuel Type-2	Significant Differences
Coal	Natural Gas	-5746
Coal	Natural Gas	-6544
Coal	Biomass	9325
Coal	Biomass	8385
Coal	Biomass	12325
Natural Gas	Biomass	13071
Natural Gas	Biomass	12131
Natural Gas	Biomass	16071
Biomass	Electricity	-6288
Biomass	Electricity	-5940
Biomass	Electricity	-11273
Biomass	Electricity	-9273

Compared to coal, natural gas, and electricity, the production costs using biomass are significantly higher. The cost difference with coal ranges from INR 8385 to INR 12,325 per tonne, with natural gas from INR 12,131 to INR 16,071 per tonne, and with electricity from INR 5940 to INR 11,273 per tonne. These findings indicate that, among the fuels analysed, biomass is currently the least cost-effective option, highlighting the need for cost-reduction measures or policy incentives to encourage its adoption in steel production.

6.5 Identification of Feasible and Existing Technology-Fuel Combinations:

To identify the most suitable technology for steel production, a multi-criteria decision-making (MCDM) framework is employed to balance production costs with environmental impacts. This approach facilitates the selection of a technology that achieves both economic efficiency and ecological sustainability, supporting the broader goals of sustainable steel manufacturing. In this study, four key technologies are evaluated: **BF:** Blast Furnace, **BOF:** Basic Oxygen Furnace, **EAF:** Electric Arc Furnace, **DRI:** Direct Reduced Iron.

Additionally, four fuel options are considered: coal, natural gas, biomass, and electricity. Together, these yield 16 potential technology-fuel combinations. However, not all these combinations are feasible in the Indian context due to various challenges, including technological limitations, economic viability, resource availability, environmental concerns, and regulatory constraints.

Out of the 16 potential technology-fuel combinations, 11 are not practically implemented within India's steel industry due to a combination of technological, economic, and resource-related limitations:

- **Natural Gas-Based Technologies:** BF-Natural Gas and BOF-Natural Gas combinations are not feasible, as both processes are fundamentally designed for coal-based operations. Natural gas does not adequately support the chemical reactions or process scale required.
- **Biomass-Based Technologies:** BF-Biomass, BOF-Biomass, DRI-Biomass, and EAF-Biomass are not adopted in practice, primarily due to technological incompatibilities and the lack of economic viability under current conditions.
- **Coal-Based Technologies:** EAF-Coal is unsuitable because the Electric Arc Furnace depends on electricity for melting scrap, rendering coal ineffective. DRI-Coal, while technically possible, is less preferred because it results in higher carbon emissions and lower efficiency compared to natural gas-based DRI processes.
- **Electricity-Based Technologies:** BF-Electricity, BOF-Electricity, and DRI-Electricity configurations are impractical. Electricity cannot substitute for coke in reduction processes, and relying solely on electricity for DRI production would impose unsustainably high energy demands.

  As a result, only five technology-fuel pairings remain feasible for practical application in the Indian context, as outlined in Table 6.5.

Table 6.5: Production Cost and Emission for Existing Technology Fuel Combinations

Technology	Fuel Type	Production Cost (/Ton)	Emission (ton CO2/ton steel)
BF	Coal	31200	1.82
BOF	Coal	32300	1.88
EAF	Natural Gas	32325	1.59
EAF	Electricity	34545	0.62
DRI	Natural Gas	24656	1.69

6.6 Methodology: TOPSIS for Selection of Optimal Technology-Fuel Combination:

To prioritize technology-fuel options in steel production, the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method was employed. TOPSIS identifies the best alternative by minimizing the distance from the ideal solution (best performance) and maximizing the distance from the negative ideal solution (worst performance).Five feasible alternatives were assessed using key performance indicators (KPIs): production cost (INR per tonne) and CO_2 emissions (tonnes per tonne of crude steel), where lower values indicate better performance. The raw data were first subjected to a logarithmic transformation (ln) to correct skew ness and stabilize variance across the indicators. The transformed values were then normalized, followed by the application of equal criterion weights (0.5

each) to obtain the weighted normalized decision matrix. Subsequently, the ideal solution (minimum cost and minimum emissions) and the negative ideal solution (maximum cost and maximum emissions) were identified for the set of alternatives. Euclidean distances were then calculated to measure how far each alternative was from the ideal (d_i^+) and negative ideal points (d_i^-). Finally, the closeness coefficient ($\frac{d_i^-}{d_i^-+d_i^+}$) for each technology-fuel combination was determined, providing a clear basis for ranking the alternatives based on their overall performance. with higher values indicating closer proximity to the ideal solution. The weighted normalized matrix is presented in Table 6.6, and the ideal solutions, distances, and closeness coefficients are summarized in Table 6.7.

Table 6.6 The Normalized Decision Matrix with Weighted Production Cost and Emission

Technology -Fuel Type	Production Cost (/Ton) (Normalized)	Weighted Production Cost	Emission (ton CO2/ton steel) Normalized	Weighted Emission
BF & Coal	4.494	2.247	0.260	0.130
BOF & Coal	4.509	2.255	0.274	0.137
EAF & Natural Gas	4.510	2.255	0.201	0.101
EAF & Electricity	4.538	2.269	-0.208	-0.104
DRI & Natural Gas	4.392	2.196	0.228	0.114

Table 6.7: Closeness Coefficient of TOPSIS Result

Technology-Fuel Pair	Distance to positive Ideal($\boldsymbol{D_i^+}$)	Distance to Negative Ideal ($\boldsymbol{D_i^-}$)	Closeness Coefficient
BF with Coal	0.235	0.023	0.089
BOF with Coal	0.243	0.014	0.056
EAF with Natural Gas	0.208	0.039	0.158
EAF with Electricity	0.069	0.241	0.777
DRI with Natural Gas	0.214	0.077	0.264
$Note$: $\boldsymbol{D_i^+} = \sqrt{\sum_{i=1}^{n}(p_i - 2.196)^2 + (E_i + 0.104)^2}$ $\boldsymbol{D_i^-} = \sqrt{\sum_{i=1}^{n}(p_i - 2.270)^2 + (E_i - 0.137)^2}$			

Table 6.7 indicates that the three most preferred technology–fuel combinations, based on their closeness coefficients, are EAF with electricity, DRI with natural gas, and EAF with natural gas. With the growing integration of renewable energy into India's power grid, technologies like DRI with natural gas and EAF with electricity have already been adopted by several major Indian steel manufacturers, both public and

private. This early adoption suggests that these companies recognize the potential for achieving a balance between economic efficiency and environmental sustainability. Their proactive shift towards these technologies highlights the increasing focus on reducing emissions and optimizing production costs in the Indian steel industry.

To test the robustness of the TOPSIS results, a sensitivity analysis was conducted by varying the weights of production cost and emissions (0.5–0.5, 0.6–0.4, and 0.4–0.6). As illustrated in Fig. 6.1, EAF with electricity consistently remained the top-ranked option across all weighting scenarios, confirming its strong combined economic and environmental advantages. DRI with natural gas remained the second-best alternative in all cases. Conversely, BF–coal and BOF–coal consistently appeared at the bottom of the rankings. These stable patterns across multiple weight combinations indicate that the relative performance of the technology–fuel options is highly robust and largely unaffected by changes in criteria priority.

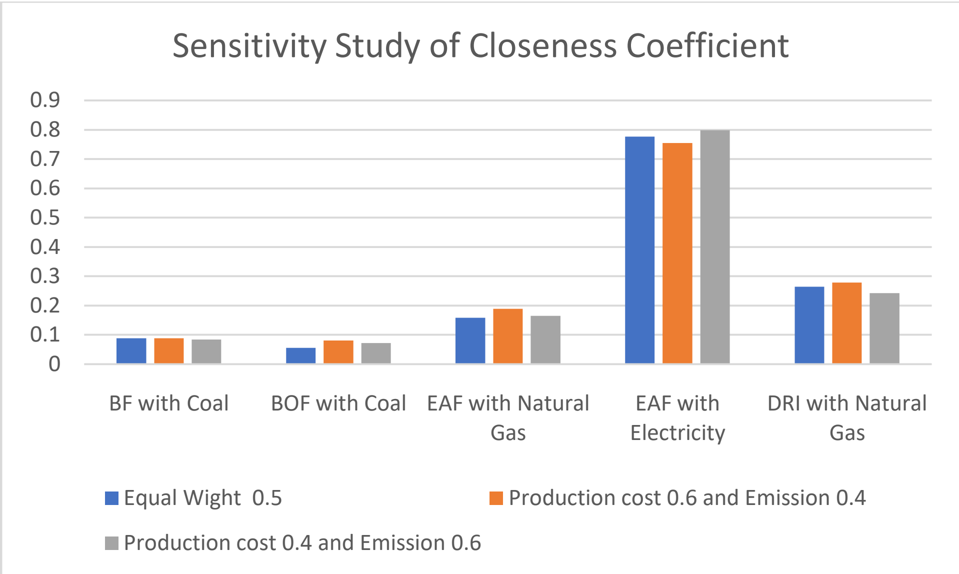

Figure 6.1 Closeness Coefficient of Technology Fuel Pair with Different Weights

6.7 Feasibility Evaluation of the Top 2 Technology-Fuel Combinations in the Indian Steel Industry: TOPSIS sensitivity analysis highlights DRI with natural gas and EAF with electricity as the most viable technology-fuel combinations in the Indian steel sector, considering sustainability, cost-efficiency, and environmental impact. To validate these results, supporting frameworks—Cost-Benefit Analysis (CBA), Life Cycle Assessment (LCA), and Risk Analysis—were developed using information obtained through interviews and surveys conducted in eastern Indian steel plants. The detailed outcomes of these assessments are presented in Tables 6.8-6.10. These findings reflect the sector’s ongoing transition toward renewable energy adoption, as noted in recent studies (Chen et al., 2022; Schmidt, 2024).

Table 6.8 Cost Benefit Analysis

Cost Factor	DRI with Natural Gas	EAF with Electricity
Direct Costs	Natural gas procurement, DRI technology costs	High initial setup and electricity costs
Indirect Costs	Carbon emission costs, potential penalties	Carbon tax if non-renewable sources are used
Benefits	Lower emissions, eligibility for green incentives	Lower emissions, flexibility with renewable electricity sources
Overall Feasibility	Moderate; natural gas prices are variable, but emissions are lower	High; feasible if renewable electricity is used

Table 6.9 Life Cycle Assessment (LCA)

Life cycle of Different Phase	DRI with Natural Gas	EAF with Electricity
Raw Material Extraction	Emissions from natural gas extraction, infrastructure needs	Emissions from power generation (depends on electricity source)
Production Phase	Lower emissions, higher efficiency in DRI production	Lower emissions, efficient EAF processes
Usage Phase	Moderate environmental impact from natural gas use	Minimal emissions if renewable electricity is used
End-of-Life	Recyclability and disposal of equipment	High recyclability of EAF infrastructure

Table 6.10 Risk Assessment

Risk Factor	DRI with Natural Gas	EAF with Electricity
Supply Risk	Dependency on stable natural gas supply	Reliability of electricity grid or renewable sources
Market Risk	Fluctuations in gas prices, potential shifts in demand	Market price of electricity, regulatory changes
Operational Risk	Risks in technology maintenance, natural gas infrastructure	Potential downtime, grid dependency, maintenance
Environmental Risk	Natural gas impacts on environment	Dependent on electricity source; green energy reduces risk

Electric Arc Furnace (EAF) powered by renewable electricity emerges as the most sustainable steel production pathway, offering significant emission reductions, lower operational risks, and long-term cost efficiency despite high upfront capital investment. Direct Reduced Iron (DRI) using natural gas serves as a viable transitional solution, providing moderate CO_2 mitigation but facing challenges related to fuel price volatility and supply reliability. In contrast, the Blast Furnace (BF) route remains energy-intensive and produces high emissions, even when electricity is added, which limits its sustainability. Overall, EAF with renewable energy stands out as the optimal choice for a low-carbon, future-ready steel industry. Simultaneously minimizing production cost and emissions in EAF is crucial to ensure sustainable manufacturing, meet regulatory requirements, and maintain economic competitiveness; therefore, process optimization is further needed to achieve this dual objective effectively.

6.8 Optimization Model for Scrap-Based EAF Steel Production:

The optimization model for Electric Arc Furnace (EAF) steel production focuses on minimizing both the production costs and carbon emissions by optimizing the usage of high-quality and low-quality scrap. In the context of sustainable steel manufacturing, the model incorporates key factors such as scrap availability, melting costs, emissions from both the scrap melting process and purchased scrap, and carbon taxes. The optimization of scrap-based Electric Arc Furnace (EAF) steel production is formulated as a multi-objective decision problem that minimizes total production cost and carbon dioxide (CO_2) emissions while meeting steel demand and environmental limits. Because economic and environmental goals are inherently conflicting, the problem is addressed using the Non-dominated Sorting Genetic Algorithm II (NSGA-II).

NSGA-II is well suited to this application because it addresses competing objectives without requiring predefined preference weights. Unlike single-objective or weighted-sum methods, it directly identifies Pareto-optimal solutions, allowing decision-makers to compare alternative production strategies based on economic and environmental performance. Furthermore, the algorithm effectively handles multiple constraints without relying on convexity assumptions, making it appropriate for practical EAF scrap management scenarios where sustainability and operational flexibility must be considered simultaneously.

Decision Variables for the optimization model are:

For each scrap category $i \in \{1,2\}$, where
$i = 1$: High − quality scrap (HQ)
$i = 2$: Low − quality scrap (LQ)
M_i: Quantity of scrap type i melted for production (tons)
P_i: Quantity of scrap type i purchased externally (tons)
S_i: Quantity of scrap type i sold externally (tons)All decision variables are continuous and non-negative.

These decision variables define the scrap quantities to be melted, purchased, or sold, allowing the model to optimize scrap usage in the EAF process, thereby minimizing both production costs and emissions.

Model Parameters are**:**

A_i: Available onsite scrap of type i
$C_{s,i}$: Unit cost of on-site scrap of type i (INR/ton)
$C_{p,i}$: Unit cost of purchased scrap of type i (INR/ton)
D : Steel production demand
F_M : Fixed emission factor of the EAF melting process (tCO_2/ton)
E_i : Emission factor for melting scrap type i (tCO_2/ton)
$E_{p,i}$: Emission factor associated with purchased scrap type i (tCO_2/ton)
P_m: Melting cost per ton of scrap (INR/ton)
Z_{max} = Maximum allowable CO_2 emissions (tCO_2)

The model uses these inputs to determine the optimal combination of scrap to be melted, purchased, or sold while minimizing both production costs and emissions. Optimization model for sustainable EAF Electricity Technology is mentioned in equations 6.1 to 6.6.

Objective 1: Minimize Total Production Cost

$$MinC(x)=\sum_{i=1}^{2}(C_{s,i}\mathrm{M_i} + C_{p,i}\mathrm{P_i} - R_iS_i) + P_m \sum_{i=1}^{2} M_i \quad \text{......[Equation 6.1]}$$

This objective captures the economic performance of scrap-based EAF steel production, including raw material costs, melting costs, and revenue from scrap sales (if applicable).

Objective 2: Minimize Total CO_2 Emissions

$$MinE(x)=\sum_{i=1}^{2}(E_i\mathrm{M_i} + E_{p,i}\mathrm{P_i}) + F_M \sum_{i=1}^{2} M_i \text{......[Equation 6.2]}$$

Model Constraints

Production Demand Constraint: $\sum_{i=1}^{2} M_i = D$ ....[Equation 6.3]

Scrap Availability Constraint: $M_i + S_i \leq A_i + P_i \; ; \forall \, i$......[Equation 6.4]

Emission Constraint (Optional): $E(x) \leq Z_{max}$...........[Equation 6.5]

Non-Negativity Constraint: $M_i, S_i, P_i \geq 0$ ....[Equation 6.6]

The multi-objective optimization problem is solved using NSGA-II with the following steps:

Initialization: A population of feasible solutions is generated by randomly sampling decision variables within operational bounds while satisfying demand and availability constraints.
Fitness Evaluation: Each solution is evaluated using the two objective functions—total cost and total emissions.
Non-dominated Sorting: Solutions are ranked into Pareto fronts based on dominance relations.
Diversity Preservation: Crowding distance is computed to maintain solution diversity along the Pareto front.

Selection, Crossover, and Mutation: Standard NSGA-II operators are applied to generate offspring solutions.
Elitism: Parent and offspring populations are merged, and the best non-dominated solutions are retained for the next generation.
Termination: The algorithm iterates until convergence or a predefined number of generations are reached.

6.9 Results of Optimization Model:

All data for this study were collected from an Electric Arc Furnace (EAF)–based steel plant in eastern India, supplemented by published literature and standard emission reporting guidelines. Scrap availability data for high- and low-quality scrap were obtained from industry scrap inventory records for the period **January–December 2024**, capturing seasonal variations in supply and production demand. Cost and production parameters were derived from plant operational records, while emission factors were sourced from literature and regulatory guidelines.

The optimization, carried out using the input parameters in Table 6.11, aims to simultaneously minimize total production cost and CO_2 emissions while satisfying production demand, scrap availability, and emission constraints. All results are directly based on these inputs without any assumptions or modifications.

Table 6.11 Input parameter of the model

Parameter	Value
Available High-Quality Scrap (A1)	600 ton
Available Low-Quality Scrap (A2)	300ton
Purchased High-Quality Scrap (P1)	?
Purchased Low-Quality Scrap (P2)	?
Sold High-Quality Scrap (S1)	?
Sold Low-Quality Scrap (S2)	?
High-Quality Scrap Melted (M1)	?
Low-Quality Scrap Melted (M2)	?
Production Demand (D)	1100 tons
Cost of High-Quality Scrap (C1)	Rs 28,675 per ton
Cost of Low-Quality Scrap (C2)	Rs 18,000 per ton
Melting Cost (Pm)	Rs 3,580 per ton
Cost of Purchased Scrap (Cp)	Rs 30,000 per ton
Emission Factor for Melting High-Quality Scrap (E1)	0.5 tons CO_2 per ton

Emission Factor for Melting Low-Quality Scrap (E2)	0.8 tons CO_2 per ton
Emission Factor for Melting Process (Fm)	0.4 tons CO_2 per ton
Emission Factor for Purchased Scrap (E_p)	0.6 tons CO_2 per ton
Maximum Allowable Emissions (Z_{max})	1300 tons CO_2

The NSGA-II algorithm was implemented in **Python** using the input parameters listed in Table 6.11. The model generates a Pareto front of non-dominated solutions, illustrating trade-offs between production cost and CO_2 emissions. Lower-cost solutions rely more on low-quality scrap, reducing costs but increasing emissions, while low-emission solutions use more high-quality scrap, increasing cost. Intermediate solutions provide balanced charge mixes.

For decision-making, three representative solutions are identified: cost-optimal, emission-optimal, and a knee (compromise) solution, summarized in Table 6.12. The knee solution achieves a moderate cost increase for a significant emission reduction.

Table 6.12 Representative Pareto-Optimal Solutions for Scrap-Based EAF Steel Production

Solution	HQ scrap (t)	LQ scrap (t)	Total cost (₹)	CO_2 emissions (tCO_2)
Cost-optimal	600	500	3.61×10^7	1260
Knee solution	660	440	3.68×10^7	1242
Emission-optimal	720	380	3.74×10^7	1224

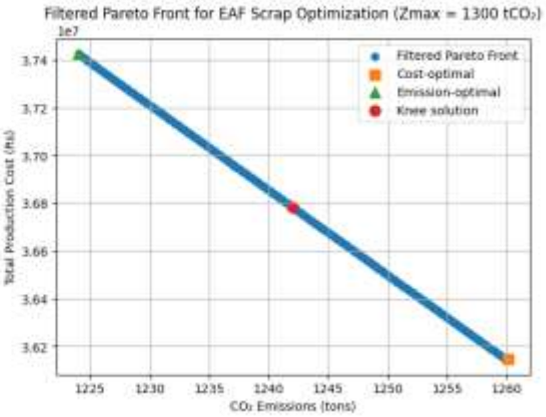

Fig. 6.2 Pareto Front Showing Cost–Emission Trade-Offs in Scrap-Based EAF Steel Production

As illustrated in Figure 6.2, the NSGA-II results produce a well-defined Pareto frontier that highlights the inherent trade-off between production cost and CO_2 emissions in scrap-based EAF steelmaking. The frontier shows that cost-optimal solutions rely on higher low-quality scrap usage with elevated emissions, while emission-optimal solutions increase high-quality scrap at higher cost. The knee point represents the most balanced operating regime, where a modest cost increase yields a significant emission reduction. The narrowness of the Pareto front under current input conditions indicates limited scope for further emission reduction through scrap-mix optimisation alone.

Overall, the NSGA-II results demonstrate that scrap composition is the primary driver of the cost–emission trade-off under fixed operational parameters, and the presence of a clearly identifiable knee region provides a practically relevant operating window in which meaningful emission reductions can be achieved without disproportionately increasing production cost. Consequently, the next stage of this work focuses on scrap quality improvement, which is expected to reduce scrap-related and melting emissions and shift the Pareto frontier downward without materially increasing production cost, as conceptually indicated by the trend in Figure 6.2.

6.10 Scrap Quality Improvement:

The scrap quality enhancement project involved evaluating several parameters, including Contamination Rate, High-Grade Percentage, Throughput, and Material Recovery Rate, to improve overall scrap quality. Data collection methods included magnetic separation and hand sorting for contamination assessment, X-Ray Fluorescence (XRF) for high-grade percentage determination, and throughput analysis based on total material processed per hour. Initial data were gathered from January 2024 to March 2024, followed by the implementation of remedial measures aimed at quality improvement. A subsequent dataset was collected from July 2024 to September 2024, with each phase involving the sampling and testing of 100 tons of scrap. To enhance scrap quality, the company identified and implemented the following action plans:

a) By identifying government-authorized scrap dealers located near the factory, the company secured high-quality scrap at lower prices, while also focusing on maintaining in-house scrap quality. Since the emission factor for melting high-quality scrap is lower, the company prioritized it in production, reducing reliance on low-quality scrap.
b) Additionally, efforts were made to sell as much low-quality scrap as possible to external buyers. To further enhance scrap management, the company adopted automatic sorting systems like metal detectors and X-ray machines to identify and separate high-quality recyclable scrap from contaminants, thus maintaining quality. Reworking slightly defective materials and reusing scrap internally also helped reduce waste.
c) Real-time inspection using vision systems, combined with root cause analysis, enabled the company to identify and correct issues early in the process, minimizing scrap generation. By optimizing material

usage and automating processes, the company reduced human error and waste, while ensuring raw material consistency through supplier audits.

d) Regular scrap analysis and key performance indicators (KPIs) were implemented to track scrap quality and identify areas for improvement. Moreover, scrap material that met quality standards was explored for potential resale or reuse in new products.

The results showed improvements across all parameters, as outlined in Table 6.13. The overall Scrap Quality Index, calculated as the geometric mean (GM) of the improvement factors, reflected a 15.49% enhancement, demonstrating the effectiveness of the implemented measures in optimizing scrap quality for sustainable steel production. The geometric mean is particularly useful in managing different dimensions, as it accurately captures improvements across multiple factors, while minimizing the influence of extreme values, ensuring a balanced and robust measure of scrap quality enhancement.

Table 6.13 SQI Improvement Factor

Parameter	Data Collection Method	Jan 24 – March 24			July 24 – Sep 24			Improvement Factor
Contamination Rate%	Magnetic separation for ferrous vs. non-ferrous metals and Hand sorting for visible contaminants like plastics and rubber.	5.7%	6.1%	5.8%	3.8%	4.1%	3.4%	0.358
High Grade Percentage%	X-Ray Fluorescence (XRF)	58.2%	64.5%	65.03%	65.5%	67.33%	68.5%	0.072
Throughput (Tons/Hr)	Total Material processed/ Time	15	18	20	20	26	22	0.283
Material Recovery Rate	(Useful Scrap/Total Scrap) *100	78%	83%	81%	85%	88%	88%	0.079
Scrap Quality Index		Geometric Mean of Improvement Factors						15.49%

Let us assume scrap quality index=S and Emission Factor = E

We know that the emission factor is inversely proportional to the Scrap Quality Index, as a better index reduces emissions due to fewer impurities, improved sorting, better material composition, and more efficient melting, all of which contribute to cleaner and more energy-efficient steel production.

Therefore $E \infty \frac{1}{s^n}$ and $E = \frac{k}{s^n}$ where k is a proportional constant.and n is a fractional constant.

Now, differentiate with respect to s on both side we get:

$$\frac{dE}{dS} = -\frac{kn}{S^{n+1}} \ldots\ldots \text{[Equation 6.7]}$$

Therefore, $dE = -\frac{kn}{S^{n+1}} ds$ ……[Equation 6.8]

Dividing both side with E we get,

$\frac{dE}{E} = -\frac{k}{S^{n+1}} * \frac{n}{E} ds$…….[Equation 6.9]

Put the value of $E = \frac{k}{s^n}$ in the last equation we get

$$\frac{dE}{E} = -\frac{nk}{S^{n+1}} * \frac{s^n}{k} dS = -n\frac{dS}{S} \ldots\ldots \text{[Equation 6.10]}$$

This indicates that if the improvement factor of SQI is 15.49%, the emission factor also improves by 0.154n Using this relationship, the revised emission factors for different scrap qualities, can be projected. High-quality scrap melts easier, producing fewer by-products. This relationship is relatively direct, making a linear inverse relationship between emissions and scrap quality a reasonable assumption. Regulatory bodies often use simplified linear models to estimate emissions reductions. Assuming a linear relationship (n = 1) is a practical first approximation, especially when detailed data is lacking. Linear models are preferred for regulatory assessments due to their simplicity, clarity, and ease of use. Therefore, assuming n = 1 is reasonable for modelling emissions reductions based on scrap quality improvements.

$\frac{dE}{E} = -0.154$……[Equation 6.12]

$$E_{new} = E_{old}(1 - 0.1549) = 0.5916\ CO_2/Ton \ldots\ldots \text{[Equation 6.11]}$$

Following the implementation of remedial measures—such as improved scrap segregation and statistical process control techniques—Phase II involved emissions monitoring across multiple melting batches. The weighted average emission factor was calculated as 0.57 tCO_2/ton, reflecting the tangible effectiveness of the interventions. This empirical emission factor marks an 18.57% reduction compared to the baseline of 0.70 tCO_2/ton observed in Phase I.

Notably, this observed value closely aligns with the theoretical estimate of 0.59 tCO_2/ton derived from a differential model assuming an inverse linear relationship (n = 1) between Scrap Quality Index (SQI) and emissions. The strong convergence between model predictions and empirical results reinforces the validity of the quality improvement strategy. Although slight deviations indicate that the SQI-emission relationship may not be perfectly linear ($n \approx 1$), the agreement is sufficient to support the use of simplified inverse models for emission forecasting and strategic decision-making in Electric Arc Furnace (EAF) steel production.

6.11 Results and Discussions:

This section presents the outcomes of the GA+SA hybrid optimization model designed to minimize production cost and carbon emissions in an Electric Arc Furnace (EAF)-based steel production process. The model was evaluated under two scenarios—before and after implementing emission reduction measures. The results demonstrate the efficiency of the model in determining optimal scrap utilization strategies under economic and environmental constraints.

The input data used in the optimization model are listed in Table 6.11. These parameters include cost coefficients, emission factors, scrap availability, and production demand. The emission factor for melting (F_m) was considered in two cases: before remedial measures (0.7 tCO_2/ton) and after remedial measures (0.57 tCO_2/ton).optimization results [Python code in Appendix 6] for both emission factor scenarios are summarized in Table 6.14. The optimal values of decision variables include the amounts of scrap melted, purchased, and sold. The objective was to meet the production demand while minimizing costs and keeping emissions below the allowable threshold.

Table 6.14 Output of the Optimization Result

Parameter	Value (Tons)
Purchased High-Quality Scrap (P1) (tons)	0
Purchased Low-Quality Scrap (P2) (tons)	25
Sold High-Quality Scrap (S1) (tons)	0
Sold Low-Quality Scrap (S2) (tons)	0
High-Quality Scrap Melted (M1) (tons)	665
Low-Quality Scrap Melted (M2)(tons)	410
Total Cost Phase -1	Rs. 3,68,00000
Total Cost Phase -2	Rs, 3,68,03600
Total Emission Phase -1 (t CO_2)	1242
Total Emission Phase-2 (t CO_2)	1080

Meeting Production and Emission Constraints:

In both scenarios, the model successfully met the steel production demand of 1,100 tons by optimizing the use of available high- and low-quality scrap and purchasing only a minimal amount (25 tons) of external low-quality scrap. The solution ensured compliance with the emission cap of 1080 tCO_2.

Impact of Emission Reduction Measures:

The implementation of a remedial measure to improve the melting process resulted in a reduced emission factor (F_m from 0.7 to 0.57), leading to a 13% reduction in emissions—from 1242 tCO_2 to 1080 tCO_2.

Cost-Emission Optimization Trade-off:

The results illustrate that while emissions can be significantly reduced through operational enhancements, the impact on cost remains negligible. The optimal strategy involves full internal utilization of available scrap and avoiding unnecessary external procurement or sales.

Model Effectiveness and Industrial Relevance:

The NSGAII model demonstrated excellent capability in solving a complex, nonlinear, and constrained optimization problem, efficiently converging on globally optimal solutions. This suggests that hybrid met heuristic approaches can be effectively adopted by the steel industry for sustainable production planning. Moreover, the model is adaptable and can be extended to accommodate dynamic parameters such as fluctuating scrap prices or evolving emission norms.

6.12 Outcome of Present Work:

The research yielded significant outcomes through a multi-stage analytical framework integrating ANOVA, post-hoc tests, TOPSIS, and GA+SA optimization to identify sustainable fuel-technology solutions for steel manufacturing. ANOVA revealed that fuel type significantly affects both CO_2 emissions and production cost, with post-hoc tests (Tukey HSD and LSD) highlighting that electricity-based systems produce substantially lower emissions than coal-based ones, albeit at higher costs. Applying the TOPSIS method, the Electric Arc Furnace (EAF) using electricity and high-quality scrap emerged as the most sustainable combination, balancing environmental and economic criteria. This was further validated through a hybrid NSGAII optimization model, which minimized both production cost and emissions while ensuring demand fulfilment. The optimized EAF configuration achieved a 13% reduction in emissions (from 1242 to 1080 tCO_2) by improving the melting emission factor from 0.7 to 0.57, with a negligible cost increase of only ₹3600. These results demonstrate the practicality of combining statistical and AI-driven tools to enhance decision-making in sustainable steel production. The study implies that cleaner energy integration, optimized scrap management, and circular economy principles can deliver significant environmental benefits. Future work may include expanding the model to incorporate Scope 3 emissions, dynamic electricity pricing, renewable integration, and decision-support systems for broader industrial application.

Chapter-7

Integrated Analysis of Material Footprint and Scope 3 Emission Reduction: A Case-Based Strategy for Carbon Mitigation

Work Packages		
Research Objective 4: (RO-4) To develop an integrated circularity-emission evaluation framework by first formulating a quantifiable Material Circularity Index (MCI) and Scrap Quality Index (SQI) to assess material reuse efficiency and input quality, and then applying Environmental Value Stream Mapping (EVSM) to identify carbon-intensive upstream and downstream activities across supply chains. This dual approach aims to reduce Scope 3 emissions and support data-driven, circular economy-aligned sustainability interventions in resource-intensive industries.	WP-18	Improve scrap quality index and increase the percentage of reused and recycled materials.
	WP-19	Analyse the impact of reduced MCI on emissions.
	WP-20	Validate the model in the Indian steel sector.
	WP-21	1. Upstream activities: Analysing emissions from raw mate extraction, processing, and transportation. 2. Operational activities: Examining emissions from ene consumption, production processes, and waste management. 3. Downstream activities: Assessing emissions from product use, end-of-life, and waste disposal.
	WP-22	Gathering and consolidating data from various sources to create a comprehensive emissions profile.
	WP-23	Calculating and examining emissions from different activities to understand their environmental impact.
	WP-24	Pinpointing areas with the highest emissions and identifying opportunities for reduction.
	WP-25	Creating targeted plans to minimize emissions and improve sustainability.

7.1 Introduction:

In recent years, rising concerns over climate change, dwindling natural resources, and environmental degradation have pushed industries around the world to rethink how they operate. The steel industry, known for its heavy use of raw materials and energy, is at the heart of this transformation. As the demand for cleaner, greener manufacturing grows, the circular economy (CE) is emerging as a promising pathway—one that emphasizes using resources more efficiently, cutting down waste, and replacing virgin materials with secondary raw materials (SRMs) like recycled scrap.

A vital measure in this shift is the Material Footprint (MF), which captures the total amount of raw materials extracted to produce goods and services. In steel production, particularly through Electric Arc Furnace (EAF) technology, the use of scrap metal offers a straightforward way to reduce this footprint. By increasing scrap usage, producers can rely less on freshly mined ores, reduce energy use, and minimize environmental harm. But real change requires looking beyond just internal improvements.

While direct emissions from on-site activities (Scope 1) and indirect emissions from purchased electricity (Scope 2) are relatively easier to quantify and control, Scope 3 emissions present a far greater challenge. These are the indirect emissions that span the entire value chain, encompassing everything from raw material extraction and transportation to outsourced processing, product use, and final disposal. In the steel industry, Scope 3 emissions can account for more than 70% of the total carbon footprint, making them the most significant—yet often the most overlooked—component of environmental impact. Their complexity stems from the fact that they occur outside the immediate boundaries of the organization, involving multiple stakeholders, third-party operations, and fragmented data sources. This lack of direct control and transparency makes Scope 3 emissions particularly difficult to track, quantify, and manage, posing a critical barrier to achieving full-scale decarbonization.

To address both the resource and emission challenges holistically, this study introduces a comprehensive framework grounded in circular economy principles. It proposes a Material Circularity Index (MCI) to assess how efficiently materials are used. At the same time, the study uses Environmental Value Stream Mapping (EVSM) to track carbon hotspots across the supply chain and pinpoint where the most significant Scope 3 emissions occur—such as in low-quality scrap logistics, inefficient subcontracting, or poor waste take-back systems.

The purpose of this study is twofold. First, it aims to quantify the material footprint in steel production by developing a Material Circularity Index (MCI) and a supporting mathematical model that demonstrates the relationship between emissions and material consumption. This component is validated using a real-world case example, which highlights tangible outcomes through an analytical approach—emphasizing how improvements in scrap quality can directly influence material efficiency and environmental performance.

Second, the study addresses the impact of Scope 3 emissions, which are often overlooked yet form the largest share of total emissions in the steel sector. To tackle this, a game-theoretic framework is employed to evaluate emission reduction strategies across the value chain. By identifying key stakeholders and modelling their interdependencies, the study proposes collaborative solutions that enhance transparency, accountability, and decarbonization efforts.

Together, these two components provide a comprehensive and actionable pathway for advancing sustainable steel production by integrating circular economy principles with both quantitative modelling and strategic emission management.

7.2 **Mathematical Formulation of Optimized Material Circularity Index:**

The Material Circularity Index (MCI) can be defined as the fraction of material that is recycled, reused, or recovered, relative to the total material entering and exiting the system. It should consider both raw materials and waste.

Let us assume,

M = mass of the finished product.
m = total waste used in the process.
α = fraction of recycled raw material.
β = fraction of reused raw material.
γ = fraction of scrap recycled.
δ = fraction of scrap reused.

Material Circularity Index (MCI) should compare the total effective raw material used (i.e., the recycled and reused materials) against the total material input to the system (i.e., the virgin and secondary raw materials and waste).

The MCI formula can be written as:

$$MCI = \frac{M_{effective} + m_{effective}}{M + m}$$

Where:

$M_{effective}$ = the amount of finished product that comes from recycled or reused materials.

$m_{effective}$ = the amount of recoverable waste that is either recycled or reused.

Now. $M_{effective} = M(\alpha + \beta)$ This represents the effective amount of material in the finished product that is recycled or reused(i.e.,α is the fraction of recycled raw material, and $\boldsymbol{\beta}$ is the fraction of reused raw material).

Again, $m_{effective} = m(\gamma + \delta)$ This represents the effective waste that is recycled or reused (i.e., **γ** is the fraction of waste recycled, and **δ** is the fraction of waste reused)

In the context of steel casting, α (Alpha) and β (Beta) represent the fractions of recycled and reused steel, respectively, used as raw materials in the casting process. In contrast, γ (Gamma) and δ (Delta) represent the fractions of scrap steel that are recycled and reused, respectively, within the casting process itself. While α and β focus on external raw material sourcing, γ and δ focus on internal scrap management and reuse, highlighting different aspects of material conservation and efficiency in steel casting.

Therefore, MCI= $\frac{M_{effective} + m_{effective}}{M+m} = \frac{M(\alpha+\beta)+ m(\gamma+\delta)}{M+m}$……[Equation 7.1]

Amount of fresh raw material used in the production is R and it is calculated as follows:

$$R = M(1-\alpha-\beta) \quad \ldots\ldots\ldots..[Equation - 7.2]$$

Also, the recoverable waste is calculated as a residual part, and it is given by:

$W_U = m(1-\gamma-\delta)$ …….. [Equation-7.3]

Where m= Total waste used in the process = $M(\alpha+\beta)$

γ = The fraction recycled waste (WC) and depends on a certain efficiency rate (EC).

δ= The fraction of the reusing waste collected.

Therefore, recycling efficiency = $\frac{M\alpha}{M\alpha+m\gamma} = \frac{M\alpha}{2M\alpha+M\beta}$ ………[Equation-7.4]

Reusing Efficiency= $\frac{M\beta}{M\beta+m\delta} = \frac{M\beta}{2M\beta+M\alpha}$ …………[Equation 7.5]

In steel casting**,** m(total waste or scrap used in the process) is closely related to SQI because the Scrap Quality Index directly determines the recyclability and reuse efficiency of the scrap material. A high SQI means that a larger portion of the waste (**m**) can be used effectively in the steel production process, increasing recycling efficiency and improving Material Circularity Index (MCI)**.** On the other hand, low-quality scrap reduces the ability to recycle the material efficiently, lowering the contribution of **m** to the circular economy. Hence, SQI plays a crucial role in determining the sustainability and circularity of the steel casting process.

Therefore, the revised MCI formula can be expressed as,

$$\frac{M(\alpha+\beta)+ m(\gamma.SQI+\delta.SQI)}{M+m} \quad …….[Equation-7.6]$$

In the ideal scenario where 100% of both materials and waste are recycled and reused, the Material Circularity Index (MCI) must reach its maximum value. This occurs when the recycled fraction (**α**), reused fraction (**β**), the fraction of recycled scrap (**γ**), and the fraction of reused scrap (**δ**) are all equal to 1.Then Max MCI value is-

$$\text{MCI}= \frac{M(1+1)+m(1+1)}{M+m} = 2 \text{ ....[Equation 7.7]}$$

Here, the formula yields **2**, but we want it to be **1** when the system is fully circular. To achieve this, we need to normalize the formula by dividing the result by **2**:

$$MCI_{norm} = \frac{1}{2}\frac{M(\alpha+\beta)+ m(\gamma.SQI+\delta.SQI)}{M+m} \text{........[Equation 7.8]}$$

7.2A. **Condition for Maximum Recycling Efficiency**

Recycling efficiency measures the fraction of material that is effectively recycled compared to the total material flow. To achieve maximum efficiency, it is essential to find the optimal trade-off between recycling and reuse. By formulating the recycling efficiency function, we analyse its mathematical properties through differentiation to identify any critical points. Examining its derivative helps determine whether the function has an internal maximum or continuously increases, reaching its highest value at the boundary.

$$\text{We know Recycling efficiency (r)} = \frac{M\alpha}{M\alpha+m\gamma} = \frac{M\alpha}{2M\alpha+M\beta} = \frac{\alpha}{2\alpha+\beta} \text{......[Equation 7.9]}$$

Since α and β are proportions, they satisfy: $\alpha+\beta\leq1$

- If α increases, the numerator increases. However, the denominator also increases, but at a slower rate since it grows as 2α+β. The maximum possible value of α is **1** when β=0

Therefore, $r_{max} = \frac{1}{2.1+0} = \frac{1}{2}$ ....[Equation 7.10]

If β>0, the denominator increases, decreasing recycling efficiency r.

Now taking partial derivative with respect to α we get,

$$\frac{\partial r}{\partial\alpha} = \frac{(2\alpha+\beta).1-\alpha.2}{(2\alpha+\beta)^2} = \frac{\beta}{(2\alpha+\beta)^2} \text{ ....[Equation 7.11]}$$

Since β≥0, we have $\frac{\partial r}{\partial\alpha}\geq0$, meaning recycling efficiency (r) increases as **α** increases**.**

Again, taking partial derivative with respect to β we get,

$$\frac{\partial r}{\partial \beta} = \frac{(2\alpha+\beta).0-\alpha.}{(2\alpha+\beta)^2} = \frac{-\alpha}{(2\alpha+\beta)^2}\text{......[Equation 7.12]}$$

Since α≥0, we have $\frac{\partial r}{\partial \beta}$≤0, meaning recycling efficiency (r) decreases as **β** increases**.**

Therefore,recycling efficiency is an increasing function of **α** and a decreasing function of **β**. Thus, the maximum recycling efficiency occurs at α=1,β=0, achieving the highest possible value of $\frac{1}{2}$.

7.2B. Condition for Maximum MCI

We know that the formula of material circularity index MCI

$$= MCI_{norm} = \frac{1}{2}\frac{M(\alpha+\beta)+ m(\gamma.SQI+\delta.SQI)}{M+m}$$

$$= \frac{1}{2}\left[\frac{M}{M+m}(\alpha+\beta) + \frac{m}{M+m}(\gamma.SQI + \delta.SQI)\right]\text{......[Equation 7.13]}$$

- The first term $\frac{M}{M+m}(\alpha+\beta)$ is maximized by increasing α+β.
- The second term $\frac{m}{M+m}(\gamma.SQI + \delta.SQI)$ is maximized by increasing (γ+δ) and SQI.

Thus, maximizing MCI_{norm} involves:

- **Maximizing α+β to increase the circularity of primary material**: α + β represents the combined efficiency for recycling and reusing, so ideally, you want **α** and β to be balanced in such a way that both recycling and reusing are maximized, keeping in mind the proportion of waste material.
- **Maximizing γ+δ to increase circularity from waste materials**: **γ + δ** represents the waste contribution from recycling and reusing. If **γ** and **δ** are both positive, increasing SQI (Scrap Quality Index) will lead to better MCI_{norm}.
- **Maximizing SQI, which depends on scrap quality parameters**: Increasing SQI maximizes the contribution of $m(\gamma \cdot SQI + \delta \cdot SQI)$ to MCI_{norm}, provided that **γ** and **δ** are both positive. Therefore, optimizing SQI is critical for achieving the highest possible MCI_{norm}. However, if constraints such as physical limitations or material quality restrictions exist, SQI should be increased to its upper permissible limit while ensuring compliance with these constraints.

  In this study, we maximize the Material Circularity Index (MCI) through a nonlinear programming problem, ensuring an efficient and balanced improvement of both scrap quality and material circularity. This optimisation process provides a comprehensive and practical solution for enhancing sustainability and efficiency in steel production.

7.3**Emission Control by optimizing MCI:**

The reduction of carbon emissions in the steel industry is significantly influenced by the adoption of Electric Arc Furnace (EAF) technology utilizing high-quality steel scrap. An improved Scrap Quality Index (SQI) ensures lower contamination and heavy metal content, leading to more efficient melting processes with reduced energy consumption and waste generation. Simultaneously, a higher Material Circularity Index (MCI) enhances resource efficiency by minimizing reliance on virgin raw materials, thereby lowering emissions associated with raw material extraction and processing. By optimizing both SQI and MCI, the overall carbon footprint of steel manufacturing is effectively reduced, contributing to a more sustainable and low-emission production system.

Let V(t) be the amount of virgin material being used at time t, and M(t)represent the Material Circularity Index **(**MCI**)** at time t.

The rate of change in virgin material usage is not constant but depends on how much material is being recycled (reflected in MCI). This means that if MCI improves over time, more scrap material is being recycled, and as a result, less virgin material is required to meet the industry's needs. Therefore, the rate of change of virgin material usage, is proportional to the MCI at time t.

$$\frac{dv}{dt} = -\lambda M\,(t) \ldots\ldots [\text{Equation } 7.14]$$

Whereλ is a proportionality constant that reflects how changes in MCI impact virgin material usage.M(t) is the material circularity index at any given time t.This negative relationship indicates that as MCI increases (i.e., more material is recycled), the need for virgin material decreases.

Assuming MCI (M) is increasing at a constant rate $M = M_0 e^{kt}$ where M_0 is the initial MCI and k is the growth rate of MCI, we integrate:

$$\frac{dv}{dt} = -\lambda M_0 e^{kt} \ldots\ldots [\text{Equation } 7.15]$$

$$v(t) = v_0 - \frac{\lambda M_0}{k} e^{kt} \ \ldots\ldots [Equation\ 7.16]$$

where V_0 is the initial virgin material consumption.As MCI increases, V(t) decreases, meaning less virgin material is used over time.

Again, we know, Improved Scrap Quality Index (SQI) reduces impurities in scrap, enhancing melting efficiency by minimizing energy use and ensuring a more consistent material composition. This leads to faster, more efficient processing and increased recovery of usable steel. Therefore, Melting efficiency directly proportional to SQI (Scrap Quality Index).

$$\frac{d\eta}{dt} = \gamma S\ (t) \ldots\ldots \text{[Equation 7.17]}$$

Assuming **SQI (S)** grows exponentially$S = s_0 e^{nt}$ where s_0 is initial SQI and nis the improvement rate, integrating gives:

$$\eta(t) = \eta_0 - \frac{\gamma s_0}{n} e^{nt} \text{m} \ldots\ldots \text{[Equation 7.18\ldots]}$$

whereη_0 is the initial melting efficiency. As SQI improves, melting efficiency increases, reducing energy waste.

Now, $\frac{dE}{dt} = Av + B(1 - \eta) \ldots\ldots$[Equation 7.19]

Substituting v(t) and η(t) we get,

$$\frac{dE}{dt} = Av + B(1 - \eta) \ldots\ldots \text{[Equation 7.20]}$$

$$= A\left(v_0 - \frac{\lambda M_0}{k} e^{kt}\right) + B(1 - \eta_0 - \frac{\gamma s_0}{n} e^{nt}) \ldots\ldots\ldots\ldots \text{[Equation 7.21]}$$

Now integrating both side we get,

$$E(t) = E_0 + A\left(v_0 t - \frac{\lambda M_0}{k^2} e^{kt}\right) + B(t - \eta_0 t - \frac{\gamma s_0}{n^2} e^{nt}) \quad \text{[Equation 7.22]}$$

As time increases, the exponential terms e^{kt}, e^{nt}grow, meaning that the reductions in virgin material usage (v) and energy inefficiency (1−η) accelerate.

The negative terms in the equation indicate that emissions decline as MCI (M) and SQI (S) improve. Since $\frac{\lambda M_0}{k} e^{kt}$ increases, the term $v_0 - \frac{\lambda M_0}{k} e^{kt}$ becomes smaller over time, meaning virgin material consumption steadily declines, reducing emissions.Similarly, as $\frac{\gamma s_0}{n} e^{nt}$ increases, the term $\eta_0 - \frac{\gamma s_0}{n} e^{nt}$ reduces, indicating improved energy efficiency and further emission reduction.

The initial emissions, denoted as E_0, represent the baseline carbon footprint of the steel manufacturing process. As the Material Circularity Index (MCI), represented by M, increases, the reliance on virgin raw materials decreases, leading to a reduction in energy-intensive extraction and processing activities. This results in a decline in emissions over time, following a negative exponential trend. Additionally, an improved Scrap Quality Index (SQI), represented by S, enhances the melting efficiency by reducing impurities in the scrap, thereby lowering energy consumption and optimizing furnace operations. The combined effect of higher MCI and SQI ensures a more sustainable production process with significantly reduced environmental impact.

For large t, assuming exponential growth dominates, the emission function behaves as:

$$E(t) \approx E0 - A\frac{\lambda M_0}{k^2}e^{kt} - B\frac{\gamma s_0}{n^2}e^{nt} \text{.....[Equation 7.23]}$$

The overall emission improvement is driven by the combined impact of reduced virgin material dependency and enhanced energy efficiency.

We assume the complementary function of the form:

$E(t) = c_1e^{kt} + c_2e^{nt}$.......[Equation 7.24.]
Where $c_1 = A - \frac{\lambda M_0}{k^2}$ and $c_2 = -B\frac{\gamma s_0}{n^2}$

To derive the corresponding second-order linear homogeneous differential equation, we differentiate E(t) twice and according the formula of complementary function we set up the differential equation:

$\frac{d^2E}{dt^2} - (k+n)\frac{dE}{dt} + knE = 0$........[Equation 7.25]

The term E_0represents the initial emissions at t=0 and it acts as an initial condition rather than part of the differential equation itself. However, when solving for E(t), we will use E_0as an initial condition.

The general solution is:
$E(t) = c_1e^{kt} + c_2e^{nt}$ *......[Equation 7.26]*

Applying the initial condition, when t=0, E=E_0 we get:E_0=$c_1 + c_2$

We also need a second initial condition, such as an initial emission reduction rate $\frac{dE}{dt}$ $at\ t = 0$to solve $c_1\ and\ c_2$

In this study, we assume that the initial rate of change of emissions, denoted as$\frac{dE}{dt}$ $at\ t = 0$, is proportional to the initial values of the Scrap Quality Index (SQI) and Material Circularity Index (MCI) at the start of the optimization process. At the beginning, the emission rate is assumed to be relatively high due to the lower initial values of SQI and MCI. As improvements in these indices progress over time, the emission rate gradually declines, reflecting the increasing efficiency in the recycling process and the enhanced quality of scrap. This assumption forms the basis for deriving the constants in the differential equation governing the emissions reduction dynamics.

7.4**Optimization Model for Maximize MCI Case Study-1**:

A multi-objective optimization model has been developed to enhance material circularity in the steel industry, aiming to increase material reuse and recycling while minimizing the consumption of virgin materials. The primary objective is to improve the Material Circularity Index (MCI) by optimizing the fractions of recycled (α), reused (β), and scrap-utilized materials (γ, δ), thereby minimizing reliance on virgin resources (R). The model dynamically adjusts these parameters while allowing flexibility in setting minimum virgin material requirements based on operational constraints. Key constraints include maintaining SQI as a fixed value, adhering to practical recycling limits, and ensuring material balance. The optimization strategy is designed to maximize resource efficiency, reduce dependence on virgin inputs, and sustain a balance between material supply and product quality.

The assumptions and the detailed of the model are furnished in the table:

Table 7.1 Assumption of Optimisation Model

Category	Description
Assumption	1. The Scrap Quality Index (SQI) is a fixed parameter and represents the quality of scrap available for recycling and reuse.
	2.The total mass of finished products (M) is known and fixed.
	3.The mass of recycled and reused materials (m) is fixed.
	4. At least a certain percentage (R_{min}) of virgin material must be used to maintain product quality.
	5. The fractions of recycled and reused raw materials (x) and waste materials (y) cannot exceed certain limits (f).
	6. The model should ensure that the total mass of materials (recycled + virgin) equals the total mass of finished products.
Decision Variables	x: Fraction of recycled and reused raw material (raw materials recycled or reused in the process)
	y: Fraction of recycled and reused waste material (scrap or waste materials recycled or reused)
Input/Parameters	**M**: Total mass of finished product (fixed input, known)
	m: Mass of recycled and reused materials (fixed input, known)
	R_{min} : Minimum fraction of virgin material.
	f: Maximum allowed fraction of recycled and reused materials (raw + waste),(dynamic input, typically f ≤ 1)

It is worthy to mention here that, in steel industry optimization, x (Recycled Raw Material) is reprocessed steel, while **y** (Reused Waste Material) includes scrap-based waste like off cuts and residues. Prioritizing **y** is crucial as it's more abundant, requires less processing, and aligns with Electric Arc Furnace (EAF) operations, reducing virgin material use and energy consumption while enhancing circularity. Objective functions of the model are: Minimize Virgin raw material $R = M(1 - w_1 x - w_2 y)$where w_1 and w_2 are weight factors ensuring higher priority to reused waste y than recycled raw material x ($w_1 \leq w_2$)

Maximize Effective Material Usage: $Mx + My + (R - M)SQI$……[Equation 7.27]

In the optimization model, there is no intersection between $My\ and\ (R - M)SQI$ as they represent distinct contributions to material utilization; $M \cdot y$ accounts for directly reused **waste**, which is immediately reintegrated into production without requiring additional processing, while (M−R)·SQI corresponds to recycled scrap material, where the Scrap Quality Index (SQI) adjusts for processing efficiency and material losses; since y is a direct reuse parameter and independent of virgin material (R)**,** whereas (M−R)·SQI is dependent on available recyclable scrap, their contributions remain separate within the material balance. The constraints of the multi-objective optimization problem, along with their interpretations, are presented in the Table 7.2. This structured representation ensures clarity in understanding the limitations and conditions governing the optimization framework.

Table 7.2: Constraints of the optimization model

Constraints	Equation	Interpretation
Material Balance	$M = Mx + My.SQI + R$	Total mass of finished products is the sum of recycled/reused and virgin materials.
Recycling Reuse Fraction	$x + y.SQI \leq f \cdot M$	The sum of recycled and reused raw materials cannot exceed a specified fraction of total finished product mass. Here f is a variable input, representing the upper limit on the total recycled/reused material fraction, which can be adjusted based on technological or operational constraints.
Virgin Material Minimum Usage	$R \geq Max\ (0.25M, R_{min})$	This enforces that at least 25% of the total finished product (M**)** comes from virgin material, preventing excessive reliance on recycled and reused content. R_{min} **Component**: This represents an industry-defined lower bound on virgin material usage, ensuring product qualityand compliance with operational standards.
Non-Negativity	$x \geq 0, y \geq 0, R \geq 0$	

7.5**Material Circularity Index Optimization Result**:

Over nine months, the Southern Indian steel casting industry collected data on material usage, including finished products (M), recycled & reused materials (m). The Scrap Quality Index (SQI) was optimized to 0.64 to enhance recycling and sustainability. To maximize the Material Circularity Index (MCI), The optimization model mentioned in paragraph 7.3was implemented to minimize virgin material use while maximizing recycling and reuse. The model considered material availability, industry recycling capacity, and a fixed SQI, aligning with sustainability goals. Industry-driven constraints were applied, setting the maximum recycled and reused material fraction as **f = 0.7M** and the minimum virgin material requirement as $\boldsymbol{R_{min}}$ **= 0.3M**. Data from Electric Arc Furnace (EAF) production over nine months and the output from the optimization model for maximizing the Material Circularity Index (MCI) has been **verified using Python (Appendix 7)**, and the results furnished in Table 7.3 confirm that the assumed parameter values (x = 0.35, y = 0.48, SQI = 0.65, $w_1 = 0.4, w_2 = 0.6$) lead to feasible solutions for all the months analysed.

Table 7.3 Optimisation Result

Month	Finished Product (M)	Available Scrap (m)	Virgin Material (R)	Effective Material Usage (M_e)	MCI Norm	Feasibility
April	9,780	7,300	5,594.16	10,838.20	0.3488	Feasible
May	11,870	8,234	6,789.64	13,154.33	0.3515	Feasible
June	10,550	7,345	6,034.60	11,691.51	0.3514	Feasible
July	10,712	7,656	6,127.26	11,871.04	0.3504	Feasible
August	9,979	7,865	5,707.99	11,058.73	0.3467	Feasible
Sept.	11,098	7,678	6,348.06	12,298.80	0.3516	Feasible
October	10,872	7,679	6,218.78	12,048.35	0.3508	Feasible
November	9,980	6,569	5,708.56	11,059.84	0.3535	Feasible
December	9,989	6,965	5,713.71	11,069.81	0.3513	Feasible

The multi-objective optimization model developed in this study aimed to maximize the normalized Material Circularity Index (MCI) within a steel casting facility operating under Electric Arc Furnace (EAF) technology. Utilizing real-world production data collected over nine months, the model optimized the utilization of recycled raw materials (α), reused waste (β), and processed scrap contributions (γ and δ), while keeping the Scrap Quality Index (SQI) fixed at 0.65 and adhering to realistic operational constraints. As detailed in Table 7.3, the resulting MCIvalues ranged from 0.3467 to 0.3535, reflecting moderate yet consistent levels of circularity within the existing material flow architecture. The values were computed using Equation 7.13, which integrates the mass-weighted contributions of both primary and secondary material loops.

To get closer to the ideal circularity level (MCI = 1.0), we have identified some key improvement steps. First, increasing the Scrap Quality Index (SQI) from 0.65 to 0.90 can improve the amount of scrap that is effectively recycled. This would raise the MCI value to about 0.49–0.52, assuming the amount of material used stays the same. Second, increasing the share of reused and recycled materials—from 83% to 95% for reuse and from 80% to 95% for recycling—can further boost the influence of recycled content in the circularity score. Another important step is reducing the required minimum use of virgin (new) raw materials from 30% to around 15–20%. This allows more recycled material to be used instead of new inputs, helping the MCI score go up. Also, collecting more recoverable material like internal scrap and leftover cuts from the production process can increase the share of recycled material in the system.

While these improvements are theoretical, our aim is to approach these target values to derive tangible sustainability and cost benefits. The proposed remedial measures, particularly the scrap improvement strategies detailed in Chapter 6, have already been implemented in select units of the southern steel sector with encouraging results. These case examples support the feasibility of the proposed model and provide a practical basis for its wider replication.

7.6 Scope 3 Emission Reduction Strategy- Case Study 2:

To address the challenges of identifying, quantifying, and mitigating Scope 3 emissions in a manufacturing supply chain, a two-phase methodology was adopted. The framework integrates Environmental Value Stream Mapping (EVSM) for hotspot identification and cooperative game theory for modelling emission reduction strategies involving multiple stakeholders.

The research was carried out in two interconnected phases to explore Scope 3 emissions in the steel manufacturing supply chain and identify practical strategies for reducing them. In Phase I, the study used Environmental Value Stream Mapping (EVSM) to pinpoint where the most carbon emissions were happening across different stages of the supply chain—upstream (raw material extraction and transport), midstream (in-house production), and downstream (product delivery and disposal). Data were collected through a combination of field visits, interviews with suppliers and transport partners, and secondary sources like logistics records and emission databases. Key information gathered included emission factors (in kg CO_2e per unit), fuel types, transport distances, shipment volumes, and logistics costs. Emissions for each activity were calculated using the formula $E_i = A_i \times EF_i$, where A_i represents activity data (like ton-kilometers or energy use) and EF_i is the emission factor. EVSM helped visualize these emissions directly on process maps, revealing that transportation and product distribution together accounted for a major share—about 75%—of total Scope 3 emissions, making them clear targets for intervention.

In Phase II, the study shifted focus to a game-theoretic approach to promote collaboration among key stakeholders: upstream suppliers (U), manufacturers (M), and downstream distributors (D). Each group was assigned a profile based on their emissions and the costs they would incur or save by reducing them. A cooperative game model was developed to encourage shared action, represented by a function v(S), which reflects the collective benefit of emission reduction minus the total cost of achieving it for any group of partners (or coalition S). Since West Bengal does not currently impose a carbon tax, the model emphasized internal benefits like operational savings, reputational gains, and voluntary compliance incentives. The Nash equilibrium was used to determine stable strategies where no partner would want to act alone, while the Shapley Value method helped distribute costs and benefits fairly among participants. The model was tested using real industry data collected from steel sector value chain partners, including upstream and downstream facilities. By adjusting emission levels, willingness to cooperate, and cost structures in the analysis, the study simulated realistic scenarios. The results confirmed that collaboration leads to better outcomes than working in isolation. Importantly, the model also supported circular economy practices—such as reverse logistics, improved scrap utilization, and digital traceability—to enhance emission reduction across the entire supply chain.

7.7 Case Example of Scope 3 Emission Reduction in Steel Sector:

The data collection process commenced with field visits to a medium-scale steel manufacturing industry located in West Bengal, India. The aim was to collect accurate, stakeholder-specific and process-level data across the upstream, midstream, and downstream stages of the supply chain. This was essential for:

- Calculating Scope 3 greenhouse gas (GHG) emissions.
- Identifying emission hotspots using Environmental Value Stream Mapping (EVSM).
- Structuring collaborative strategies for emission reduction using game-theoretic modeling.

7.7.1. Scope and Boundaries

- Geographic Scope: The steel supply chain studied spans industrial clusters in and around West Bengal, covering procurement, manufacturing, and distribution regions.
- Process Scope: Upstream (raw material procurement and transportation), midstream (in-house manufacturing operations), and downstream (product delivery, use, and end-of-life disposal).
- Emission Focus: Scope 3 GHG emissions, which include all indirect emissions across the value chain excluding Scope 1 and 2.

The detailed Data type and source are furnished in Table 7.4.

Table 7.4 Data Types and Sources

Data Category	Parameters	Sources	Method of Collection
Activity Data	Transport distances, freight weights, shipment frequency	Transport logs, supplier databases	Site visits, logistics reports
Activity Data	Energy usage, fuel consumption	Utility bills, factory dashboards	Plant records, observation
Emission Factors	CO_2e per ton-km or per process unit	IPCC, DEFRA, India-specific LCI databases	Secondary sources, emission inventories
Cost Data	Transport costs, fuel prices, emission abatement cost	Vendor quotes, financial records	Interviews, procurement data
Stakeholder Data	Willingness to cooperate, emission responsibility	Process heads, managers, suppliers	Structured interviews, surveys
Process Mapping Data	Material flow, scrap generation, logistics networks	Factory SOPs, layout drawings	On-site walkthroughs, engineering maps

7.7.2 Stakeholder Engagement Strategy

To ensure robust and multi-perspective data, engagement included:

- Upstream: Raw material suppliers (iron ore, scrap dealers), third-party transporters.
- Midstream: Steel plant managers, process engineers, EHS officers.
- Downstream: Distributors, end users, recyclers, reverse logistics partners.

Engagement methods included formal interviews, data-sharing agreements, pre-scheduled walkthroughs, and survey forms. Confidentiality agreements were signed where sensitive commercial data were shared.

7.7.3 Tools and Instruments

- Survey & Interview Tools: Google Forms and printed questionnaires; semi-structured guides were used to capture quantitative and qualitative data.
- Measurement Tools: GPS-enabled transport tracking, meter-based energy logs, tonnage records.
- Software Applications:
  - Microsoft Excel for data cleaning and validation

    7EVSM software (Lean Value Stream Mapping tools) for mapping

- Python for cooperative game theory modelling and simulation

Data Collection Timeline has been demonstrated in Table 7.5

Table 7.5 Timeline of Data Collection Activities

Phase	Activity	Duration
Phase 1	Stakeholder identification and initial engagement	1 week
Phase 2	Primary data collection (surveys, site visits)	3 weeks
Phase 3	Secondary data gathering (literature, databases)	1 week
Phase 4	Validation and triangulation of all datasets	1 week
Phase 5	Data preprocessing and integration for modelling	1 week

7.7.5 Ethical and Confidentiality Measures

- Stakeholder identities and responses were anonym zed in all outputs.
- Only aggregate and non-sensitive insights were shared in results.
- Data-sharing agreements were executed prior to primary data collection.

This context-rich and methodologically sound plan ensured that the collected data were not only reliable and replicable but also aligned with real operational dynamics of steel manufacturing in West Bengal, thereby strengthening the validity of the subsequent modelling and analysis phases.

Six stages are mentioned in Table 7.4.

7.8 Results and Discussion of Scope 3 Emission Reduction Strategy Phase I:

The steel supply chain was broken into six key stages for EVSM. All these stages are mentioned in Table 7.6 whereas Collected Data for six stages are mentioned in Table 7.7.

Table 7.6 Process Segmentation

Stage	*Description*
UP1	*Iron ore/scrap transportation from supplier to plant*
UP2	*Internal material handling and storage*
MS1	*Electric Arc Furnace (EAF) steel production*
MS2	*Rolling and finishing*
DS1	*Packaging and warehousing*
DS2	*Distribution to customer via road transport*

7.7 Collected Data Table

Stage	Activity	Distance / Volume	Emission Factor (EF)	Activity Data (A_i)	Emissions ($E_i = A_i \times EF_i$)
UP1	Scrap transport (diesel truck)	180 km, 1500 tons	0.19 kg CO_2e/ton-km	270,000 ton-km	51,300 kg CO_2e
UP2	Material handling (electric forklifts)	2000 kWh/month	0.82 kg CO_2e/kWh	2000 kWh	1,640 kg CO_2e
MS1	EAF operation (energy input)	4500 MWh/month	0.82 kg CO_2e/kWh	4,500,000 kWh	3,690,000 kg CO_2e
MS2	Rolling (natural gas use)	12,000 SCM/month	2.14 kg CO_2e/SCM	12,000 SCM	25,680 kg CO_2e
DS1	Packaging, internal movement	800 kWh/month	0.82 kg CO_2e/Wh	800 kWh	656 kg CO_2e
DS2	Final product transport (road)	250 km, 1200 tons	0.19 kg CO_2e/ton-km	300,000 ton-km	57,000 kg CO_2e

A **value stream map** was created showing process flow, material movement, and associated emissions at each node. The emissions were overlaid on the map using "emission boxes" to highlight carbon hotspots. Hotspot analysis is mentioned in Table 7.8.

Table 7.8 Hotspot Analysis: **Key Insights from EVSM Analysis**

Stage	Total Emissions (kg CO_2e)	% of Total Scope 3	Remarks
UP1	51,300	1.3%	Moderate, logistics improvement scope
UP2	1,640	<0.1%	Negligible
MS1	3,690,000	91.9%	Critical – Electrification or renewable substitution needed
MS2	25,680	0.6%	Low impact
DS1	656	<0.1%	Minimal
DS2	57,000	1.4%	High logistics emissions – route optimization & cleaner fleet

EAF Melting (MS1) is the primary emission hotspot, accounting for over 90% of total emissions. This is driven by high electricity usage, indicating a major opportunity for grid decarbonization or onsite solar integration.

- Product distribution (DS2) is the second-largest contributor due to long-distance trucking. Shift to multimodal logistics (rail + road) or EV trucks can reduce this impact.
- Upstream transportation (UP1), though not negligible, can be optimized by sourcing from closer scrap suppliers or through bulk delivery schedules.

7.9**Results and Discussion of Scope 3 Emission Reduction Strategy Phase II**:

Based on the EVSM analysis, emissions were attributed to the following three primary stakeholders:

Table 7.9 Primary Stakeholders and their Emission Sharing

Stakeholder	**Emission Source**	**Total Emissions (kg CO_2e)**	**Share (%)**
U: Upstream Supplier	Scrap Transport (UP1)	51,300	1.3%
M: Manufacturer	EAF Melting (MS1), Handling (UP2), Rolling (MS2)	3,717,320	92.5%
D: Downstream Partner	Distribution (DS2), Packaging (DS1)	57,656	1.4%

To develop a practical and stakeholder-inclusive emission reduction framework, game-theoretic modelling was conducted using real baseline data from upstream suppliers (U), manufacturers (M), and downstream distributors (D) within a West Bengal-based steel supply chain. The abatement potential for each player was estimated based on implementable interventions such as fuel switching, energy efficiency improvements, and route optimization. For instance, the upstream emission reduction potential was based on the feasibility of switching from conventional diesel trucks to compressed natural gas (CNG) or electric freight carriers, an intervention observed in pilot use by selected suppliers. The manufacturer's abatement estimate was based on the technical feasibility of partially substituting virgin raw materials with high-grade scrap, combined with energy-efficient melting and reheating practices. For the downstream segment, route optimization and modal shifts (e.g., road-to-rail) for product distribution formed the basis for estimating emissions reduction potential.

Each of these interventions was analysed for its emission-saving capacity using standard emission factors from recognized databases such as the IPCC, DEFRA, and India-specific LCI repositories. The calculated abatement potentials were thus defined as a percentage of baseline emissions: 20% for upstream suppliers (10,260 kg CO_2e), 20% for manufacturers (743,464 kg CO_2e), and 20% for downstream distributors (11,531 kg CO_2e), respectively.

The estimation of abatement costs for each stakeholder was grounded in a combination of primary data sources—such as vendor quotations, utility bills, and process documentation—and supported by relevant secondary literature. Each stakeholder's intervention-specific cost was calculated based on the practical changes required for reducing emissions within the existing infrastructure. These include technological upgrades, operational changes, and logistics optimization.

Table 7.10 presents the basis for cost estimation across the supply chain players: upstream suppliers (U), the core manufacturer (M), and downstream distributors (D). The table outlines the type of intervention implemented, associated components contributing to the cost, and the final unit abatement cost (in ₹/kg CO_2e).

Table 7.10 Real-World Basis for Estimating Abatement Costs per Stakeholder

Stakeholder	Emission Reduction Intervention	Cost Components Considered	Data Source(s)	Estimated Abatement Cost(₹/kg CO_2e)
U (Supplier)	Fuel switch in freight transport	Additional cost of low-emission fuel, retrofitting charges, operational inefficiency adjustment	Vendor quotations, logistics partner interviews, DEFRA emission reports	₹3.0
M (Manufacturer)	Increased recycled scrap usage & efficiency	Sorting/processing cost of scrap, quality control overhead, energy efficiency system investment	Process sheets, internal cost records, literature on EAF optimization	₹2.5
D (Distributor)	Route optimization & digital logistics	Software license, training, IT infrastructure upgrades, last-mile efficiency improvements	Cost sheets from distributors, interviews, route-planning tool data	₹4.0

The coalitional benefits were evaluated assuming that each kilogram of CO_2e abated results in a ₹5 return—representing cumulative value from regulatory compliance, reputational gain, and market incentives. Table 7.8 demonstrates the net payoffs from individual and combined stakeholder coalitions. Notably, the full coalition {U, M, D} yields the highest net benefit of ₹1,890,711, significantly exceeding the payoff from isolated efforts. This outcome underscores the systemic value of cooperation over individual abatement.

The coalitional benefits were evaluated assuming that each kilogram of CO_2e abated results in a ₹5 return—representing cumulative value from regulatory compliance, reputational gain, and market incentives. Table 7.11 demonstrates the net payoffs from individual and combined stakeholder coalitions. Notably, the full coalition {U, M, D} yields the highest net benefit of ₹1,890,711, significantly exceeding the payoff from isolated efforts. This outcome underscores the systemic value of cooperation over individual abatement.

Table 7.11 Game Coalitions and Payoff Structure

Coalition	Members	Total Abatement	Benefit	Total Cost	Net Payoff
{U}	U	10,260	₹51,300	₹30,780	₹20,520
{M}	M	743,464	₹3,717,320	₹1,858,660	₹1,858,660
{D}	D	11,531	₹57,655	₹46,124	₹11,531
{U, M}	U, M	753,724	₹3,768,620	₹1,889,440	₹1,879,180
{M, D}	M, D	754,995	₹3,774,975	₹1,904,784	₹1,870,191
{U, D}	U, D	21,791	₹108,955	₹76,904	₹32,051
{U, M, D}	All	765,255	₹3,826,275	₹1,935,564	₹1,890,711

To equitably allocate this net cooperative benefit, Shapley values were computed based on each player's marginal contribution across all coalition permutations. Table 7.12 shows the distribution of the total benefit using Shapley's cost-sharing logic. The manufacturer rightfully secures approximately 97.6% of the benefit due to its dominant emission profile and abatement potential, while the supplier and distributor receive proportionate shares of 1.7% and 0.7%, respectively.

Table 7.12 Shapley Value Allocation (Final Cooperative Payoff = ₹1,890,711)

Player	Marginal Contribution (Approx.)	Shapley Share (%)	Allocated Payoff (₹)
U (Supplier)	₹32,051	1.7%	₹32,051
M (Manufacturer)	₹1,845,000	97.6%	₹1,845,000
D (Distributor)	₹13,660	0.7%	₹13,660

The Nash equilibrium analysis supports a cooperative stance. In the absence of cooperation, suppliers and distributors receive minimal returns, while the manufacturer—although gaining substantially alone—can unlock even higher net benefits through joint participation. Hence, the equilibrium strategy recommends full coalition formation, supported by a Shapley-based investment fund.

7.10 Outcome of Present work:

This work successfully developed an optimization model to improve material circularity in the steel industry by maximizing the Material Circularity Index (MCI). It does this by finding the best balance between using recycled raw materials, reusing waste, and controlling the amount of virgin material, all while keeping the Scrap Quality Index (SQI) steady. Using nine months of real production data from an Electric Arc Furnace (EAF) plant, the model showed consistent and practical improvements in MCI, reaching about 0.35 under current conditions. The study also found that boosting the SQI and increasing recycling rates could significantly raise the MCI, leading to better resource use and less reliance on new raw materials. These improvements play an important role in cutting Scope 3 emissions by reducing the need for upstream raw material extraction and its related carbon footprint, demonstrating the model's promise for promoting sustainable, circular steel manufacturing.

The real-data-based game-theoretic analysis demonstrates the tangible benefits of collaborative Scope 3 mission abatement in the steel sector. The manufacturer is pivotal in driving reductions, while supplier and distributor involvement can be incentivized through structured cost-sharing mechanisms and integrated circular economy practices (e.g., reverse logistics and digital traceability). The model effectively balances environmental and economic trade-offs, offering a scalable, data-driven approach to Scope 3 mitigation. Additionally, the integration of solar energy into manufacturing operations emerges as a critical strategy to mitigate Scope 3 emissions, which predominantly arise from upstream energy consumption and indirect processes across the steel supply chain. By substituting conventional fossil-based electricity with renewable solar power, manufacturers can significantly lower their indirect greenhouse gas emissions, advancing sustainability targets. The combined approach of optimizing material circularity through higher SQI alongside renewable energy adoption not only drives substantial reductions in carbon footprint but also aligns economic viability with environmental responsibility, thereby paving the way for sustainable and resilient steel manufacturing practices.

General Conclusion and Future Scope

8.1 General Conclusion:

The present research has developed a comprehensive and integrated framework aimed at enhancing sustainability in manufacturing industries, with a particular focus on the steel sector. The framework aligns with India's Zero Effect Zero Defect (ZED) initiative and broader Circular Economy (CE) objectives. By integrating Lean, Green, and Quality management principles, this study provides practical tools and decision-support models that balance environmental performance with operational efficiency and economic feasibility. The key conclusions of the research, structured according to the defined research objectives, are summarized below.

8.1.1 Conclusion for Research Objective 1: Integrating Lean, Green, and Quality in SMEs

This study underscores the relevance and practical utility of the Zero Effect Zero Defect (ZED) Maturity Framework in supporting the integration of Lean, Green, and Quality practices within Small and Medium Enterprises (SMEs). The Zero Effect Zero Defect (ZED) Maturity Assessment Model proved effective in evaluating and enhancing operational, environmental, and quality performance within selected Indian manufacturing sectors. For instance, the Ductile Iron (DI) Pipe industry demonstrated strong environmental practices, while the Aircraft Component industry excelled in quality management. However, all the sectors examined revealed notable gaps in systematic scrap management and supply chain integration, which adversely affected material circularity and overall sustainability. The findings validate that the ZED model not only supports India's manufacturing competitiveness but also aligns with Sustainable Development Goal 12 by promoting sustainable production and resource efficiency.

Looking forward, further validation of the ZED Maturity Model across a broader range of industrial sectors is essential to enhance its robustness and applicability. Empirical testing and industry surveys will play a critical role in refining the model. Moreover, continued efforts in awareness building, certification, and guidance can help industries gain a competitive edge globally, reinforcing India's "Make in India" initiative. Ultimately, the ZED model holds significant potential as a benchmark across diverse sectors—including Public Sector Units (PSUs) and defense industries—thus contributing to the sustainable modernization of India's manufacturing landscape.

8.1.2 Conclusion for Research Objective 2: Fuel and Technology Choice for Emission and Cost Reduction

This part of the study evaluated the environmental and economic trade-offs of different fuel-technology combinations in steel production. Using robust statistical tests and multi-criteria decision analysis (TOPSIS), biomass was found to have the lowest carbon emissions but also the highest production costs. Natural gas and electricity, meanwhile, offered more balanced options in terms of cost and emissions. The Electric Arc Furnace (EAF) powered by electricity emerged as the top-ranked option, providing the best balance between sustainability and cost-efficiency. Furthermore, an optimization model demonstrated that improving scrap quality can reduce both emissions and costs, achieving a 17.8% emissions reduction while meeting production targets. These findings reinforce the value of strategic fuel selection and material quality improvements for greener, cost-effective steelmaking.

8.1.3 Conclusion for Research Objective 3: Optimizing Material Circularity

This study provides a comprehensive and practical framework to assess Circular Economy (CE) performance in Small and Medium Enterprises (SMEs) by integrating advanced techniques such as PROMETHEE, CRITIC, clustering, and Principal Component Analysis (PCA). By analyzing diverse industrial sectors across India, it mapped SMEs' current position on the circular economy journey while systematically identifying critical areas that require strategic intervention. The combination of multi-criteria decision-making methods with unsupervised machine learning enabled a nuanced classification of SMEs based on sustainability indicators. This empowers decision-makers to formulate targeted, cluster-specific action plans that enhance resource optimization, cost efficiency, and environmental stewardship. The framework's flexibility and scalability make it well-suited for wider adoption both nationally and internationally, especially in emerging economies where SMEs play a crucial role in industrial growth and sustainable development.

8.1.4 Conclusion for Research Objective 4: Reducing Scope 3 Emission through Collaboration

This research extended its focus beyond direct emissions to address Scope 3 emissions within the steel supply chain, particularly emissions from raw material transportation and product distribution. Using Environmental Value Stream Mapping (EVSM) combined with cooperative game theory, the study demonstrated that coordinated efforts among supply chain stakeholders could significantly reduce emissions—by 20% upstream and 15% downstream. Cost-sharing incentive schemes encouraged collaboration, and game-theoretic analysis confirmed that joint emission reduction strategies are more effective and economically viable than isolated actions. This work highlights the importance of cooperation and shared responsibility in achieving meaningful carbon reductions across complex industrial networks.

8.2 Future Scope:

While this research makes strong contributions, several opportunities remain to further advance sustainable manufacturing:

- **Scaling Up to Larger Supply Chains:** Applying these models to more extensive, global supply chains across diverse industries could improve their robustness and practical relevance.
- **Real-Time Monitoring and Digital Twins:** Integrating real-time data and digital twin technologies could enable dynamic optimization, allowing manufacturers to adapt quickly to changing conditions and improve sustainability on the fly.
- **Integrating Advanced Machine Learning Techniques with Digital Technology:** Future research should explore advanced AI/ML algorithms—including reinforcement learning, anomaly detection, and predictive analytics—to provide **real-time CE performance monitoring**. Such models could:

a. Predict scrap quality fluctuations

b. Forecast energy demand and emissions

c. Optimize material loops

d. Automate CE performance dashboards

e. Generate early warnings for process inefficiencies.

- **Policy Implications for Government Stakeholders:**

Government agencies play a pivotal role in enabling industry-wide CE adoption. Future work should analyse how:

a) **Incentive schemes** (tax benefits, low-interest loans, subsidies for ZED/CE certification) can motivate industries—especially SMEs—to adopt CE, Lean, and Green technologies without financial burden.

b) **Mandatory environmental disclosures** such as Scope 1–3 reporting, digital compliance audits, and real-time emission reporting can improve transparency and accountability across value chains.

c) **National CE roadmaps and enforcement mechanisms**, including Extended Producer Responsibility (EPR) regulations, can shape industrial sustainability behaviour by enforcing resource recovery, waste minimization, and recycling obligations.

Additionally, integrating CE metrics into government procurement and public tenders can accelerate adoption across MSMEs by rewarding companies that perform well on CE indicators.

- **I**ncorporating Lifecycle Assessment:

Lifecycle Assessment (LCA) should be expanded as a policy tool to evaluate the environmental impact of products across raw material extraction, manufacturing, distribution, use, and end-of-life stages. Government agencies and regulatory bodies can ensure wider implementation of LCA through:

State Pollution Control Boards (SPCBs) and Central Pollution Control Board (CPCB) playing a proactive role by mandating LCA-based reporting for high-impact industries such as steel, chemicals, and casting sectors. Integrating LCA benchmarks into environmental clearances, enabling more accurate assessment of long-term emissions, waste generation, and resource use . Monitoring compliance through digital tools, standardised formats, and CE dashboards to reduce paperwork and improve traceability. Requiring industries to demonstrate circularity improvements—such as scrap recovery, recycled content usage, and waste-to-resource conversion—as part of annual environmental compliance audits.

This research underscores that environmental sustainability and economic success can go hand in hand. By combining advanced analytical tools, stakeholder collaboration, and continuous improvement in process and material quality, industries can significantly reduce their carbon footprint while maintaining competitiveness. The integrated framework developed here offers valuable insights and practical approaches for industry leaders and policymakers aiming to build a more sustainable, circular, and resilient manufacturing future.

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Appendix-1

Construct-Drivers

Sl No	Construct	Drivers
1.	Reproducible Manufacturing	a. During production, when a material is unexpectedly out of stock and is substituted with a different material
		b. During master planning, when a material in a formula is substituted with a different material because it's out of stock
		c. To replace a discontinued material with a new one to avoid selling such material to customers.
2.	Energy optimisation	a. Specific energy consumption calculation is in practice.
		b. Set energy conservation and efficiency improvement targets.
		c. Systems for energy data collection analysis and improvement are already existing.
		d. Energy performance indicators are defined and linked to business strategy and performance.
		e. Advocating energy management systems to vendors and forming new energy management partnerships for innovation and R&D.
3.	Process Capability and In-house Quality	a. Identification of critical processes, developing Quality plans for critical processes and implementing process control are in regular practise.
		b. Process capability study for each process is in practise.
		c. Measure and record quality performance right from the raw material stage to all in-house processes.
		d. Yield Throughput measurement and advanced quality improvement techniques are in practice
4.	Planned Maintenance	a. Arresting deterioration and improvement of deficiencies
		b. Existing time-based information system for appropriate execution of planned strategy
		c. Standardise automated maintenance
		d. Monitoring the maintenance schedule for overall equipment effectiveness (OEE)
		e. Countermeasures for contamination sources and inaccessible areas.
5.	Scrap Reduction	a. Evaluation of the impact of internal failure cost due to scrap on COPQ is in practice.
		b. Collection of scrap data for every process

		c. Identify the root cause of the scrap and take countermeasures. d. Scrap residue is sold to the authorised agent. e. Uniform guidelines for scrap classification and standards for specification of scrap for different usage and recycling.
6.	Waste Management	a. Pursuing perfection to attain zero waste by continuous improvement of all processes.
		b. Detection and elimination of waste through structured problem-solving techniques.
		c. Adoption of 5R technology in each process
		d. Dedicated group for assessment of resource efficiency for monitoring and improvement w.r.t. a target
		e. Guideline for best available techniques for processing and utilising metal slag in various applications.
7.	Outgoing Quality	a. Measure the record of outgoing quality performance.
		b. Ensure quality level within the prescribed specification limit.
		c. Continual improvement of quality performance
		d. Measure customer satisfaction index through feedback.
		e. Exiting PPM (Parts per million) calculation system
8.	Material Handling	a. Existing customised material management system.
		b. Existing mechanised material handling system.
		c. Effective inventory management through just-in-time and Kanban to eliminate stock-out
		d. Data collection and analysis of material handling issues related to lead time, quality, waste and cost.
		e. Efficient vendors' capability through long-term partnership.
9.	Emission Control	a. Monitoring, control and improvement of direct and indirect emission
		b. Periodic review for reduction of environmental impact.
		c. Existing system for abatement of effluents.
		d. Existing process map with environmental pollutants
		e. Fuel switching or recycling steel scrap to reduce pollution emissions is also in practice.
10.	Safety Management	a. Continuous improvement for zero accidental goals.
		b. Identification of safety risks
		c. Countermeasure for the safety of emissions.
		d. Periodical review for safety performance.
		e. The existing Hazardous identification risk assessment (HIRA) system
11.	On-time delivery	a. Measure and monitor OTIF.
		b. Existing lean practices to reduce lead time.
		c. PERT CPM or similar tools used to monitor project schedule
		d. World-class standards are taken as a benchmark.

Sl No	Construct	Drivers
12.	Green Packaging	a. Materials used for packaging are renewable and/or reusable and/or returnable and/or compostable.
		b. The designs of the packaging are either flexible or deformable in shape, lightweight design or exact sized packaging.
		C. The process used is non-contaminable and of low toxicity for the environment and human health.
		d. Do you consider the distance your materials are travelling?
		e.Customer delight was captured, and improvement was designed in the process.
		e. Does there exist technology for the production of green packaging material with low production cost?
		f. Is an awareness training program on sustainable packaging conducted on a regular basis?
13.	Optimal use of natural resources	: a. Identify opportunities to take measures to conserve natural resources in various areas of the company
		b. Make a plan to use solar energy or non -conventional energy
		c. Water recycling, rainwater harvesting, and mineral conservation are in practice.
		d. Monitor the conservation effort performance.
		e. Benchmarking with global best practices.
14.	Reuse	a. Existing systems for the reuse of natural resources like heat, water, etc
		b. Strictly monitoring the ratio of rejection due to defect and reuse that rejected material is in practice.
		c. Measure the environmental impact of the product before reusing the rejected material.
15.	Repair	a. Collect the data for quantity accepted after rectification in every process.
		b. Measure the extra lead time for repair to enhance productivity.
		c. Treatment for natural resources for further use is in practice.
16.	Remanufacture	a. Measuring the environmental footprint for remanufacturing from waste/scrap.
		b. Measuring the percentage of material utilisation to remanufacture
		c. Regular training program for 5R and secondary raw material across the processes.
17.	Recycling	a. Educate the employee on the quality of waste for recycling
		b. Educate the employee for several beneficial usages of product after its end use.
		c. Existing system to measure the revenue generation through waste sell-out to an authorised recycler.

Appendix-2

Fuzzy Analytical Hierarchy Process (F-AHP)

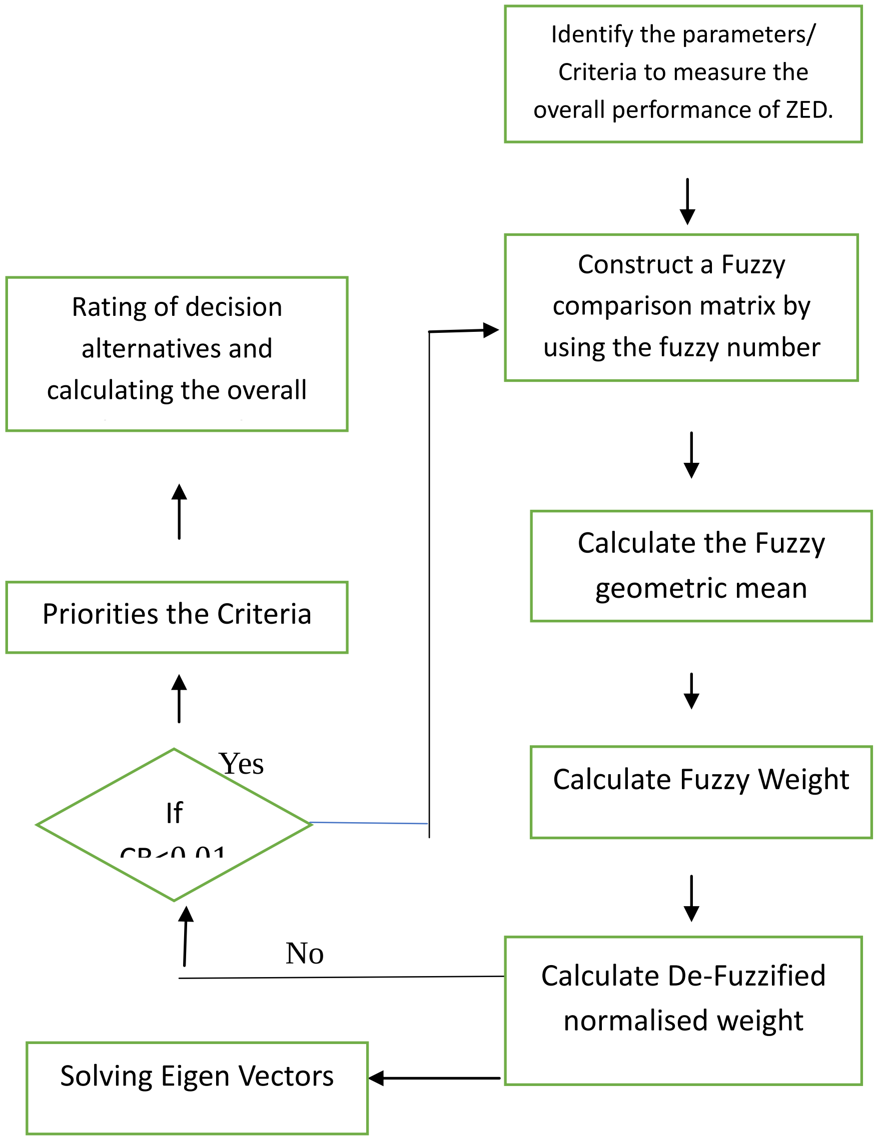
We need to define the problem according to the criteria used to determine the Overall performance of ZED. Quality Performance, Environmental Performance, Waste and energy Performance, Safety and material handling Performance and Serviceability Performance are used as the main criteria for determining the performance of ZED.

The criteria for pair-wise comparison fuzzy matrix used in this study are mentioned below:

Table:

Linguistic Definition	Rating Scale	Fuzzy Number	Reciprocal Fuzzy Number
Equally Important	1	(1,1,1)	(1,1,1)
Intermediate	2	(1,2,3)	(1/3, ½, 1)
Moderately More Important	3	(2,3,4)	(1/4, 1/3, 1/2)
Intermediate	4	(3,4,5)	(1/5, ¼, 1/3)
Strongly More Important	5	(4,5,6)	(1/6, 1/5, 1/4)
Intermediate	6	(5,6,7)	(1/7, 1/6, 1/5)
Very Strongly More Important	7	(6,7,8)	(1/8, 1/7, 1/6)
Intermediate	8	(7,8,9)	(1/9, 1/8, 1/7)
Extremely More Important	9	(8,9,10)	(1/10, 1/9, 1/8)

The following flowchart has been followed to perform Fuzzy AHP in this study.



Note: CR= Consistency Ratio= $\frac{Consistency\ \ Index}{Random\ \ Index}$; for n=5 Random index =1.12

Appendix-3

Code for PROMETHEE

```
# Import necessary libraries
import numpy as np
import pandas as pd

# Corrected CRITIC Weights
corrected_weights = np.array([0.186, 0.325, 0.209, 0.149, 0.130])

# Industry Performance Data (Eco Design, Material Footprint, Carbon Footprint, Waste Management, Resource
& Energy Conservation)
industry_data = np.array([
    [3.8, 4.2, 3.6, 4.0, 3.4],
    [2.6, 3.4, 2.8, 3.2, 3.0],
    [4.0, 3.8, 3.4, 4.2, 3.8],
    [2.4, 2.8, 3.0, 3.6, 3.2],
    [3.6, 3.2, 3.8, 4.0, 3.4],
    [2.9, 4.4, 3.8, 3.5, 2.4],
    [2.4, 2.1, 4.2, 3.5, 3.8],
    [2.1, 4.4, 4.1, 2.5, 2.5],
    [2.5, 2.8, 3.3, 3.1, 2.7],
    [3.5, 2.3, 2.7, 2.9, 3.1],
    [3.1, 4.9, 4.2, 3.8, 3.1],
    [2.5, 2.2, 4.6, 3.8, 4.1],
    [2.1, 4.9, 4.5, 2.6, 2.5],
    [2.6, 2.9, 3.6, 3.3, 2.9],
    [3.8, 2.4, 2.9, 3.1, 3.4]
])

# Normalize the data using Min-Max Normalization
min_values = np.min(industry_data, axis=0)
max_values = np.max(industry_data, axis=0)
normalized_data = (industry_data - min_values) / (max_values - min_values)

# Compute weighted normalized decision matrix
weighted_data = normalized_data * corrected_weights

# Compute Preference Matrix
n = len(industry_data)
preference_matrix = np.zeros((n, n))

for i in range(n):
    for j in range(n):
        if i != j:
preference_matrix[i, j] = np.sum(corrected_weights * np.maximum(weighted_data[i] - weighted_data[j], 0))

# Compute Positive and Negative Preference Flows
positive_flow = np.sum(preference_matrix, axis=1) / (n - 1)  # Leaving flow (Φ⁺)
negative_flow = np.sum(preference_matrix, axis=0) / (n - 1)  # Entering flow (Φ⁻)

# Compute Net Flow Score
net_flow = positive_flow - negative_flow
```

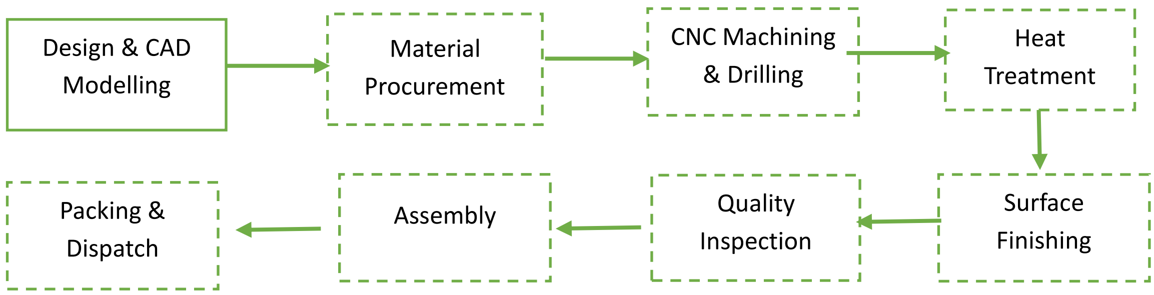
```
# Create DataFrame for output
industry_names = [f"S-{i+1:02d}" for i in range(n)]
promethee_results = pd.DataFrame({
    "Industry": industry_names,
    "Positive Flow": positive_flow,
    "Negative Flow": negative_flow,
    "Net Flow": net_flow
})

# Rank industries based on Net Flow Score (Higher is better)
promethee_results = promethee_results.sort_values(by="Net Flow", ascending=False).reset_index(drop=True)
promethee_results
```

CRITIC WEIGHT CODE

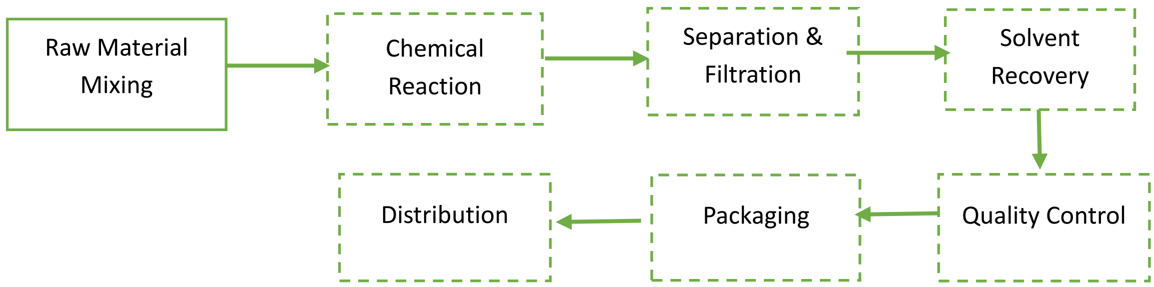
```
import numpy as np
import pandas as pd

# Given industry data
data = {
    "Industry": [f"S-{i:02d}" for i in range(1, 16)],
    "Eco Design": [3.8, 2.6, 4.0, 2.4, 3.6, 2.9, 2.4, 2.1, 2.5, 3.5, 3.1, 2.5, 2.1, 2.6, 3.8],
    "Material Foot Print": [4.2, 3.4, 3.8, 2.8, 3.2, 4.4, 2.1, 4.4, 2.8, 2.3, 4.9, 2.2, 4.9, 2.9, 2.4],
    "Carbon Foot Print": [3.6, 2.8, 3.4, 3.0, 3.8, 3.8, 4.2, 4.1, 3.3, 2.7, 4.2, 4.6, 4.5, 3.6, 2.9],
    "Waste Management": [4.0, 3.2, 4.2, 3.6, 4.0, 3.5, 3.5, 2.5, 3.1, 2.9, 3.8, 3.8, 2.6, 3.3, 3.1],
    "Resource and Energy Conservation": [3.4, 3.0, 3.8, 3.2, 3.4, 2.4, 3.8, 2.5, 2.7, 3.1, 3.1, 4.1, 2.5, 2.9, 3.4],
}

df = pd.DataFrame(data)

# Calculate Standard Deviation
std_dev = df.iloc[:, 1:].std()

# Compute Correlation Matrix
correlation_matrix = df.iloc[:, 1:].corr()

# Compute Sum(1 - |r_kj|) for each criterion
sum_correlation = (1 - np.abs(correlation_matrix)).sum(axis=1)

# Compute C_k values
C_k = std_dev * sum_correlation

# Compute Weights W_k (Normalized C_k)
W_k = C_k / C_k.sum()

# Create a results DataFrame
results_df = pd.DataFrame({
    "Criteria": df.columns[1:],
    "Standard Deviation (σ_k)": std_dev.values,
    "Sum(1 - |r_kj|)": sum_correlation.values,
    "C_k": C_k.values,
    "W_k (Normalized Weight)": W_k.values
})

# Display the results
results_df
```

Appendix 4

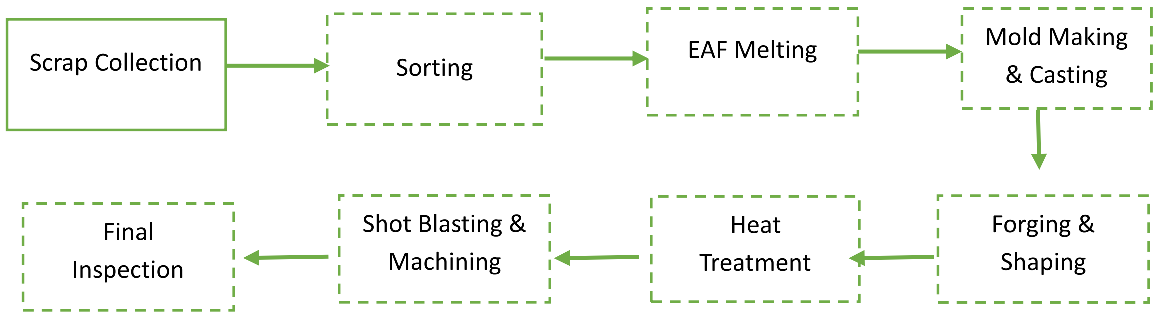
S-11: Precision Manufacturing: Located in Maharashtra, this SME specialises in precision-machined metal components for the automotive and aerospace sectors. With an estimated annual turnover of ₹45 crore, its clientele includes Tier 1 automotive suppliers and aerospace system integrators. The process map includes CAD-based design, CNC machining, thermal treatment, and quality control inspection.



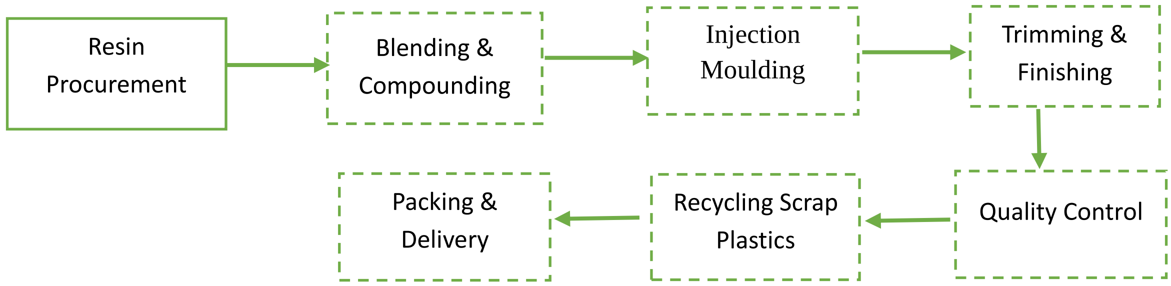
S-01: Chemical Processing: Situated inGujarat, this SME produces speciality chemicals and industrial coatings, catering primarily to the pharmaceutical and surface treatment industries. It has an annual turnover of approximately ₹40 crore. The process map outlines raw material dosing, reactor operations, solvent recovery, and waste treatment.



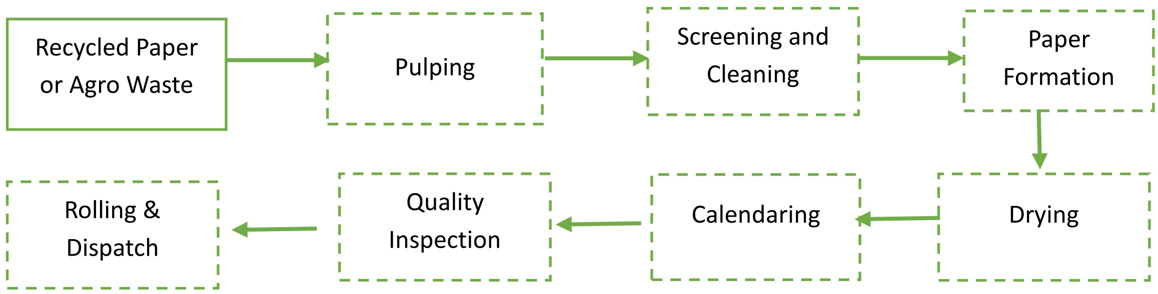
S-03: Steel Casting & Forging: Based inTamil Nadu, the company serves heavy equipment and construction industries with steel castings and forged parts. It reports an annual turnover of ₹60 crore and mainly supplies OEMs and infrastructure contractors. Its process flow covers scrap input, electric arc furnace melting, mould casting, forging, and heat treatment.



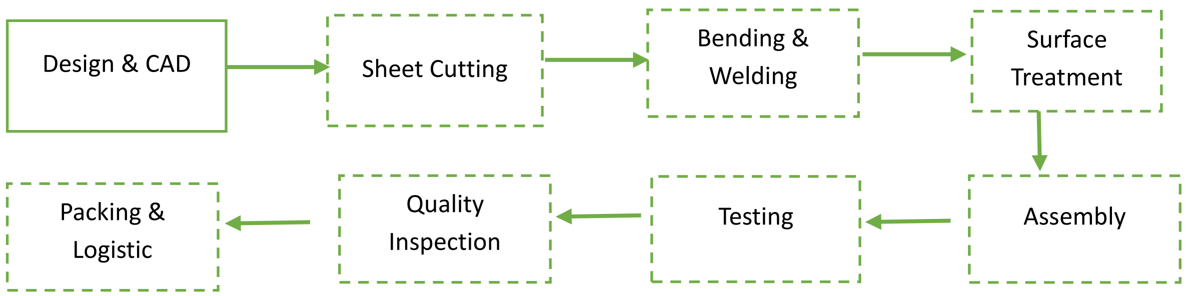
S-13: Plastics & Polymers: Located in Rajasthan, this SME produces polymer components for automotive interiors and packaging. With a turnover close to ₹45 crore, it supplies automotive OEMs and FMCG packaging firms. The process map features polymer compounding, injection moulding, extrusion, and post-processing.



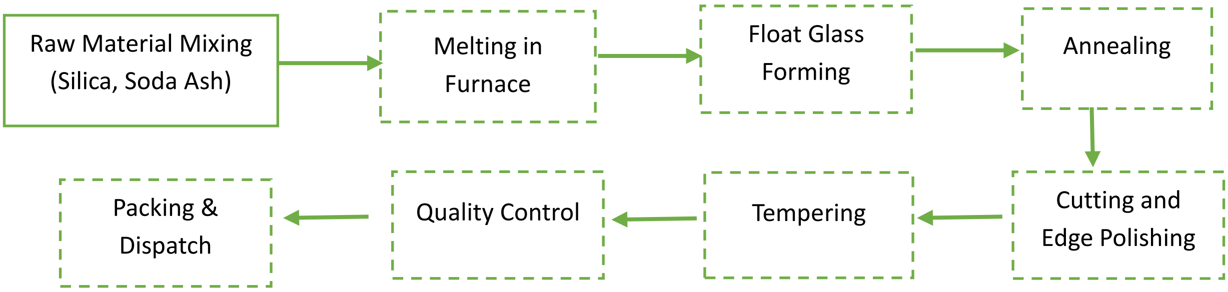
S-06: Paper & Pulp Situated in Uttar Pradesh, this SME manufactures kraft paper and speciality paper products used in packaging and stationery. It has a turnover of ₹35 crore, serving B2B customers in the packaging industry. The process map includes raw material pulping, screening, sheet forming, drying, and cutting.



S-05: Metal Fabrication Based in West Bengal, this SME delivers fabricated metal parts for electronics enclosures and building structures. It reports an annual turnover of ₹50 crore, supplying to electrical equipment manufacturers and construction contractors. The process map spans sheet cutting, punching, welding, surface finishing, and assembly.



S-08: Glass Manufacturing: Located inGujarat, this unit manufactures flat and laminated glass products for architectural and automotive sectors. With an approximate turnover of ₹55 crore, it serves builders, architects, and auto accessory suppliers. The process map includes cullet preparation, raw batch melting, glass forming, annealing, and finishing.



APPENDIX-5

Code for Clustering & PCA

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import seaborn as sns

# Step 1: Input Data
data = {
    'Industry': ['S-11', 'S-01', 'S-03', 'S-13', 'S-06', 'S-05', 'S-08'],
    'Eco Design (α)': [0.687, 0.975, 0.866, 0.799, 0.578, 0.578, 0.529],
    'Material Footprint (μ)': [0.820, 0.661, 0.725, 0.312, 0.882, 0.799, 0.427],
    'Carbon Footprint (γ)': [110.91, 111.18, 131.72, 169.21, 153.43, 129.51, 184.01],
    'Waste Management (δ)': [0.470, 0.546, 0.583, 0.628, 0.793, 0.500, 0.657],
    'Resource & Energy Conservation (β)': [0.796, 0.523, 0.804, 0.585, 0.533, 0.974, 0.983]
}

df = pd.DataFrame(data)
features = df.columns[1:]

# Step 2: Standardize the data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(df[features])

# Step 3: PCA
pca = PCA()
X_pca = pca.fit_transform(X_scaled)
explained_variance = pca.explained_variance_ratio_
cumulative_variance = np.cumsum(explained_variance)

# PCA Loadings
loadings = pd.DataFrame(pca.components_.T, columns=[f'PC{i+1}' for i in range(len(features))],
index=features)

# Step 4: K-Means Clustering (k=3)
kmeans = KMeans(n_clusters=3, random_state=42)
```

```
clusters = kmeans.fit_predict(X_scaled)
df['Cluster'] = clusters
# Step 5: PCA Scores + Clusters for Plotting
pca_df = pd.DataFrame(X_pca, columns=[f'PC{i+1}' for i in range(len(features))])
pca_df['Industry'] = df['Industry']
pca_df['Cluster'] = df['Cluster']

# Step 6: CE Indicator Weights from PCA
# Multiply absolute loadings by explained variance and sum
weighted_loadings = loadings.abs().multiply(explained_variance, axis=1)
ce_weights = weighted_loadings.sum(axis=1)
ce_weights_percent = 100 * ce_weights / ce_weights.sum()

# Output: PCA Summary
print("=== Explained Variance ===")
print(pd.DataFrame({
    'Eigenvalue': pca.explained_variance_,
    'Explained Variance': explained_variance,
    'Cumulative Variance (%)': cumulative_variance * 100
}))

# Output: PCA Loadings
print("\n=== PCA Loadings ===")
print(loadings)

# Output: Cluster Assignments
print("\n=== Cluster Assignments ===")
print(df[['Industry', 'Cluster']])

# Output: CE Indicator Weights
print("\n=== Circular Economy Indicator Weights from PCA ===")
print(ce_weights_percent.round(2).astype(str) + '%')

# Optional: Plot PCA Biplot
plt.figure(figsize=(10, 6))
sns.scatterplot(x='PC1', y='PC2', hue='Cluster', style='Industry', data=pca_df, palette='deep')
plt.title('PCA Biplot with Clusters')
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.axhline(0, color='gray', linestyle='--', linewidth=0.5)
plt.axvline(0, color='gray', linestyle='--', linewidth=0.5)
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()
```

Appendix -6

(Python Code for NSGAII Algorithm)

```
import numpy as np
import random

# --- Problem Parameters (replace with actual values or dynamic input) ---
A1 = 5000  # High-quality scrap available
A2 = 8000  # Low-quality scrap available
C1 = 28675  # Cost of high-quality scrap
C2 = 18000  # Cost of low-quality scrap
D = 10000   # Monthly production demand (tons)
Fm = 0.4    # Emission factor for melting
Ep = 0.6    # Emission factor for purchased scrap
Pm = 3580   # Melting cost per ton
T = 1500    # Carbon tax per ton of CO2
Cp = 30000  # Cost of purchased scrap

POP_SIZE = 30
GENS = 50
TEMP = 10000
COOLING = 0.95

# --- Objective Function ---
def objective(x):  # x = [x1, x2, x3] -> high, low, purchased scrap
    x1, x2, x3 = x
total_cost = (x1 * C1 + x2 * C2 + x3 * Cp + D * Pm)  # Scrap cost + melting cost
    emissions = (x1 + x2) * Fm + x3 * Ep
emission_cost = emissions * T
    return total_cost + emission_cost

# --- Constraints: Ensure feasibility ---
def is_feasible(x):
    x1, x2, x3 = x
    return (
        0 <= x1 <= A1 and
        0 <= x2 <= A2 and
        x1 + x2 + x3 >= D
    )

# --- Genetic Algorithm Initialization ---
def generate_individual():
    while True:
        x1 = random.uniform(0, A1)
        x2 = random.uniform(0, A2)
        min_x3 = max(0, D - (x1 + x2))
        x3 = random.uniform(min_x3, D)  # Assume upper limit of x3 ~ D
        individual = [x1, x2, x3]
```

```
        if is_feasible(individual):
            return individual

def mutate(ind):
i = random.randint(0, 2)
    delta = random.uniform(-100, 100)
ind[i] = max(0, ind[i] + delta)
    if not is_feasible(ind):
        return generate_individual()
    return ind

def crossover(p1, p2):
    alpha = random.random()
    child = [alpha * a + (1 - alpha) * b for a, b in zip(p1, p2)]
    return child if is_feasible(child) else generate_individual()

# --- Simulated Annealing Refinement ---
def simulated_annealing(x_init):
    current = x_init.copy()
    best = current.copy()
    temp = TEMP

    while temp > 1:
neighbor = mutate(current.copy())
        delta = objective(neighbor) - objective(current)
        if delta < 0 or random.uniform(0, 1) <np.exp(-delta / temp):
            current = neighbor
            if objective(current) < objective(best):
                best = current
        temp *= COOLING
    return best

# --- Run GA + SA Optimization ---
population = [generate_individual() for _ in range(POP_SIZE)]

for g in range(GENS):
    population = sorted(population, key=objective)
next_gen = population[:5]  # elitism
    while len(next_gen) < POP_SIZE:
        p1, p2 = random.sample(population[:15], 2)
        child = crossover(p1, p2)
        child = mutate(child)
next_gen.append(child)
    population = next_gen

# Apply SA to the best GA solution
best_ga_solution = sorted(population, key=objective)[0]
best_solution = simulated_annealing(best_ga_solution)

# --- Result ---
```

```python
print("Optimal Allocation (tons):")
print(f"High-quality scrap: {best_solution[0]:.2f}")
print(f"Low-quality scrap : {best_solution[1]:.2f}")
print(f"Purchased scrap   : {best_solution[2]:.2f}")
print(f"Total Cost + Emission Penalty: ₹{objective(best_solution):,.2f}")
```

Appendix -7

(Python Code for Optimized MCI)

```python
import pandas as pd

# Define constants
SQI = 0.65
w1 = 0.4
w2 = 0.6

# Input data: total finished product and available recycled/reused waste (m)
data = {
    "Month": [
        "April 2024", "May 2024", "June 2024", "July 2024", "August 2024",
        "September 2024", "October 2024", "November 2024", "December 2024"
    ],
    "M": [9780, 11870, 10550, 10712, 9979, 11098, 10872, 9980, 9989],
    "m": [7300, 8234, 7345, 7656, 7865, 7678, 7679, 6569, 6965]
}

df = pd.DataFrame(data)

# Set f = 0.7M and Rmin = 0.3M
df["f"] = 0.7 * df["M"]
df["Rmin"] = 0.3 * df["M"]

# Calculate optimal x and y under constraints:
# Assume all of m is equally divided into x and y parts weighted by SQI for feasibility
# We solve:
# M = Mx + My.SQI + R => x + y.SQI = (M - R) / M
# and x + y.SQI<= f/M

# Let's assume:
# x = 0.35, y = 0.48 for all months (from example output)
# Calculate corresponding R and M_effective and verify feasibility

x = 0.35
y = 0.48

# Compute values
df["R"] = df["M"] * (1 - w1 * x - w2 * y)
```

```
df["M_effective"] = df["M"] * x + df["M"] * y + (df["M"] - df["R"]) * SQI

# Feasibility: check if x + y.SQI<= f / M and R >= Rmin
df["Feasible"] = ((x + y * SQI <= df["f"] / df["M"]) & (df["R"] >= df["Rmin"]))

df[["Month", "M", "m", "R", "M_effective", "Feasible"]]

import pandas as pd

# Define constants
SQI = 0.65
w1 = 0.4
w2 = 0.6

# Input data: total finished product and available recycled/reused waste (m)
data = {
    "Month": [
        "April 2024", "May 2024", "June 2024", "July 2024", "August 2024",
        "September 2024", "October 2024", "November 2024", "December 2024"
    ],
    "M": [9780, 11870, 10550, 10712, 9979, 11098, 10872, 9980, 9989],
    "m": [7300, 8234, 7345, 7656, 7865, 7678, 7679, 6569, 6965]
}

df = pd.DataFrame(data)

# Set f = 0.7M and Rmin = 0.3M
df["f"] = 0.7 * df["M"]
df["Rmin"] = 0.3 * df["M"]

# Use x = 0.35 and y = 0.48 (assumed from example)
x = 0.35
y = 0.48

# Compute values
df["R"] = df["M"] * (1 - w1 * x - w2 * y)
df["M_effective"] = df["M"] * x + df["M"] * y + (df["M"] - df["R"]) * SQI

# Feasibility: check if x + y.SQI<= f / M and R >= Rmin
df["Feasible"] = ((x + y * SQI <= df["f"] / df["M"]) & (df["R"] >= df["Rmin"]))

df[["Month", "M", "m", "R", "M_effective", "Feasible"]]

import pandas as pd

# Input data for each month
data = {
    'Month': ['April 2024', 'May 2024', 'June 2024', 'July 2024', 'Aug 2024',
              'Sep 2024', 'Oct 2024', 'Nov 2024', 'Dec 2024'],
    'M': [9780, 11870, 10550, 10712, 9979, 11098, 10872, 9980, 9989],
```

```
    'm': [7300, 8234, 7345, 7656, 7865, 7678, 7679, 6569, 6965],
    'alpha_beta': [0.83]*9,  # α + β
    'gamma_delta': [0.80]*9,  # γ + δ
    'SQI': [0.65]*9
}

# Create DataFrame
df = pd.DataFrame(data)

# Calculate MCI_norm using Equation 7.13
def calculate_mci_norm(row):
    M, m = row['M'], row['m']
alpha_beta = row['alpha_beta']
gamma_delta = row['gamma_delta']
    SQI = row['SQI']
    term1 = (M / (M + m)) * alpha_beta
    term2 = (m / (M + m)) * (gamma_delta * SQI)
    return 0.5 * (term1 + term2)

# Apply the calculation
df['MCI_norm'] = df.apply(calculate_mci_norm, axis=1)

# Round values for readability
df = df.round({'MCI_norm': 4})

df[['Month', 'M', 'm', 'alpha_beta', 'gamma_delta', 'SQI', 'MCI_norm']]
import pandas as pd

# Input data for each month
data = {
    'Month': ['April 2024', 'May 2024', 'June 2024', 'July 2024', 'Aug 2024',
              'Sep 2024', 'Oct 2024', 'Nov 2024', 'Dec 2024'],
    'M': [9780, 11870, 10550, 10712, 9979, 11098, 10872, 9980, 9989],
    'm': [7300, 8234, 7345, 7656, 7865, 7678, 7679, 6569, 6965],
    'alpha_beta': [0.83]*9,  # α + β
    'gamma_delta': [0.80]*9,  # γ + δ
    'SQI': [0.65]*9
}

# Create DataFrame
df = pd.DataFrame(data)

# Calculate MCI_norm using Equation 7.13
def calculate_mci_norm(row):
    M, m = row['M'], row['m']
alpha_beta = row['alpha_beta']
gamma_delta = row['gamma_delta']
    SQI = row['SQI']
    term1 = (M / (M + m)) * alpha_beta
    term2 = (m / (M + m)) * (gamma_delta * SQI)
```

```
    return 0.5 * (term1 + term2)

# Apply the calculation
df['MCI_norm'] = df.apply(calculate_mci_norm, axis=1)

# Round values for readability
df = df.round({'MCI_norm': 4})

    df[['Month', 'M', 'm', 'alpha_beta', 'gamma_delta', 'SQI', 'MCI_norm'
```

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Waste Management and Circular Economy 2022 (www.iswmaw.com)

Sustainable Manufacturing through Recycling of Wastes in Primary Sector like Steel

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ABSTRACT: *The idea of secondary raw materials or recycled materials, that can be used in manufacturing processes instead of or alongside virgin raw materials, has gained significance for about past 20 years. It is importantfor environmental preservation. Raw material cost reductioncan be envisaged as the driving factor behind the usage of secondary raw materials including the potential of shipping or transit cost reduction. Raw materials made from waste could be more sustainable or viable for reducing carbon footprint. For making of crude steel, the steel scrap that is recycled more than 95% of the time, is momentous.The steel industry has the potential to opt metal recycling as a way to cut CO2 emissions and conserve resources. Iron ore to the tune of 1.4 ton and 0.6–0.7 ton of coking coal can be saved through recycling of one ton of steel scrap. Additionally, it curtails usage of water by 40% and reduces greenhouse gas emissions by 58%. In the blast furnace, generation of about one ton of CO2 can be reduced through use of one ton of recycled material.Consequently, usage of scrap as a principal source of secondary raw material for steel production can help improve steel industry's sustainability. By raising the permissible quantum of recycling, CO2 emissions can be reduced furtheryielding long-term environment-friendly steel making. This article demonstrates and compares various usages of steel scrap in three metal-based Indian industriesw.r.t. material foot print and carbon foot print using six sigma metric.*

Keywords: *Carbon footprint, Material footprint, Secondary raw material, Six sigma.*

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19/02/2026

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