Study and Optimization of Cellular Manufacturing Systems

A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Engineering

By

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CERTIFICATE FROM THE SUPERVISOR

This is to certify that the thesis entitled "**Study and Optimization of Cellular Manufacturing Systems**" submitted by Sri Manash Hazarika, who got his name registered on August 22, 2014 for the award of Ph. D. (Engineering) degree of Jadavpur University is absolutely based upon his own work under the supervision of Dr. Dipak Laha and that neither his thesis nor any part of the thesis has been submitted for any degree / diploma or any other academic award anywhere before.

Dr. Dipak Laha
(Thesis Supervisor)

To my Parents

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Manash Hazarika

Table of Contents

List of Tables

List of Figures

ALINK	Average linkage clustering
ANN	Artificial neural network
BEA	Bond energy algorithm
CMS	Cellular manufacturing system
CARI	Correlation analysis and relevance index
CF	Cell formation
CFP	Cell formation problem
CLINK	Complete linkage clustering
CU	Cell utilization
DCA	Direct clustering analysis
EDM	Euclidean Distance Matrices
EE	Exceptional elements
EM	Exceptional machines
EP	Exceptional parts
GA	Genetic algorithm
GC	Grouping efficacy
GE	Grouping efficiency
GLCA	Grouping league championship algorithm
GRASP	Randomized greedy algorithm from scratch by partially
GT	Group technology
HGA	Hybrid genetic algorithm
HGBPSO	Hybrid grouping based particle swarm optimization
HGGA	Hybrid grouping genetic algorithm
KHM	K-harmonic means
LA	linear assignment
MD-based	Mahalanobis distance based
MODROC	Modified rank order clustering
MPCF	Machine-part cell formation
NP- hard	Non-deterministic polynomial-time hardness
OM	Operation management
OR	Operation research
PCA	Principal component analysis
PSO	Particle swarm optimization
QM	Quantification methods
ROC	Rank order clustering
SA	Simulated annealing
SACF	Simulated annealing to cell formation
SCM	Similarity coefficients method
SLC	Single linkage clustering
SLINK	Single linkage clustering
VE	Void elements
ZODIAC	Zero-one data ideal seed algorithm for clustering

Chapter 1

INTRODUCTION

1.1 Cellular manufacturing system

Manufacturing systems deal with the set of procedures used by the company to operate the production facilities to manage production efficiently by solving the technical and logistics problems encountered in the factory, and ensuring that products meet quality standards. The cellular manufacturing system (CMS) is considered as an efficient production strategy to make batch manufacturing as efficient and productive as possible. The CMS relies on the principle of group technology (GT) for grouping dissimilar machines into machine cells and grouping parts into part families to take the advantage of their similarities in design and production.

Cell formation in CMS is an important problem in today’s automated batch production systems. It reduces work-in-process inventory cost, material handling cost, processing time, labor requirement and number of setups. It also simplifies the process planning and production scheduling, and improves the quality of products by promoting standardization of tooling, fixturing, and setups. Since manufacturing equipment of automated manufacturing systems are highly multifunctional, production processes can be accomplished by using multiple process routings. An optimum cell formation leads to more independent cells and less intercellular movement of parts.

1.2 Motivation of the current research work

In order to be successful in today's competitive manufacturing environment, managers have had to look for new approaches to facilities planning. For years, the industrial job shop has faced an increase in complexity and a decline in productivity due to an increase in part mix, volume of parts, plant size, machine production rates, and part complexity (Greene and Sadowski, 1984). It has been seen that between twenty and fifty percent of the total costs within manufacturing are related to material handling and as a result, effective planning can reduce these costs by ten to thirty percent (Balakrishnan and Cheng, 2007).

One innovative approach to facilities planning is called GT. GT is based on the principle of grouping parts into families based on similarities in design or manufacturing. The GT and cellular manufacturing aims to eliminate or minimize the complexity and to improve or maximize productivity.

Manufacturing cells, which consist of machines or workstations, are then, physically grouped together and dedicated to producing the parts into families. Cells combine the advantages of flow shops and job shops with characteristics such as reduced cycle times compared to jobs shops and increased flexibility and greater job satisfaction as compared to flow shops. It is reasonable to believe that the processing of each part of a given family of parts would result in manufacturing efficiencies.

Manufacturing takes opportunities under all types of economic systems. In a free market economy system, manufacturing is usually motivated to the mass production of products for sale to consumers at a profit. Therefore, optimization of formation of cells and part families in CMS results in improving the process efficiency as well as reducing the cost of production. The objective of this research work aims at improving the existing optimization techniques as well as developing new optimization techniques for optimum design of cell formation in cellular manufacturing systems.

1.3 Objectives and scope of the current research work

Cellular manufacturing is a rich area for research and one that encompasses wide variety of distinct issues such as cell formation, cell scheduling and lot sizing, where, there is scope of improvement on the existing solution methods or development of new methods to enhance the efficiencies of the CMS systems.

These issues can be explored in details using the model-oriented tools of OR/OM investigations (such as exact optimization techniques, namely, linear programming and branch and bound algorithm, approximation optimization techniques, including heuristic algorithms, metaheuristics, and simulation). The objective of the current research work has been summarized as follows:

i) To conduct a comprehensive literatures review on various optimization methods and applications of different problems and identify the gaps in the literature related to cellular manufacturing systems.
ii) To develop new construction heuristics in improving the efficiencies of the CMS problems.

iii) To develop effective and efficient metaheuristics for the CMS problems.
iv) To examine the application of the proposed solution methods in a real-life manufacturing system.
v) Finally, to compare the performance of the proposed optimization methods with the state-of-the-art procedures based on a set of benchmark problems with respect to both solution quality and computational times.

The present research investigates two types of cell formation problems that frequently appear in the cellular manufacturing literature. The first problem deals with the cell formation with single routing and no process sequences with the objective of maximizing grouping efficacy and the cell utilization. We consider another cell formation problem with multiple routings, process sequences and part volumes, with the objective of minimizing total inter-cellular movement of parts.

The present work proposes a heuristic approach based on Euclidean distance matrix for the machine-part cell formation problem. The objective of this study is to generate optimal machine cells and part families considering the correlations between machines or parts in cellular manufacturing systems. The correlations between machines or parts are generated based on their similarities in processes and are represented in the form of Euclidean distance matrix. In order to cluster the machines for machine cells and parts for part families, we used Euclidean distance matrix. Computational comparative results of the proposed method with the well-known existing methods considering twenty benchmark problems from the literature show that the proposed method outperforms the existing algorithms. In the second research work, we proposed a genetic algorithm to maximize the grouping efficacy for the machine-part cell formation problem.

Next, we presented a heuristic approach for the cell formation problem considering multiple routings. In this research work, we computed the minimum Euclidean distances of machines for processing the parts considering parts volume, batch size, and number of batches by using the single linkage clustering technique in order to generate optimum machine cells having minimum intercellular movement of parts. Computational results of the proposed algorithm and comparisons with the well-known existing methods considering a set of five benchmark problems depict that the proposed algorithm is either better than or competitive with the well-known existing algorithms. Finally, we propose a genetic algorithm for the cell formation problem considering alternative routings for a real-life problem. The experimental results reveal that the proposed algorithm gives solutions in terms of intercellular movement either better than or competitive with the existing metaheuristic algorithms. This research work considers the cell formation problem allowing cell load variation in alternative routes of parts and process sequences with the objective of minimizing intercellular movements of parts.

1.4 Organization of this thesis

The organization of this thesis in the subsequent chapters is given below:

Chapter 2 (*Cellular Manufacturing System – An Overview*) – This chapter briefly reviews the existing literature on the theory of cell formation problems with reference to the problem formulation, various noteworthy optimization methods, and different performance criteria to assess the performance of the proposed optimization methods.

Chapter 3 (*A Heuristic based on Euclidean Matrix for the Cell Formation*) – This chapter presents a heuristic approach based on Euclidean distance matrix. We conducted the computational experiments based on a set of twenty benchmark problems taken from the literature. The computational results demonstrate that the performance of the proposed heuristic in terms of grouping efficacy are either better than or competitive with the well-known existing construction algorithms, namely, ROC, ZODIAC, GRAFICS, PCA, LA and SCM.

Chapter 4 (*Cell Formation using GA to Maximize Grouping Efficacy*) – This chapter provides a genetic algorithm heuristic to solve the cell formation problem. Computational experiments considering twenty benchmark problem sets show that the proposed heuristic has produced solutions in terms of grouping efficacy that are either better than or competitive with the existing metaheuristic algorithms such as GRASP, GA, SA, and PSO algorithms.

Chapter 5 (*A Heuristic for the Cell Formation with Alternative Routings*) - In this chapter, a heuristic approach is proposed based on Euclidean distance matrix for the cell formation problem considering multiple routes, process sequences and parts volume (including batch size and number of batches). We carried out the computational experiments with five benchmark problem sets taken from the literature and the results demonstrate that the proposed heuristic in terms of the intercellular movements of parts is relatively more effective than the well-known existing algorithms.

Chapter 6 (*A GA for the Cell Formation with Alternative Routings*) - In this chapter, a genetic algorithm based heuristic is presented for the cell formation problem with multiple process routes, sequence of processes and parts volume. The experimental results based on some standard benchmark problem instances demonstrate that the performance of the proposed approach in terms of total intercellular movements of parts and the selection of the best route is better than the well-known existing methods.

Chapter 7 (*Application of GA to a Real-life Cell Formation Problem*) - The objective of this study is to determine the optimal processing route and the balanced machine cells for a real-life cell formation problem involving parts volume and process sequences to minimize intercellular movements of parts. A genetic algorithm is applied to solve this problem. Computational results show that the proposed approach produces comparatively better results compared to the well-known existing methods in respect of total intercellular movements of parts.

Chapter 8 *(Conclusions, Limitations and Future Research Directions)* – This chapter summarizes the conclusion of this dissertation and it includes the limitations and future directions of research.

Chapter 2

CELLULAR MANUFACURING SYSTEM: AN OVERVIEW

2.1 Cellular manufacturing system

Grouping technology (GT) is a manufacturing philosophy that deals with the grouping of similar parts that are classified based on their similarities in design and production, resulting in manufacturing efficiencies of a cellular manufacturing system (CMS). The application of GT in a manufacturing system improves productivity, product quality, manufacturing lead times, utilization of resources and on the other hand, it reduces work in process inventory, setup time, and material handling cost.

The cell formation problem (CFP) usually attempts to obtain a solution with the formation of completely independent machine cells, where each machine cell assigns a set of independent part families so that the cell can carry out all operations of that particular part family. However, in actual practice, it is sometimes difficult to execute all the operations of a part family belonging to a particular machine cell. Therefore, the principal objective of applying GT in manufacturing systems is to minimize intercellular movements of parts i.e., to minimize the exceptional machines and parts and to maximize utilization of machines. Since the CFP belongs to the class of NP- hard, heuristic and meta-heuristic approaches are mostly preferred to obtain optimal or near-optimal solution for these problems, especially for solving large-sized problems in reasonable time.

2.2 Problem definition

The cell formation problem is formulated as $n\times m$ binary incidence matrix (where, n is the number of parts and m is the number of machines) as shown in Table 2.1. Here, rows and columns represent parts and machines of a problem respectively. The element of the binary matrix is denoted as a_{ij}. If the part *i* is processed on machine *j*, then a_{ij} =1; Otherwise, a_{ij} = 0.

Table 2.1 A seven parts and five machines incidence matrix for a CFP

	M1	M2	M3	M4	M5
P1	0	0	1	1	0
P2	1	0	1	0	0
P3	0	1	0	1	1
P4	1	0	1	0	1
P5	0	1	0	0	1
P6	0	0	0	1	1
P7	1	0	1	0	0

The main objective of applying GT in the CFP is to minimize the movements of the inter-cells of the parts and to maximize the utilization of machines within a cell by converting the machine-part incidence matrix into some diagonally arranged blocks, where each block represents a combination of a machine cell and a part family (King and Nakornchai, 1982).

Table 2.2 shows the solution of the CFP problem given in Table 2.1 in the form of block diagonal machine-part incidence matrix.

Table 2.2 Solution of the CFP problem given in Table 2.1

	M2	M4	M5	M1	M3
P3	1	1	1		
P5	1		1		
P6		1	1		
P1		1			1
P2				1	1
P4			1	1	1
P7				1	1

2.3 Objective functions

The quality of the solution of a CFP can be evaluated by the grouping efficacy (GC) to measure the clustering effectively. It is defined as the ratio of total number of operations in the blocks to the sum of total number of operations in the incidence matrix and total number of void elements in the blocks. Grouping efficacy can be determined from the following expression:

$$GC = \frac{O-EE}{O+VE} \tag{2.1}$$

Where, O is the total of total number of operations in the machine-part incidence matrix i.e., total number of 1's. EE is the number of operations appeared outside the diagonal blocks and it is called exceptional elements and VE is the number of zeros inside the diagonal blocks and it is called void elements.

Cell utilization (CU_c) for a cell$c$ can be defined as:

$$CU_c = \frac{\sum_{i=1}^{m_c} MU_{ic}}{m_c} \tag{2.2}$$

Where, m_c is the number of machines in cell c and MU_{ic} = utilization of machine i in cell c. Alternatively, the cell utilization (CU_k) for a machine or a part in cell k can be defined by

$$CU_k = \frac{UE_e - EE_e}{m_k n_k} \tag{2.3}$$

Where, UE_e = total number of operations by the exceptional machine or for the exceptional part, EE_e = exceptional elements for the exceptional machine or part for that particular machine or part after merging, m_k = total number of machines in cell k, n_k = number of parts in family k. For merging an exceptional machine, $m_k = 1$ and for an exceptional part, $n_k = 1$.

2.4 Numerical illustration

In order to compute the *GC*, let us consider a problem of five machines and seven parts with the corresponding the part-machine incidence matrix given in Table 2.1. Consider the generated solution of the cells formation problem as given in Table 2.2. From the results of Table 2.2, we can see that one operation of part P1 and one operation of part P4 are outside the blocks. Hence, EE = 2. Additionally, we find that there are three zeros in the blocks. The number of zeros inside the diagonal cells denote the number of void elements (VE). Hence, VE=3. Therefore, for the given problem, $GC = \frac{16-2}{16+3} = \frac{14}{19}$ =0.7368 or 73.68%.

We consider a cell formation problem consisting of eight parts, six machines and with alternative routings and parts volume.

The objective of the problem is to minimize the intercellular movements of n parts. Table 2.4 shows the solution of the CFP problem given in Table 2.3 in the form of block diagonal machine-part incidence matrix. The results of Table 2.4 show that there are no intercellular movements of the parts except the part P6 having intercellular movements of ten. Hence, total number of intercellular movements for the entire production system will be ten.

Table 2.3 The CFP of 8 parts and 6 machines with alternative routings

Parts	Part volume	Part route	Machines					
			M1	M2	M3	M4	M5	M6
P1	50	1	1	3		2		
		2		1	2		3	4
		3		2	1		3	4
P2	30	1			1		3	2
P3	20	1			1		2	3
P4	30	1	1			2		
		2	2	1		3		
P5	20	1		3	2		4	1
		2			1			2
P6	10	1	1	2	3			
		2	1	2				3
P7	15	1		3			1	2
		2			3		1	2
		3		1				2
P8	40	1		2		1		

Table 2.4 Solution of the CFP given in Table 2.3

Parts	Part volume	Selected part route	Machine cell 1			Machine cell 2			Total intercellular movements for each part
			M1	M2	M4	M3	M5	M6	
P1	50	1	1	3	2				0
P4	30	1	1		2				0
P6	10	1	1	2		3			10
P8	40	1		2	1				0
P2	30	1				1	3	2	0
P3	20	1				1	2	3	0
P5	20	2				1		2	0
P7	15	2				3	1	2	0

2.5 Literature review on cellular manufacturing

The main goal of CMS design is to divide the production system into some production cells and part families. The cell formation methods are classified into three categories such as (a) hierarchical clustering, (b) non-hierarchical clustering, and(c) array-based clustering procedures, apart from the mathematical models, heuristics, metaheuristics, and simulation.

2.5.1 Heuristics for the CFP with single routing and no sequences

A number of remarkable heuristics in the CMS have been suggested in the literature. In hierarchical clustering methods, based on similarity correlation values, the techniques include the single linkage clustering (SLC) (McAuley, 1972), the average linkage clustering (ALINK) (Seifoddini, 1989b) and complete linkage clustering algorithm (CLINK) (Gupta and Seifoddini, 1990). In the category of non-hierarchical clustering methods, nodes and arcs are connected by the nodes of the graph representing machines-parts and operations of parts respectively. GRAFICS (Srinivasan and Narendran, 1991) and ZODIAC (Chandrasekharan and Rajagopalan, 1987) belong to this category.

In the area of array-based clustering, machine cells and part families for a problem are constructed by altering the position of the respective rows and columns. Rank order clustering (ROC) (King, 1980), modified rank order clustering (MODROC) (Chandrasekharan and Rajagopalan, 1986a), bond energy algorithm (McCormicket al. 1972), and direct clustering algorithm (Chan and Milner, 1982) are examples of this array-based clustering class.

Similarly, some noteworthy SLC-based heuristics have been proposed in the CMS literature. Mahdavi, Aalaei, Paydar and Solimanpur (2010) presents mathematical model to obtain optimum cell utilization considering minimization of exceptional elements and voids. McAuley (1972) used SLC in CMS for forming machine-cells through an iterative process. Waghodekar and Sahu (1984) considered cluster machines by SLC based on maximum similarity. Seifoddini and Djassemi (1991) used average linkage clustering algorithm (ALINK), and Gupta, and Seifoddini (1990) used complete linkage clustering algorithm (CLINK). Suer, Huang and Maddisetty (2010) proposed a configuration-based clustering algorithm for family formation and considered the number of machines of each type for calculation of similarity coefficient. Yin, and Yasuda (2002) proposed a new clustering methodology based on average voids value, which indicates the average number of voids when two machine groups are combined.

In addition, some notable matrix-based heuristic approaches have been developed by Sneath (1957a), Romesburg (1984), Sneath (1957b), Seifoddini and Djassemi (1991), Sarker and Xu (1998), and Mosier and Taube (1985b). Sneath (1957a) first used SLC analysis for the classification of bacteria. McAuley (1972) used SLC in CMS for forming machine-cells through an iterative process. To solve the CFP by the similarity coefficient method (SCM), similarity coefficient matrices (for machines and parts separately) are obtained from the original machine-part incident matrix. Then, from the generated similarity matrices, machines (or parts) with maximum similarity coefficient are grouped to form machine-cells (or part-families). Various researchers (Romesburg, 1984; Sneath, 1957b; Seifoddini and Djassemi, 1991) have proposed different similarity coefficients. McAuley (1972) first used the Jaccard similarity coefficient (Jaccard, 1908). Among these coefficients, Seifoddini and Djassemi (1991), and Sarker and Xu (1998) used production data based similarity coefficient such as production volume, processing times, and sequence of operations which incorporates in production process. Mosier and Taube (1985b) applied weighted similarity coefficients.

To evaluate the quality of solution, Chandrasekharan and Rajagopalan (1989) analyzed the grouping efficiency. Kumar and Chandrasekharan (1990), Chu and Tsai (1990) investigated both the grouping efficacy and the grouping efficiency of array-based machine-part grouping methods: ROC, DCA and BEA. Garbie, Parsaei and Leep (2005) used machine and cell utilization in flexibility systems for accepting a new part into existing CMS. Dimopoulos and Mort (2001) used the grouping efficacy to measure performance of a genetic programming based on SLC method with five other procedures.

2.5.2 Heuristics for multiple routings with process sequences and parts volume

In the cell formation literature, most of the cell formation problems consider single process routing. However, in the current practice, manufacturing equipment are multifunctional and therefore, production processes can be done by more than one number of process routes. Alternative process routes provide better configuration and flexibility in the cell design (Amel and Arkat, 2008). Alternative process routes also reduce intercellular material movements, reduce capital investment in machines and give more independent cells and machine utilization (Hwang and Ree, 1996).

Kusiak and Cho (1992) and Chow and Hawaleshka (1992) suggested similarity coefficient methods for the CFP in alternative routing of parts. Chow and Hawaleshka (1992) considered parts volume in their model. Gupta (1993) extended Jaccard’s similarity coefficient incorporation with process routes, operation sequence, processing time and parts volume.

Won and Kim (1997) used a generalized Jaccard’s similarity coefficient, integrating with process routing factors only. Yin and Yasuda (2002) extended the Won and Kim (1997) used Jaccard’s similarity coefficient by incorporation of process sequence, parts volume, processing time. Alhourani (2013) proposed a modified Jaccard’s similarity coefficient incorporated with process sequences and parts volume.

Other heuristic techniques for multiple routings, parts volume and sequential cell formation problem include simulated annealing (Sofianopoulou, 1999), fuzzy approach (Chu and Hayya, 1991), tabu search (Chung, Wu and Chang, 2011), genetic algorithm (Saeidi, Solimanpur, Mahdavi and Javadian, 2014).

2.5.3 Metaheuristics for the CFP with single routing and no sequences

Since the application of soft computing techniques in CF problems, they have been increasingly gaining popularity due to its consistent, robust performance results and easy to implement. Various soft computing techniques in the literature include fuzzy theory (Li, Ding and Lei, 1986; Chu and Hayya, 1991), ANN (Xing, Fulufhelo, Battle, Gaoand Marwala, 2009; Miljkovic and Babic, 2005), SA (Wu, Chang and Chung, 2008), GA (Onwubolu and Mutingi, 2001; Goncalves and Resende, 2004), tabu search (Zolfaghari and Liang, 2002), and PSO (Ali, Karimi and Noktehdan, 2014). Zolfaghari and Liang (2002) carried out a comparative study of effectiveness of GA, SA, and tabu search in cell formation problems and they found that SA is superior to other existing methods.

Recently, hybrid heuristics and metaheuristics have been applied in the CFPs such as HGGA (James, Brown and Keeling, 2007), GRASP (Diaz, Luna and Luna, 2012), HGA (Tariq, Hussain and Ghafoor, 2009), CARI (Gupta, Devika, Valarmathi, Sowmiya and Shinde, 2014), and HGBPSO (Ali, Karimi and Noktehdan, 2014).

2.5.4 Metaheuristics for multiple routings with process sequences and part volumes

Some noteworthy metaheuristic algorithms for the CF problems with alternative routings, uneven part volumes and process sequences include simulated annealing (Sofianopoulou, 1997 and Chen, Cotruvo and Baek, 1995), fuzzy approach (Chu and Hayya, 1991), and tabu search (Sun, Lin and Batta, 1995).

2.6 Design of computational experimentation in cell formation

We considered a set of thirty standard benchmark problems to evaluate the proposed algorithms with the best-known existing algorithms. We used the standard cell formation benchmark experimental framework as given in Table 2.5.

2.7 Conclusion

This chapter focuses on an overview of two different cell formation problems to satisfy some cell formation criteria. The formulation of these problems along with the corresponding numerical illustrations is presented. Next, different types of the relevant state-of-the-art algorithms for these problems are provided. Finally, the experimental setup procedure and the performance criteria to evaluate the comparative performance of the heuristics are discussed.

Table 2.5 Test problems and their sizes in the experimental framework

Prob. No.	Problem source	Size (n x m)
1	Waghodekar and Sahu (1984)	7×5
2	King and Nakornchai (1982)	7×5
3	Waghodekar and Sahu (1984)	7×5
4	Seifoddini (1989a)	18×5
5	Kusiak and Cho (1992)	8×6
6	Boctor (1991)	11×7
7	Kusiak and Chow (1987)	11×7
8	Seifoddini and Wolfe (1986)	12×8
9	Chandrasekharan and Rajagopalan (1986a)	20×8
10	Chan and Milner (1982)	15×10
11	Asktn and Subramantan (1987)	23×14
12	Stanfel, 1985	24×14
13	McCormick et al. (1972)	24×16
14	Srinivasan et al. (1990)	30×16
15	King (1980)	43×16
16	Carrie (1973)	24×18
17	Mosier and Taube (1985b)	20×20
18	Kumar et al. (1986)	23×20
19	Carrie (1973)	35×20
20	Boe and Cheng (1991)	35×20
21	Chandrasekharan and Rajagopalan (1989)	40×24
22	Chandrasekharan and Rajagopalan (1989)	40×24
23	Chandrasekharan and Rajagopalan (1989)	40×24
24	Chandrasekharan and Rajagopalan (1989)	40×24
25	Carrie (1973)	46×28
26	Kumar and Vannelli (1987)	41×30
27	Stanfel, 1985	50×30
28	King and Nakornchai (1982)	90×36
29	McCormick et al. (1972)	53×37
30	Chandrasekharan and Rajagopalan (1987)	100×40

Chapter 3

A HEURISTIC BASED ON EUCLIDEAN MATRIX FOR THE CELL FORMATION

3.1 Introduction

The objective of the cell formation problem (CFP) is to obtain an optimal solution with formation of completely independent machine cells corresponding to a set of independent part families with the objective of satisfying some cell formation criteria. In the particular solution, the machines in each machine cell can carry out all operations of the parts of a particular part family. However, in actual practice, it is sometimes difficult to execute all the operations of a part family belonging to a particular machine cell. Therefore, the objective of applying GT in manufacturing systems is to generate the optimal solution to minimize intercellular movements of parts i.e., to minimize the exceptional machines and parts and to maximize utilization of machines (Sofianopoulou, 1997).

Since the CF problem belongs to the class of NP- hard (Sofianopoulou, 1997), heuristic and metaheuristic approaches are mostly preferred to obtain optimal or near-optimal solutions for these problems, especially for solving large-sized problems in reasonable time.

A number of noteworthy heuristics have been proposed in the CMS literature, namely, ROC (King, 1980), MODROC (Chandrasekharan and Rajagopalan, 1986a), PCA (Hachicha et al., 2008), Hamiltonian path heuristic (Askin et al., 1991), cluster identification method (Kusiak et al., 1993), MD (Gupta et al., 2014), QM (Kitaoka et al., (1999), and similarity coefficients method (Wu et al., 2009). Sneath (1957b) first used SLC analysis for the classification of bacteria. Then, using this concept, McAuley (1972) used SLC in the CFP for forming the machine-cells through an iterative procedure.

To solve the CFP by the similarity coefficient method (SCM), heuristics make use of the similarity coefficient matrices (for machines and parts separately) from the original machine-part incident matrix. Then, from the generated similarity matrices, machines (or parts) with maximum similarity coefficient are grouped to form machine-cells (or part-families). Heuristics based on similarity coefficients have been proposed by Romesburg (1984), Sneath and Sokal (1973) and Seifoddini and Djassemi (1991). Among different similarity coefficients, McAuley, (1972) first used the Jaccard similarity coefficient (Jaccard, 1908).

Seifoddini and Djassemi, (1991), and Sarker and Xu, (1998, 2000) used production databased similarity coefficient such as production volume, processing times, and sequence of operations in production processes. Mosier and Taube (Mosier and Taube, 1985b) applied weighted similarity coefficients.

To evaluate the quality of solution of the CFP, Chandrasekharan and Rajagopalan (1989) analyzed the grouping efficiency. Kumar and Chandrasekharan (1990) and Chu and Tsai (1990) also applied the grouping efficacy in their methods, namely, ROC, DCA and BEA. Garbie et al. (2005) used the machine cell utilization in flexibility system for accepting a new part into existing CFP. Dimopoulos and Mort (2001) used the grouping efficacy to compare the performance of a genetic programming based on SLC method with five other procedures.

The objective of the proposed approach based on Euclidean distance matrix is to identify the exceptional machines and parts from the binary machine-part incidence matrix, if exists and to allocate them to some predefined groups or new cells by using cell utilization approach.

3.2 Single linkage clustering (SLC)

The goal of clustering is to incrementally group a number objects with the help of some correlations in the form of the similarity of processing of machines or parts. In the SLC procedure, in each step, merge the highest similar pairs as a single entity and the clustering process continued until certain termination conditions are satisfied. Clustering algorithms convert the machine-part incidence matrix into some diagonally arranged blocks and each block represents a combination of a machine cell and a part family group.

3.3 Euclidean distance matrix (EDM)

Consider a list of points $\{x_i, i = 1, \dots, n\}$ in the Euclidean space R^{η} of dimension η. A matrix D $\in R_+^{n\times n}$ is called a Euclidean Distance Matrices (EDM), where, its entries, $d_{i,j}^2$ are the Euclidean distance- squares between points of x_i and x_j, i.e.,$D[i,j] = d_{i,j}^2 = \left\|x_i - x_j\right\|^2$.As a result, any element of an EDM must satisfy the basic Euclidean matrix properties:

i. Non-negativity: $d_{i,j} \geq 0$.
ii. Self-distance: $d_{i,j} = 0 \iff x_i = x_j$.
iii. Symmetry: $d_{i,j} = d_{j,i}$.
iv. Triangle inequality: $d_{i,j} \leq d_{i,k} + d_{k,j}$.

Using the Euclidean distance matrix, cluster two entities based on minimum distance and consider them as a single entity for further cluster analysis.

3.4 Proposed Heuristic

Step 1: Standardize the machine-part incidence binary matrix.

Obtain the standardized matrix from the original matrix Abased on the procedure by Hachicha et al. (2008). Say, the initial machine-part incidence matrix for n parts and $m$machines is

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1m} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2m} \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ a_{n1} & a_{n2} & a_{n3} & \cdots & a_{nm} \end{bmatrix} \quad (3.1)$$

Where, each row represents a part and each column represents a machine. The values of the elements are binary (i.e., 1 or 0). If the part i is needed to process on machine j, then $a_{ij} = 1$; Otherwise $a_{ij} = 0$.

To obtain the standardized matrix B from A, first find the sum of each column individually, e.g., for machine j,

$$A_j = \sum_{i=1}^{n} a_{ij} \;, i = 1,2,3, \dots, n \text{ and } j = 1,2,3, \dots, m \quad (3.2)$$

Next, find the average of A_j, s.t., $\bar{A_j} = A_j / n$ (3.3)

Next, find $\sigma_j^2 = \bar{A_j} - \bar{A_j}^2$. (3.4)

Now, compute $b_{ij} = \left(a_{ij} - \bar{A_j}\right) / \sigma_j$for each individual elements of column j. (3.5)

The standardized machine-part incidence matrix will be

$$B = \begin{bmatrix} b_{11} & b_{12} & b_{13} & \cdots & b_{1m} \\ b_{21} & b_{22} & b_{23} & \cdots & b_{2m} \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ b_{n1} & b_{n2} & b_{n3} & \cdots & b_{nm} \end{bmatrix} \quad (3.6)$$

Step 2: Compute the Euclidean distance matrix.

The Euclidean distance between two machines, say, for machine x and $y$is given by the relation

$$d_{xy} = \sqrt{\sum_{i=1}^{n} \left(b_{ix} - b_{iy}\right)^2} \quad (3.7)$$

Compute the Euclidean distance matrix (*n* x *m*) for all the machines.

$$D = \begin{bmatrix} d_{11} & d_{12} & d_{13} & \cdots & d_{1m} \\ d_{21} & d_{22} & d_{23} & \cdots & d_{2m} \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ d_{n1} & d_{n2} & d_{n3} & \cdots & d_{nm} \end{bmatrix} \quad (3.8)$$

Step 3: Cluster the machines considering the required number of cells.

In single linkage clustering (SLC), two machines are clustered which have the smallest Euclidean distance and the generated machine cell is considered as a single entity for proceeding for other machines.

Step 4: Cluster the exceptional machines.

To merge the exceptional machines with machine cells, calculate the cell utilization of each exceptional machine with each cell as well as cell utilization of individual exceptional machine and accordingly, either merge the exceptional machine with the cell or consider the exceptional machine as a separate cell based on maximum cell utilization value. Garbie et al., (2005) defined the cell utilization.

To find part families following in the similar manner and to merge the exceptional parts with part families, we calculate the cell utilization of each exceptional part individually with each family and merge the exceptional part with the family based on maximum cell utilization value.

3.5 Performance criteria

The quality of solution can be evaluated either by grouping efficacy (GC) (Chandrasekharan and Rajagopalan, 1986b) or by grouping efficiency (GE) (Kumar and Chandrasekharan, 1990). In this study, we have considered *GC* only to measure the effectiveness of the clustering.

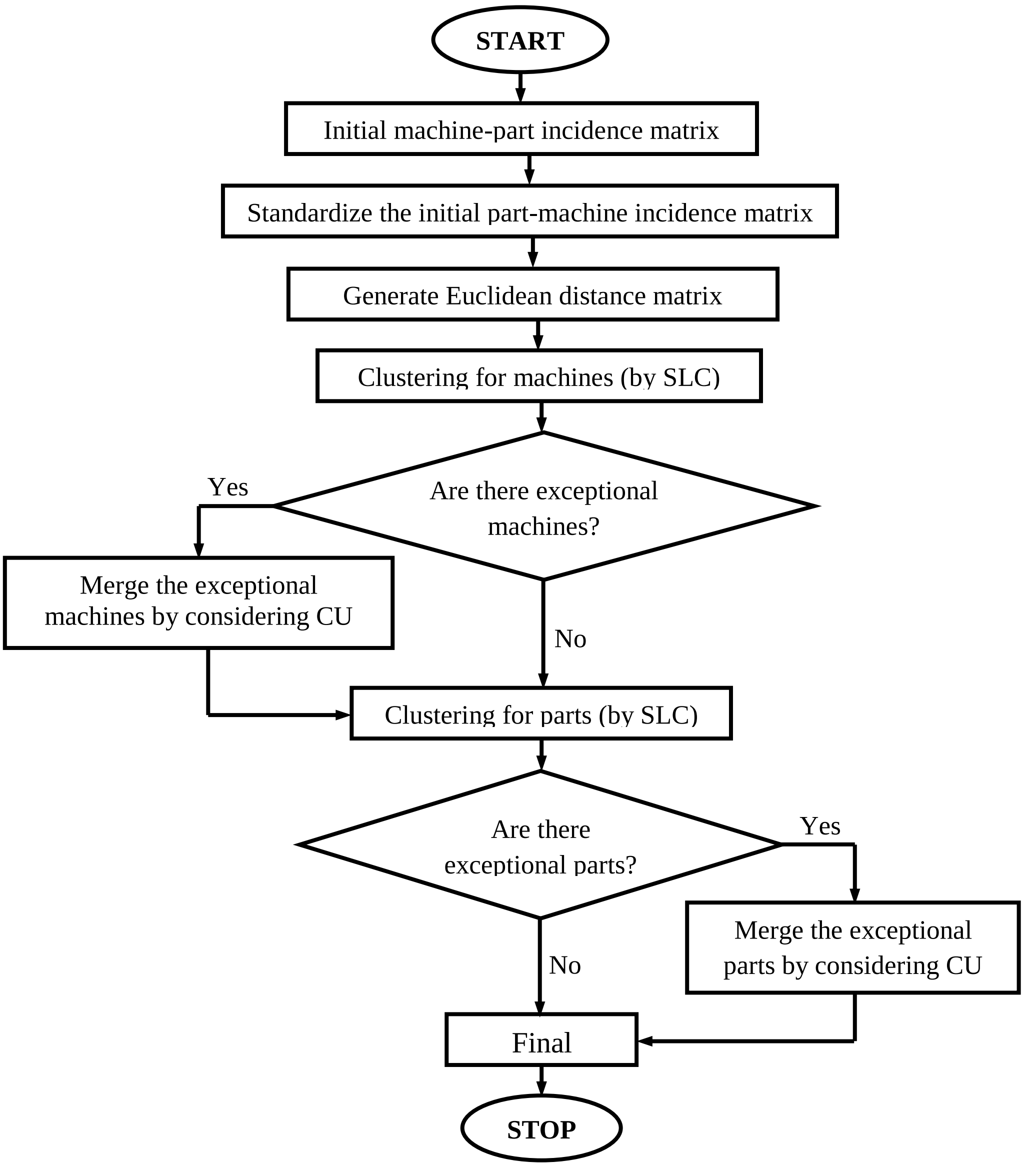

Fig.3.1 Flow Chart for the proposed clustering method

3.6 Numerical illustration

A CF problem having 7 parts and 5 machines is shown in Table 3.1. In this section, we illustrate the proposed procedure in details considering this problem.

Table 3.1 A problem having seven parts and five machines

Parts	Machines				
	M1	M2	M3	M4	M5
P1			1	1	
P2	1		1		
P3		1		1	1
P4	1		1		1
P5		1			1
P6				1	1
P7	1		1		

Step 1: The machine-part incidence matrix is

$$A = \begin{bmatrix} 0 & 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 1 \\ 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 \\ 1 & 0 & 1 & 0 & 0 \end{bmatrix}$$

Step 2: With the help of Equations (3.1) to (3.6), the machine-part incidence matrix A can be standardized as the machine-part incidence matrix B. To standardize the matrix A, find the sum of each column individually, e.g., for machine 1,

$$A_1 = \sum_{i=1}^{n} a_{i1} = 3 \text{ Where, } i = 1,2,3,\ldots,7.$$

For machine 2, $A_2 = \sum_{i=1}^{n} a_{i2} = 2$, and so on.

Find the average of A_j, s.t., $\bar{A}_j = A_j/n$ i.e., $\bar{A}_1 = A_1/n = 3/7 = 0.42857$.

Similarly, $\bar{A}_2 = A_2/n = 2/7 = 0.28571$, and so on.

Then, find $\sigma_j = \left\{\bar{A}_j - \left(\bar{A}_j\right)^2\right\}^{1/2}$ Where, $j = 1,2,\ldots,5$.

For machine 1, $\sigma_1 = \{\bar{A}_1 - (\bar{A}_1)^2\}^{1/2} = 0.49487$; for machine 2, $\sigma_2 = \{\bar{A}_2 - (\bar{A}_2)^2\}^{1/2} = 0.45175$ and so on.

Now, compute $b_{ij} = \left(a_{ij} - \bar{A}_j\right)/\sigma_j$ Where, $i = 1,2,\ldots,7$; $j = 1,2,\ldots,5$.

For example, $b_{11} = (a_{11} - \bar{A}_1)/\sigma_1 = (0 - 0.42857)/0.49487 = -0.8660$,

$b_{21} = (a_{21} - \bar{A}_1)/\sigma_1 = (1 - 0.42857)/0.49487 = 1.1547$,

$b_{12} = (a_{12} - \bar{A}_2)/\sigma_2 = (0 - 0.28571)/0.45175 = -0.6325$.

The standardized part-machine incidence matrix B,

$$B = \begin{bmatrix} b_{11} & b_{12} & b_{13} & \cdots & b_{1m} \\ b_{21} & b_{22} & b_{23} & \cdots & b_{2m} \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ b_{n1} & b_{n2} & b_{n3} & \cdots & b_{nm} \end{bmatrix} = \begin{bmatrix} -0.8660 & -0.6325 & 0.8660 & 1.1547 & -1.1547 \\ 1.1547 & -0.6325 & 0.8660 & -0.8660 & -1.1547 \\ -0.8660 & 1.5811 & -1.1547 & 1.1547 & 0.8660 \\ 1.1547 & -0.6325 & 0.8660 & -0.8660 & 0.8660 \\ -0.8660 & 1.5811 & -1.1547 & -0.8660 & 0.8660 \\ -0.8660 & -0.6325 & -1.1547 & 1.1547 & 0.8660 \\ 1.1547 & -0.6325 & 0.8660 & -0.8660 & -1.1547 \end{bmatrix}$$

Step 3: The Euclidean distance between two machines can be computed from Equation (3.7). For example, for machine 1 and machine 2,

$$d_{12} = d_{12} = \sqrt{\sum_{i=1}^{n}(b_{i1} - b_{i2})^2}=[\{(-0.8660) - (-0.6325)\}^2 + \{1.1547 - (-0.6325)\}^2 + \{(-0.8660) - 1.5811\}^2 + \{1.1547 - (-0.6325)\}^2 + \{(-0.8660) - 1.5811\}^2 + \{(-0.8660) - (-0.6325)\}^2 + \{1.1547 - (-0.6325)\}^2]^{1/2} = 4.6549$$

For machine 1 and machine 3,

$$d_{13} = \sqrt{\sum_{i=1}^{n}(b_{i1} - b_{i3})^2}=[\{(-0.8660) - 0.8660\}^2 + \{1.1547 - 0.8660\}^2 + \{(-0.8660) - (-1.1547)\}^2 + \{1.1547 - 0.8660\}^2 + \{(-0.8660) - (-1.1547)\}^2 + \{(-0.8660) - (-1.1547)\}^2 + \{1.1547 - 0.8660\}^2]^{1/2}=1.8708$$

Therefore, the Euclidean distance matrix for all the machines is

$$D = \begin{bmatrix} d_{11} & d_{12} & d_{13} & \cdots & d_{1m} \\ d_{21} & d_{22} & d_{23} & \cdots & d_{2m} \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ d_{n1} & d_{n2} & d_{n3} & \dots & d_{nm} \end{bmatrix} = \begin{bmatrix} 0 & 4.6549 & 1.8708 & 4.9497 & 4.4534 \\ 4.6549 & 0 & 4.9218 & 3.5668 & 2.5163 \\ 1.8708 & 4.9218 & 0 & 4.4534 & 4.9497 \\ 4.9497 & 3.5668 & 4.4534 & 0 & 3.4156 \\ 4.4534 & 2.5163 & 4.9497 & 3.4156 & 0 \end{bmatrix}$$

Table 3.2. The Euclidean distance matrix *D*

	M1	M2	M3	M4	M5
M1	0				
M2	4.6549	0			
M3	***1.8708***	4.9218	0		
M4	4.9497	3.5668	4.4534	0	
M5	4.4534	2.5163	4.9497	3.4156	0

Table 3.2 shows the Euclidean distance matrix *D* before clustering the machines.

Step 4: Cluster two machines, which have minimum Euclidean distance in distance matrix and considered them as a single entity for further cluster. Here the Euclidean distance of M1 and M3 is minimum (*1.8708*). Therefore, merge M1 and M3 and consider them as a single entity. Consider the minimum value of Euclidean distances for other machines from M1-M3. Table 3.2.1 shows the Euclidean distance matrix after merge M1 and M3.

Table 3.2.1. The Euclidean distance matrix after merge M1 and M3

Cell	M1-M3	M2	M4	M5
M1-M3	0			
M2	4.6549	0		
M4	4.4534	3.5668	0	
M5	4.4534	***2.5163***	3.4156	0

In this stage, the Euclidean distance of M2 and M5 is minimum (*2.5163*). So, merge M2 and M5 and consider them as another single entity. Table 3.2.2 shows the Euclidean distance matrix after clustering M1, M2, M3 and M5.

Table 3.2.2. The Euclidean distance matrix after clustering M1, M2, M3 and M5

Cell	M1-M3	M2-M5	M4
M1-M3	0		
M2-M5	4.4534	0	
M4	4.4534	***3.4156***	0

The Euclidean distance of M2-M5 and M4 is minimum (*3.4156*). So, merge M2-M5 and M4 and consider them as another single entity. Table 3.3 shows the Euclidean distance matrix after clustering all machines.

Table 3.3 The Euclidean distance matrix after clustering all machines

Cell	M1-M3	M2-M4-M5
M1-M3	0	
M2-M4-M5	4.4534	0

At the end of *Step 4*, machine cells are as follows.

(1) M1-M3= machine cell C1and (2) M2-M4-M5= machine cell C2

Following in the same manner, find the part families. Here the part families are as:

(1) P1-P2-P4-P7 = part family F1 and (2) P3-P5-P6 = part family F2

The final solution is shown in Table 3.4.

Table 3.4 Final solution

Parts	Machine cell 1		Machine cell 2		
	M1	M3	M2	M4	M5
P1		1		1	
P2	1	1			
P4	1	1			1
P7	1	1			
P3			1	1	1
P5			1		1
P6				1	1

3.7 Comparison of the proposed approach with the best-known algorithms

A set of 20 benchmark problems (described in Chapter 2) taken from the literature are solved to evaluate the performance of the proposed method. The proposed method is coded in MATLAB R2010a and run on a PC with Intel Core i5 CPU with 8 GB RAM at 3.30 GHz.

To compare the proposed approach with the following existing methods, we consider the grouping efficacy values:

- ZODIAC (Chandrasekharan and Rajagopalan,1987)
- GRAFICS (Srinivasan and Narendran, 1991)
- PCA: Principal component analysis (Hachicha et al., 2008)
- LA (Wang, 2003)
- QM (Kitaoka et al., 1999)
- ROC (King, 1980)
- MD-based (Gupta et al., 2014)
- KHM (Unler and Gungor, 2009)

SCM (Wu et al., 2009) Table 3.5 shows the grouping efficacies of above mentioned methods and the proposed method for all benchmark problems. The results of Table 3.5 reveal that the performance of the proposed method with respect to the grouping efficacies as compared with the existing algorithms is either improved or comparable for most of the problems except one problem instance.

In addition, in Table 3.5, the third last row shows the percentage of best solutions on the basis of all 20 problems and second last row shows the percentage of best solutions on the basis of solutions available in the literature. For example, the LA (Wang, 2003) algorithm has generated six best solutions out of eight problems. So, for LA, the percentage of best solution 1 $= (6/20) \times 100\,\% = 30\,\%$ and the percentage of best solution 2= $(6/8) \times 100\ \% = 75\,\%$. The last row of Table 3.5 shows the summation of the percentage gaps between the generated solution and the best solution for each problem and it is calculated as:

$$\text{Percentage of total Gap (\%)} = \sum_{k=1}^{N} \left(\frac{Best\ solution_k - Obtained\ solution_k}{Best\ solution_k} \right) \times 100\,\% \qquad (3.9)$$

Where, N= total number of problems solved and k=index of problems.

Table 3.5 Percentage of Grouping Efficacy of the proposed model and different methods

Prob No.	Methods										Best-known results
	ZODIAC	GRAFICS	PCA	LA	QM	ROC	MD-based	KHM	SCM	Proposed method	
1	76.92	82.35	-	82.35	-	82.35	-	-	-	82.35	82.35
2	**73.68**	**73.68**	**73.68**	**73.68**	**73.68**	**73.68**	**73.68**	**73.68**	**73.68**	**73.68**	73.68
3	56.52	60.87	-	-	-	62.50	**68.00**	62.50	62.50	**68.00**	68.00
4	77.36	-	-	-	-	**79.59**	**79.59**	**79.59**	**79.59**	**79.59**	79.59
5	**76.92**	-	-	-	-	**76.92**	**76.92**	**76.92**	**76.92**	**76.92**	76.92
6	**70.37**	-	**70.37**	-	67.86	53.33	70.37	70.37	70.37	70.37	70.37
7	39.13	53.12	-	48.78	-	48.78	53.13	53.13	53.13	**58.62**	58.62
8	68.30	68.30	-	-	-	68.29	68.30	-	68.29	69.44	69.44
9	85.24	85.24	85.24	**85.25**	-	79.03	84.20	-	**85.25**	85.25	85.25
10	**92.00**	**92.00**	-	-	78.18	71.93	**92.00**	-	**92.00**	92.00	92.00
11	64.36	64.36	-	-	-	69.86	69.62	65.75	69.86	72.85	72.85
12	65.55	65.55	66.29	67.04	-	67.04	67.04	69.33	69.33	**71.62**	71.62
13	32.09	45.54	-	-	-	-	50.00	50.48	-	**51.64**	51.64
14	67.83	67.83	-	-	-	67.83	66.90	67.83	67.83	68.34	68.34
15	53.76	54.39	53.55			**60.89**	54.39	54.80	54.60	54.86	60.89
16	41.84	48.91	-	-	-	54.46	50.46	52.83	54.46	56.60	56.60
21	**100.00**	**100.00**	**-**	**100.00**	**-**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	100.00
22	**85.10**	**85.10**	-	**85.11**	-	**85.11**	**85.11**	-	**85.11**	**85.11**	85.11
23	37.85	**73.51**	-	**73.51**	-	**73.51**	**73.51**	-	**73.51**	**73.51**	73.51
24	20.42	43.27	-	-	-	51.97	-	-	51.97	**52.74**	52.74
Percentage of best solution 1	30.00	30.00	10.00	30.00	5.00	40.00	45.00	25.00	45.00	95.00	100.00
Percentage of best solution 2	30.00	35.29	40.00	75.00	33.33	42.11	50.00	38.46	50.00	95.00	100.00
Percentage of total Gap (%)	267.50	96.43	19.50	23.18	18.58	96.34	49.87	50.05	42.72	9.90	0.00

As seen from Table 3.5, the percentage of best solution 1, and the percentage of best solution 2 of the proposed method is maximum (95.00 % each) as well as percentage of total gap is minimum (9.90 %) among all the competing methods. The percentage of best solution 1 for MD-based (Gupta et al., 2014) and SCM (Wu et al., 2009) is same (45.00 % each) and is the second best. Similarly, the percentage of best solution 2 for LA (Wang, 2003) is the second best (75.00 %).

3.8 Conclusion

The objective of this research is to generate optimal machine cells and part families by correlations between the machines or the parts in cellular manufacturing systems. The correlations between the machines or the parts are generated considering their similarities in processes to represent them in Euclidean distance matrix. Then, we used Euclidean distance matrix to cluster machines for machine cells and parts for part families. Computational results of the proposed method and comparison with the well-known existing methods for 20 benchmark problems show that the proposed method outperforms the existing algorithms.

Chapter 4

CELL FORMATION USING GA TO MAXIMIZE GROUPING EFFICACY

4.1 Introduction

The cell formation problems can be classified into three categories: (a) either grouping machine cells (Rajamani et al., 1990) or part families (Kusiak, 1987), (b) formation of part families and machine cells separately (Choobineh, 1988) and (c) formation of machine cells and part families simultaneously (Adilet al., 1993).

Recently, some noteworthy metaheuristics such as hybrid grouping GA (HGGA) (Jameset al., 2007), randomized greedy algorithm from scratch by partially (GRASP) (Diaz et al., 2012), hybrid GA (HGA) (Tariq et al., 2009), hybrid grouping based PSO (HGBPSO) (Ali et al., 2014) have been are being applied in the CFP problems.

In this chapter, we present a genetic algorithm heuristic. We conduct computational experiments with a set of twenty benchmark problem sets. Computational results show that the proposed heuristic has shown to produce solutions in terms of the grouping efficacy that are either better than or competitive with the existing algorithms.

4.2 Genetic algorithm

GA developed by Holland and Goldberg is a stochastic based global search optimization algorithm guided by the natural evolution and genetics principles. It initializes with a set of solutions, known as initial population and then executes sequentially selection, reproduction, crossover and mutation operations for a fixed number of iterations as stopping criterion. Members of the population are selected by an evaluation function, called fitness function according to its objective function or best neighborhood solution. For the next iteration, a new

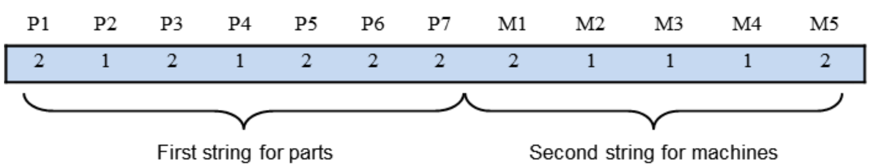

Fig. 4.1 Randomly generated chromosome for 5 machines and 7 parts problem

set population is generated from selected best neighborhood solutions by crossover and mutation. In this manner, the procedure is executed repeatedly for a fixed number of iterations. The steps of GA are as follows:

Step 1 Generate the initial random populations.
Step 2 Evaluate the fitness of each individual population.
Step 3 Select or sort populations.
Step 4 Generate new set of population from the best individual by the crossover operator.
Step 5 Apply the mutation operator.
Step 6 Repeat Steps 2-5 for the maximum number of iterations as the stopping criterion.
Step 7 Obtain the best solution.

4.2.1 Initial Population

GA initializes the population with the generation of a set of initial random solutions. In this study, each individual of the initial population consists of two parts, called strings. In the first string, we use integers for parts in the same order as is given by the indexing of jobs and in the second part, we use integers for machines in the same order as is given by the indexing of machines. Integers vary from one to the maximum number of possible groups (i.e., number of machines). For n number of parts, the length of the first string is n and for m number of machines, the length of the second string is m and total length of a chromosome is $n + m$.

A problem having 7 parts and 5 machines is shown in Table 4.1. Here, we initially randomly generate a population in which each individual in the population has two strings. As the part size is seven and machine size is five, the length of first string is 7 and that of the second string is 5. We consider a candidate solution or a randomly generated chromosome for two groups as shown in Fig. 4.1.

4.2.2 Evaluation of fitness of each individual population

Computation of fitness probability of each chromosome in the population is a criterion of the selection process to assess the high probability of selecting the candidate solution to the next iteration. The larger fitness is having the higher probability of survival in the next generation. The objective function of each individual population is measured by the grouping efficacy which is to be maximized.

4.2.3 Selection or sorting population

Selection is the procedure through which a new population is selected so that an individual in the population is accepted due to its higher fitness value (called parent chromosome) and an individual in the population is ignored for its smaller fitness value. The commonly used techniques are roulette-wheel-selection and tournament 50% truncation. In this work, we use here roulette-wheel-selection procedure.

4.2.4 Generation of new set of population from best individual by crossover

Crossover is analogous to biological reproduction. It is a process of taking more than one parent chromosome and producing offspring from them. The most useful crossover operators used in the literature are uniform, one-point, two-point, and single point. In this GA approach, we use the single point crossover.

For the above-mentioned problem, crossover point of two selected chromosomes, say, parent 1 and parent 2 are taken at a randomly selected location and they generate another two new chromosomes say, offspring 1 and offspring 2. Fig. 4.2 shows two parent chromosomes and their crossover points and Fig. 4.3 shows two offspring (offspring 1 and offspring 2) generated after the crossover of parent 1 and parent 2.

Parent 1	2	1	2	1	2	2	2	2	1	1	1	2

Crossover point

Parent 2	2	2	2	1	2	2	1	1	2	1	2	2

Fig. 4.2 Two parent chromosomes and their crossover points

Offspring 1	2	1	2	1	2	2	1	1	2	1	2	2
Offspring 2	2	2	2	1	2	2	2	2	1	1	1	2

Fig. 4.3 Two offspring, generated after the crossover of parent 1 and parent 2

4.2.5 Mutation

Mutation operator in the GA is required to introduce diversity in the population from one generation to another in order to get rid of being stuck at local optimum. It is also analogous to biological mutation. It swaps randomly the gene values (or bit value) in the individuals with a probability equal to the mutation probability. It does not guarantee that mutation provides a positive direction towards the optimal solution.

For mutation, consider a chromosome as shown in Fig. 4.4 Fig. 4.5 shows the new chromosome after mutation. Here, mutation point is 7-th gene.

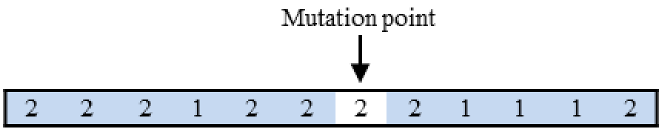

Fig. 4.4 A chromosome with mutation point (before mutation)

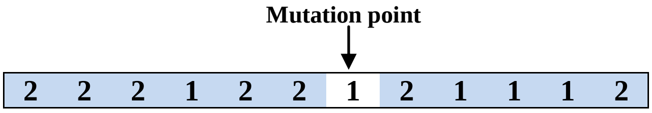

Fig. 4.5 Changed form of the previous chromosome (after mutation)

4.2.6 Adopted parameters

The proposed algorithm starts with generation of initial population in which each population has two strings (first string for parts and second string for machines). After the generation of initial population, the GA procedure executes in the loop. In the loop, the algorithm first selects the feasible solutions from initial population based on selection probability. The crossover and mutation operators are then executed sequentially within the loop. Offspring are generated considering the single point crossover operator from the selected population. For mutation, we use single point mutation operator.

The proposed GA seeks better solutions having maximum grouping efficacy ignoring inferior solutions within the neighborhood of the search space and updates better solution in each iteration. In order to obtain the best-so-far feasible solution, the above procedure is repeated for a predetermined maximum number of iterations. The number of iterations depends upon the size of problems. The selected parameters of the proposed GA are as follows.

- Crossover operator: single-point crossover
- Chromosome length: sum of part size and machine size
- Maximum cell numbers: machine size
- Selection: Rank-based roulette wheel selection
- Population size: 20
- Probability of mutation: 0.01 to 0.015
- Number of generations: $2 \times n \times m$
- Number of selected chromosomes: 2
- Number of iterations: 10

4.3 Computational results

A set of 20 standard benchmark problems are solved to evaluate the proposed GA with the existing algorithms. The source of benchmark problems and their sizes are given in Table 2.5. The proposed GA was coded in MATLAB R2010a programming and executed on a processor with Intel Core i5 CPU with 8 GB RAM at 3.30 GHz.

To compare the comparative performance of the proposed GA with respect to GC, the following algorithms are considered.

- HGGA- hybrid grouping genetic algorithm (Jameset al., 2007)
- SACF- simulated annealing to cell formation (Wu et al., 2008)
- GLCA- grouping league championship algorithm (Noktehdan et al., 2016)
- HGBPSO- hybrid grouping based PSO (Ali et al., 2014)
- CARI- correlation analysis and relevance index (Gupta et al., 2014)
- GRASP- randomized greedy algorithm from scratch by partially (Diaz et al., 2012)

Table 4.1 Comparisons of proposed algorithm with different methods for grouping efficacy

Prob. No.	Size	HGGA	GRASP	SACF	GLCA	HGBPSO	CARI	Proposed GA		Avg. CPU time (sec)
								Min.	*Max.*	
2	5×7	-	73.68	-	-	-	73.68	52.63	**75.00**	0.0469
4	5×18	79.59	79.59	79.59	**80.85**	79.59	79.59	76.92	79.59	0.1174
5	6×8	**76.92**	**76.92**	**76.92**	**76.92**	**76.92**	**76.92**	76.92	**76.92**	0.0662
11	14×23	72.06	69.86	71.21	**73.53**	72.06	69.86	68.75	73.13	0.8048
12	14×24	**71.83**	69.33	-	**71.83**	**71.83**	69.33	52.90	**71.83**	0.8442
14	16×30	**68.99**	67.83	-	-	**68.99**	67.83	68.70	**68.99**	1.3790
15	16×43	**57.53**	56.52	52.44	**57.53**	**57.53**	54.86	48.10	**57.53**	2.1594
16	18×24	57.73	54.46	-	57.73	57.73	54.46	56.00	**57.89**	1.2034
17	20×20	43.18	42.96	41.04	**43.45**	43.26	41.48	38.10	43.36	1.2664
18	20×23	50.81	49.65	50.81	50.81	50.81	49.65	49.15	**52.07**	0.9286
19	20×35	**77.91**	76.54	78.40	**77.91**	**77.91**	76.14	77.50	**77.91**	2.4342
20	20×35	57.98	58.15	56.04	57.98	57.98	56.98	56.47	**58.60**	2.4523
21	24×40	48.95	47.37	47.13	-	48.95	46.34	45.71	**48.97**	4.0181
22	24×40	47.26	44.87	44.64	-	47.26	44.10	41.73	**48.91**	4.0128
25	28 × 46	46.91	46.06	-	-	-	44.35	44.98	**47.35**	6.0339
26	30 × 41	**63.31**	59.52	62.42	**63.31**	**63.31**	58.11	58.87	63.27	6.0862
27	30 × 50	59.77	60.00	-	59.77	59.77	58.47	57.67	**60.12**	7.7374
28	36 × 90	46.35	45.93	-	-	-	44.18	44.76	**46.87**	22.0573
29	37 × 53	60.57	59.85	-	**60.64**	**60.64**	56.42	56.09	**60.64**	11.5920
30	40×100	**84.03**	**84.03**	-	-	-	**84.03**	82.03	**84.03**	55.7633

Table 4.1shows the grouping efficacies of above-mentioned methods and the proposed GA for the all problems. It is seen from the Table 4.2 that comparing with the existing algorithms, the proposed GA produces improved or same GC for 16 problems, whereas, it is inferior in solution quality for only 4 problem sets.

Since the objective of the study is to minimize exceptional elements as well as void elements, it is often seen that either machine cells are formed without clustering all the machines or part families are formed without clustering all the parts, resulting in infeasible solutions, which is not acceptable. In this study, we generate feasible solutions of all the 20 problem sets using the proposed GA and the corresponding solutions in terms of GC are shown in Table 4.1.

Table 4.2 Improved grouping efficacies produced by the proposed method

Problem No.	Size	HGGA	GRASP [26]	SAC F	GLCA	HGBPSO	CARI	Proposed method (Max.)	Best solution
2	5×7	-	73.68	-	-	-	73.68	**75.00**	**75.00**
16	18×24	57.73	54.46	-	57.73	57.73	54.46	**57.89**	**57.89**
18	20×23	50.81	49.65	50.81	50.81	50.81	49.65	**52.07**	**52.07**
20	20×35	57.98	58.15	56.04	57.98	57.98	56.98	**58.60**	**58.60**
21	24×40	48.95	47.37	47.13	-	48.95	46.34	**48.97**	**48.97**
22	24×40	47.26	44.87	44.64	-	47.26	44.10	**48.91**	**48.91**
25	28 × 46	46.91	46.06	-	-	-	44.35	**47.35**	**47.35**
27	30 × 50	59.77	60.00	-	59.77	59.77	58.47	**60.12**	**60.12**
28	36 × 90	46.35	45.93	-	-	-	44.18	**46.87**	**46.87**

The improved solutions of the problems generated by the proposed genetic algorithm are given in Table 4.2 and the details of some of the corresponding block diagonal matrices of the improved solutions are given in Appendix.

4.4 Conclusions

The objective of the study is to minimize exceptional elements as well as void elements simultaneously to maximize the grouping efficacy. In this study, a genetic algorithm based heuristic is presented for the cell formation problems. Computational results and comparisons with well-known methods for 20 benchmark problems show that the proposed heuristic has shown to produce solutions in terms of grouping efficacy that are either better than or competitive with the existing algorithms.

Chapter 5

A HEURISTIC FOR THE CELL FORMATION WITH ALTERNATIVE ROUTINGS

5.1 Introduction

The application of GT in today's automated manufacturing systems plays an important role, especially, in batch production systems, where the classification of part families and machine cells have simplified the layout design and products flow processes. Application of GT in production systems caters many advantages, e.g., reduction of material handling cost, time, labor requirement, paper works, in-process inventories, manufacturing lead time, frequency of setups. It, also, enhances quality of product, productivity, customers' satisfaction and efficient management (Spiliopoulos and Sofianopoulou, 2007).

GT classifies part families and allocates them to machine groups or machine cells for minimum number of intercellular movements of parts. Part families are selected based on their design, manufacturing processes, sequences, parts volume, and process routings. For machine cells, dissimilar machines in functions are usually grouped into a machine cell so that it can process operations with minimum intercellular movement of parts or family. However, similar types of machines may be required for different cells to cater similar processing operations of different part families. This leads to increase in number of similar machines, thereby reducing the process flexibility and utilization of machines (Suer et al., 2010).

In the cell formation literature, most of the cell formations techniques have been applied to solve the CF problem with the single process route, equal production volume and without any sequence of processes. However, in batch production systems, a part can be processed in multiple process routings with unequal production volume of parts and parts process on a particular sequence. Consideration of minimum intercellular movement of parts or routings may reduce capital investment in machines and increase machines utilizations (Hwang and Ree, 1996).

In this chapter, a heuristic approach based on Euclidean distance matrix is proposed for the CF problem in multiple routes, process sequential and parts volume (including the batch size and number of batches). Computational experiments were performed with five benchmark problem sets taken from the literature and the results demonstrate that the performances of the proposed heuristic in terms of intercellular movements of parts are either better than or competitive with the well-known existing algorithms.

5.2 Proposed clustering procedure

In the proposed algorithm, every part routes is considered as an individual part.

Step 1. Convert the CF problem into the part-machine incidence binary matrix.

For *n* parts and *m* machines problem, the machine-part binary incidence matrix is

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1m} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2m} \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ a_{n1} & a_{n2} & a_{n3} & \cdots & a_{nm} \end{bmatrix} \tag{5.1}$$

Where, every row represents a particular part with its route and every column represents a particular machine.

Step 2. Convert the binary matrix into the part-machine volume incidence matrix.

To convert the binary incidence matrix into the part-machine volume incidence matrix, multiply each element of binary incidence matrix by their respective part volume (matrix product). For *n* parts with *n* routes, the part volume matrix (it is an $n \times 1$ matrix) *V* is

$$V = \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix} \tag{5.2}$$

The part-machine volume incidence matrix *B* is

$$B = AV = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1m} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2m} \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ a_{n1} & a_{n2} & a_{n3} & \cdots & a_{nm} \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} & b_{13} & \cdots & b_{1m} \\ b_{21} & b_{22} & b_{23} & \cdots & b_{2m} \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ b_{n1} & b_{n2} & b_{n3} & \cdots & b_{nm} \end{bmatrix} \tag{5.3}$$

Step 1 : Standardize the part-machine volume incidence matrix.

Step 2 : Compute the Euclidean distance matrix.

Step 3 : Cluster the machines considering the required number of cells.

Step 4 : Cluster the exceptional machines.

Step 5 : Cluster the parts for part families up to the number of cells.

5.3 Implementation of the proposed approach

The proposed method is applied in five part-machine cell formation problems considering multiple process routes, process sequence and production volume. We compared the proposed method in terms of intercellular movements with the best-known existing methods.

5.3.1 Problem 1

A problem of five parts and five machines given in Won and Lee (2001) is shown in Table 5.1. This is the case of single route, part volume and sequential cell formation problem.

Table 5.1 Five parts and five machines -Problem 1

Parts	Part volume	Machines				
		M1	M2	M3	M4	M5
P1	20		1,3		2,4	5
P2	10	1		2		
P3	50	1,3		2		4
P4	40		2		1,3	
P5	30	2,4,6,8	1,5			3,7

Step 1. Convert the part-machine incidence into binary matrix.

The '5×5' binary incidence matrix is

$$A = \begin{bmatrix} 0 & 1 & 0 & 1 & 1 \\ 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 & 1 \end{bmatrix}$$

Step 2. Convert the binary matrix into part-machine volume incidence matrix.

Here, the part-machine volume matrix is given as:

$$V = \begin{bmatrix} 20 \\ 10 \\ 50 \\ 40 \\ 30 \end{bmatrix}$$

The corresponding part-machine volume incidence matrix is given below.

$$B = AV = \begin{bmatrix} 0 & 1 & 0 & 1 & 1 \\ 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 20 \\ 10 \\ 50 \\ 40 \\ 30 \end{bmatrix} = \begin{bmatrix} 0 & 20 & 0 & 20 & 20 \\ 10 & 0 & 10 & 0 & 0 \\ 50 & 0 & 50 & 0 & 50 \\ 0 & 40 & 0 & 40 & 0 \\ 30 & 30 & 0 & 0 & 30 \end{bmatrix}$$

Step 3. Standardize the part-machine volume incidence matrix.

The standardized machine-part volume incidence matrix *C* is

$$C = \begin{bmatrix} c_{11} & c_{12} & c_{13} & \cdots & c_{1m} \\ c_{21} & c_{22} & c_{23} & \cdots & c_{2m} \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ c_{p1} & c_{p2} & c_{p3} & \cdots & c_{pm} \end{bmatrix} = \begin{bmatrix} -1.0290 & 0.1143 & 1.0445 & -0.6963 & 0 \\ -0.4573 & -1.0290 & 0.1741 & 1.0445 & 1.0260 \\ 1.8293 & -1.0290 & -3.3075 & 1.0445 & -1.5390 \\ -1.0290 & 1.2577 & 1.0445 & -2.4371 & 1.0260 \\ 0.6860 & 0.6860 & 1.0445 & 1.0445 & -0.5130 \end{bmatrix}$$

Step 4. Compute the Euclidean distance matrix.

The Euclidean distance between two machines 1 and 2 is d_{12} = 3.8772. For machine 1 and machine 3, $d_{13} =$ 2.2935 and similarly, for other pairs of machines.

The Euclidean matrix D is

$$D = \begin{bmatrix} d_{11} & d_{12} & d_{13} & \cdots & d_{1m} \\ d_{21} & d_{22} & d_{23} & \cdots & d_{2m} \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ d_{m1} & d_{m2} & d_{m3} & \cdots & d_{mm} \end{bmatrix} = \begin{bmatrix} 0 & 3.8772 & 2.2935 & 5.1564 & 1.2233 \\ 3.8772 & 0 & 5.4012 & 2.1736 & 3.4427 \\ 2.2935 & 5.4012 & 0 & 5.9033 & 2.7148 \\ 5.1564 & 2.1736 & 5.9033 & 0 & 4.6452 \\ 1.2233 & 3.4427 & 2.7148 & 4.6452 & 0 \end{bmatrix}$$

Table 5.2 Tabular form of Euclidian distance matrix D for Problem 1

	M1	M2	M3	M4	M5
M1	0				
M2	3.8772	0			
M3	2.2935	5.4012	0		
M4	5.1564	2.1736	5.9033	0	
M5	***1.2233***	3.4427	2.7148	4.6452	0

Step 5. Cluster the machines considering the required number of cells, keeping in mind the maximum permissible number of machines in a cell.

Here, the Euclidean distance of M1 and M5 is minimum (***1.2233***). Therefore, merge M1 and M5 and consider them as a single entity. Consider the minimum value of Euclidean distances for other machines from M1-M5. Table 5.2.1 shows the Euclidean distance matrix after merging M1 and M5.

Table 5.2.1 The Euclidean distance matrix after merge M1 and M5

Cell	M1-M5	M2	M3	M4
M1-M5	0			
M2	3.4427	0		
M3	2.2935	5.4012	0	
M4	4.6452	***2.1736***	5.9033	0

In this stage, the Euclidean distance of M2 and M4 is minimum (***2.1736***). So, merge M2 and M4 and consider them as another single entity. Table 5.2.2 shows the Euclidean distance matrix after clustering M1, M2, M4 and M5.

Table 5.2.2 The Euclidean distance matrix after clustering M1, M2, M4 and M5

Cell	M1-M5	M2-M4	M3
M1-M5	0		
M2-M4	3.4427	0	
M3	***2.2935***	5.4012	0

The Euclidean distance of M1-M5 and M3 is minimum (***2.2935***). So, merge M1-M5 and M3 and consider them as another single entity. Table 5.2.3 shows the Euclidean distance matrix after clustering all machines.

Table 5.2.3 The Euclidean distance matrix after clustering all machines

Cell	M1-M3-M5	M2-M4
M1-M3-M5	0	
M2-M4	3.4427	0

At the end of *Step 5*, the generated two machine cells are as

(1) M1-M3-M5= machine cell C1 and

(2) M2-M4= machine cell C2

Step 6. Cluster the parts for part families up to the number of cells.

Following in the same manner, find the part families. Here, the part families are as:

(1) P2-P3-P5 = part family F1 and

(2) P1-P4 = part family F2.

The final cell formation and individual intercellular movement of parts is presented in Table 5.3.

Table 5.3 Final solution of Problem 1

Parts	Part volume	Machine cell 1			Machine cell 2		Intercellular movements of parts
		M1	M3	M5	M2	M4	
P2	10	1	2				-
P3	50	1,3	2	4			-
P5	30	2,4,6,8		3,7	1,5		3
P1	20			5	1,3	2,4	1
P4	40				2	1,3	-

From the results of Table 5.3, it is seen that intercellular movements for parts P1 is one and for the part, P5 is 3. Therefore, total intercellular movements with the volume $=3 \times 30 + 1 \times 20 = 110$. This is an optimum solution and it is same with those reported by Won and Lee (2001), and Kumar and Sharma (2014).

5.3.2 Problem 2

A problem of 8 parts and 6 machines taken from Yin and Yasuda (2002) is shown in Table 5.4. This is the case of multiple routes, part volume and sequential cell formation problem.

Table 5.4 Eight parts and six machines -Problem 2

Parts	Part volume	Part route	Machines					
			M1	M2	M3	M4	M5	M6
P1	50	1	1	3		2		
		2		1	2		3	4
		3		2	1		3	4
P2	30	1			1		3	2
P3	20	1			1		2	3
P4	30	1	1			2		
		2	2	1		3		
P5	20	1		3	2		4	1
		2			1			2
P6	10	1	1	2	3			
		2	1	2				3
P7	15	1		3			1	2
		2			3		1	2
		3		1				2
P8	40	1		2		1		

The tabular form of Euclidian distance matrix D for Problem 2 is shown in Table 5.4.1.

Table 5.4.1 Euclidian distance matrix D for Problem 2

	M1	M2	M3	M4	M5	M6
M1	0					
M2	7.2087	0				
M3	10.2368	5.2689	0			
M4	4.6978	6.3821	10.2178	0		
M5	10.5450	5.2967	2.0506	10.4418	0	
M6	9.8795	4.7622	1.8253	9.8485	2.1115	0

At the end of *Step 5*, formed two machine cells are as (considering cell utilization),

(1) M1-M2-M4= machine cell C1 and

(2) M3- M5-M6= machine cell C2

Following in the same manner, find the part families. Here the part families are as:

(1) P1(1)-P4(1)-P4(2)-P6(1)-P6(2)-P7(3)-P8(1) and

(2) P1(2)-P1(3)-P2(1)-P3(1)-P5(1)-P5(2)-P7(1)-P7(2)

Now, select the best routes of parts that which have minimum intercellular movements between cells or maximum intracellular movements within a cell. For example, for part P1 routes 1, 2 and 3 have zero, one and two intercellular movements respectively, so we select the route 1. Following the same procedure for both part families, we obtain the part families:

(1) P1(1)-P4(1)-P6(1)-P8(1)= part family F1 and

(2) P2(1)-P3(1)-P5(2)-P7(2)= part family F2.

The final solution of the cell formation along with the individual intercellular movement of parts is presented in Table 5.5.

Table 5.5 Final solution of Problem 2

Parts	Part volume	Machine cell 1			Machine cell 2			Intercellular movements of parts
		M1	M2	M4	M3	M5	M6	
P1(1)	50	1	3	2				-
P4(1)	30	1		2				-
P6(1)	10	1	2		3			1
P8(1)	40		2	1				-
P2(1)	30				1	3	2	-
P3(1)	20				1	2	3	-
P5(2)	20				1		2	-
P7(2)	15				3	1	2	-

As seen from Table 5.5, the intercellular movement for part P6 is one. Therefore, total intercellular movements considering the part volume $= 1 \times 10 = 10$. This is an optimum solution and it is same with those given by Yin and Yasuda (2002), and Alhourani (2013), whereas, Gupta (1993) obtained a total number of 50 intercellular movements of parts in the final solution.

5.3.3 Problem 3

A problem of 7 parts and 5 machines given in Gupta (1993) is shown in Table 5.6. This is the case of multiple routes, part volume and sequential cell formation problem.

Table 5.6 Seven parts and five machines-Problem 3

Parts	Part volume	Part route	Machines				
			M1	M2	M3	M4	M5
P1	50	1	2			1	
		2	1		2	3	
P2	5	1	1			2	
P3	20	1		2			1
		2		1	3		2
P4	30	1	2	1			3
		2		1	3		2
P5	40	1	1			2	
		2	1		2	3	
P6	10	1		1			2
P7	35	1		2			1

The tabular form of Euclidian distance matrix D for Problem 3 is shown in Table 5.6.1.

Table 5.6.1 Euclidian distance matrix D for Problem 3

	M1	M2	M3	M4	M5
M1	0				
M2	6.4926	0			
M3	5.1085	6.6203	0		
M4	1.7657	7.4404	5.0936	0	
M5	6.4926	0	6.6203	7.4404	0

At the end of Step 5, the generated two machine cells (considering cell utilization) are as

(1) M1-M4= machine cell C1 and

(2) M2-M3-M5= machine cell C2

Following in the same manner, find the part families. Here, the part families are as:

(1) P1(1)-P1(2)-P2(1)-P5(1)-P5(2) and

(2) P3(1)-P3(2)-P4(1)-P4(2)-P6(1)-P7(1).

Selecting the best routes of the parts, which have minimum intercellular movements between cells or maximum intracellular movements within a cell for both part families, the part families will be obtained as given below.

(1) P1(1)-P2(1)-P5(1)= part family F1 and

(2) P3(1)-P4(2)-P6(1)-P7(1)= part family F2.

The final solution of the cell formation with individual intercellular movement of parts is presented in Table 5.7.

Table 5.7 Final solution of Problem 3

Parts	Part volume	Machine cell 1		Machine cell 2			Intercellular movements of parts
		M1	M4	M2	M3	M5	
P1(1)	50	2	1				-
P2(1)	5	1	2				-
P5(1)	40	1	2				-
P3(1)	20			2		1	-
P4(2)	30			1	3	2	-
P6(1)	10			1		2	-
P7(1)	35			2		1	-

From Table 5.7, it is seen that there are no intercellular movements of parts. Therefore, total number of intercellular movements is zero. This is an optimum solution and it is same with Yin and Yasuda (2002). However, total 30 intercellular movements have been shown by Gupta (1993) and total 5 intercellular movements reported by Kumar and Sharma (2014).

5.3.4 Problem 4

A problem of 20 parts and 8 machines taken from Nair and Narendran (1998) is shown in Table 5.8. This is the case of single route, unit volume part, single batch and sequential cell formation problem. Here, maximum permissible number of machines in a cell is five.

Table 5.8 Twenty parts and eight machines-Problem 4

Part	Machines							
	M1	M2	M3	M4	M5	M6	M7	M8
P1					2	1		
P2	1		2					
P3	2	1		5			3	4
P4		1		2			3	4
P5					2	1		
P6		1		2	5		3	4
P7		4		2			3	1
P8	1		2					
P9	1		3			2		
P10				2	3	1		
P11	3		2				1	
P12					1	3	2	
P13	1		2					
P14	1	2	3					
P15				1	2			
P16	1		2					
P17	3		1		2			
P18		2		1			4	3
P19	1		2					
P20		2		1		3	4	5

The tabular form of Euclidian distance matrix D for Problem 2 is shown in Table 5.8.1.

Table 5.8.1 Euclidian distance matrix D for Problem 3

	M1	M2	M3	M4	M5	M6	M7	M8
M1	0							
M2	7.2512	0						
M3	1.9541	7.6237	0					
M4	8.0309	3.5511	8.3392	0				
M5	7.8081	7.2627	7.6237	6.1877	0			
M6	7.5801	7.0757	7.4104	6.6003	4.7555	0		
M7	7.5053	3.5511	7.8317	4.0825	6.8445	6.6003	0	
M8	7.5801	2.0771	7.9804	2.8158	7.0757	6.9007	2.8158	0

The clustering procedure is continued until the maximum permissible number of machines in a cell is not more than five and the generated two machine cells are

(1) M1-M3-M5-M6= machine cell C1 and

(2) M2-M4-M7-M8= machine cell C2

The part families are as:

(1) P1-P2-P5-P8-P9-P10-P11-P12-P13-P14-P15-P16-P17-P19= part family F1 and

(2) P3-P4-P6-P7-P18-P20= part family F2.

The final solution of the cell formation along with individual intercellular movement of parts is shown in Table 5.9.

Table 5.9 Final solution of Problem 4

Parts	Machine cell 1				Machine cell 2				Intercellular movements of parts
	M1	M3	M5	M6	M2	M4	M7	M8	
P1			2	1					-
P2	1	2							-
P5			2	1					-
P8	1	2							-
P9	1	3		2					-
P10			3	1		2			2
P11	3	2					1		1
P12			1	3			2		2
P13	1	2							-
P14	1	3			2				2
P15			2			1			1
P16	1	2							-
P17	3	1	2						-
P19	1	2							-
P3	2				1	5	3	4	2
P4					1	2	3	4	-
P6			5		1	2	3	4	1
P7					4	2	3	1	-
P18					2	1	4	3	-
P20				3	2	1	4	5	2

From Table 5.9, it is seen that there are 13 intercellular movements of parts. This is an optimum solution and it is same with the solution obtained by Alhourani and Seifoddini (2007). While, Nair and Narendran (1998) and Kumar and Sharma (2014) reported a total of 17 and 16 intercellular movements respectively.

5.3.5 Problem 5

A problem of 12 parts and 12 machines taken from Sofianopoulou (1999) is shown in Table 5.10. This is the case of multiple routes, unit part volume and sequential cell formation problem. Here, maximum permissible number of machines in a cell is five.

Table 5.10 Twelve parts and twelve machine-Problem 5

Part	Routes	Machines											
		M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
P1	1			3		2	1		5			6	4
	2					4	3	5			1	2	
P2	1	4	2		3	5					1		
	2	2		4	1		5				3		
	3		2				3						1
P3	1		3			2			1				4
	2								2				1
P4	1		2		3					1			
	2		1	3				2		4			
P5	1	1	4		3		2		5				
P6	1		3	2		6			5			4	1
	2					3			4		2	1	
P7	1					4		2			1	3	
	2			1	2			4			3		
P8	1		2		3	1							
P9	1		5	4			1	2				3	
	2		1	2			4					3	
P10	1				1	3			2				
P11	1		2	1						4	3		5
P12	1		3				1	2					

The proposed method produced three machine cells and the generated machine cells are

(1) M1-M9= machine cell C1

(2) M2-M3-M4-M6-M11= machine cell C2 and

(3) M5-M7-M8-M10-M12= machine cell C3.

Selecting the best route, the part families are as:

(1) P11(1)= part family F1,

(2) P1(2)-P2(3)-P4(1)-P5(1)-P6(2)-P8(1)-P9(2)-P10(1)-P12(1)= part family F2 and

(3) P3(2)-P7(2)= part family F3.

The final solution of the cell formation along with the individual intercellular movement of parts is shown in Table 5.11.

Table 5.11 Final solution of Problem 5

Parts	Routes	Cell 1		Cell 2					Cell 3					Intercellular movement
		M1	M9	M2	M3	M4	M6	M11	M5	M7	M8	M10	M12	
P11	1		4	2	1							3	5	3
P1	2						3	2	4	5		1		2
P2	3			2			3						1	1
P4	1		1	2		3								1
P5	1	1		4		3	2				5			2
P6	2							1	3		4	2		1
P8	1			2		3			1					1
P9	2			1	2		4	3						-
P10	1					1			3		2			1
P12	1			3			1			2				2
P3	2										2		1	-
P7	2				1	2				4		3		1

From Table 5.11, it depicts that there are 15 intercellular movements of parts generated by the proposed algorithm. This is an optimum solution and it is same with those obtained by Alhourani (2013), and Yin and Yasuda (2002).

5.4 Conclusion

In this research work, Euclidean distances of machines for processing the parts considering parts volume, batch size, and number of batches are calculated. Then the clustering of machines and parts is done by using the SLINK method based on minimum Euclidean distance. The aim of this chapter is to generate optimum machine cells having minimum intercellular movement of parts. Computational results of the proposed algorithm and comparison with the well-known existing methods for five benchmark problem instances show that proposed algorithm is either better than or competitive with the well-known existing algorithms.

Chapter 6

A GA FOR THE CELL FORMATION WITH ALTERNATIVE ROUTINGS

6.1 Introduction

GT in the cell formation helps to minimize number of intercellular movements of parts Sofianopoulou (1997). For grouping the machines into machine cells, dissimilar machines are clustered into a machine cell such that processing operations can be accomplished with minimum number of intercellular movements, resulting in reduced overall cost.

In the literature survey, it is seen that most of the cell formation techniques have been applied for single process route, equal production volume and without any sequence of process (James et al., 2007; Ali et al., 2014, and Laha and Hazarika, 2017). In advanced cellular manufacturing systems, or in batch production systems, a part can be processed following multiple process routings and unequal production volume of parts (Kusiak, 1987).

In this chapter, a genetic algorithm approach is proposed to solve the CF problem with alternative routings, operation sequence of the parts and uneven part volume.

6.2 Proposed Genetic Algorithm

GA proposed by Holland (1975) is a stochastic search and optimization technique, based on mechanism of natural selection and natural genetics. The basic steps of the GA are as follows:

Step 1: Generate the initial random populations.
Step 2: Evaluate the fitness of each individual population.
Step 3: Select or sort populations.
Step 4: Generate new set of population from the best individual by the crossover operator.
Step 5: Apply the mutation operator.
Step 6: Repeat Steps 2-5 for the maximum number of iterations as the stopping criterion.
Step 7: Obtain the best solution.

6.3 GA parameters

The proposed algorithm searches better solutions (minimizing intercellular movement) and ignore inferior solutions (or chromosome) while running each iteration. Therefore, in each iteration, a new solution is generated and better solution is selected. To run the algorithm, following parameters are considered and these have a crucial role on optimal solutions. The parameters are as follows:

- Population size: 20
- Number of generations: $2 \times n \times m$
- Crossover operator: single-point crossover
- Selection: rank-based roulette wheel selection
- Probability of mutation: 0.01 to 0.015
- Number of selected chromosomes: 2
- Number of trials: 10

6.4 Computational results

Five problems taken from the literature are solved to evaluate the performance of the proposed algorithm. The source of the benchmark problems and their sizes are shown in Table 6.1. The proposed algorithm was coded in MATLAB R2010a and run on a PC of Core i5, 3.30 GHz speed with 8.00 GB of RAM.

Table 6.1 Source of test problems and their sizes

Problem No.	Problem source	Size
1.	Raja and Anbumalar (2016)	5×7
2.	Yin and Yasuda (2002).	5×7
3.	Yin and Yasuda (2002).	6×8
4.	Nair and Narendran (1998)	8×20
5.	Yin and Yasuda (2002)	12×12

6.4.1 Problem 1

This is the case of single route, unit volume part (and single batch) and sequential CF problem. The problem is given in Table 6.2.

Table 6.2 Seven parts and five machines for problem 1

Parts	Machines				
	M1	M2	M3	M4	M5
P1	1		2	3	
P2	2		1	3	
P3	1	2			3
P4	1	2	3		
P5		1			2
P6	3		1	2	
P7		1			2

Table 6.3 Machine cells using different approaches of Problem 1

Approach	Reference	Machine cells		Number of intercellular moves
		I	II	
CLASSPAVI	Raja and Anbumalar (2016)	M1,M3,M4	M2,M5	3
Proposed GA		M1,M3,M4	M2,M5	3

The solution of the proposed approach is shown in Table 6.3 and it shows that 2 machine cells and 3 intercellular moves. This solution is same as reported by Raja and Anbumalar (2016). The block diagonal matrix of the proposed GA is shown in Table 6.4.

Table 6.4 Solution of problem 1 produced by the proposed GA

Parts	Machine cell I			Machine cell II		Intercellular movements of each part
	M1	M3	M4	M2	M5	
P1	1	2	3			--
P2	2	1	3			--
P4	1	3		2		2
P6	3	1	2			--
P3	1			2	3	1
P5				1	2	--
P7				1	2	--

6.4.2 Problem 2

The problem is given in Table 6.5. This is the case of multiple routes, part volume and sequential CF problem.

Table 6.5 Seven parts and five machines for problem 2

Parts	Part volume	Part route	Machines				
			M1	M2	M3	M4	M5
P1	50	1	2			1	
		2	1		2	3	
P2	5	1	1			2	
P3	20	1		2			1
		2		1	3		2
P4	30	1	2	1			3
		2		1	3		2
P5	40	1	1			2	
		2	1		2	3	
P6	10	1		1			2
P7	35	1		2			1

Table 6.6 Solutions using different approaches for problem 2

Approach	Reference	Machine cells		Number of intercellular moves
		I	II	
Similarity coefficient method	Yin and Yasuda (2002)	M2,M3,M5	M1,M4	0
Similarity coefficient method (CLINK)	Gupta (1993)	M1,M4,M3	M2,M5	30
Proposed GA		M2,M3,M5	M1,M4	0

The proposed procedure produced two machine cells and zero intercellular moves. This is the same as reported by Yin and Yasuda (2002). A total number of 30 intercellular moves is obtained by Gupta (1993). The best route of the proposed approach is P1(1)-P2(1)-P3(2)-P4(2)-P5(1)-P6(1)-P7(1). Table 6.6 shows the solutions of Problem 2. The solution of problem 2 given by the proposed GA is shown in Table 6.7.

Table 6.7 Block diagonal solution of Problem 2 by the proposed GA

Parts	Part volume	Selected part route	Machine cell I			Machine cell II		Intercellular movements of each part
			M2	M3	M5	M1	M4	
P3	20	2	1	3	2			--
P4	30	2	1	3	2			--
P6	10	1	1		2			--
P7	35	1	2		1			--
P1	50	1				2	1	--
P2	5	1				1	2	--
P5	40	1				1	2	--

6.4.3 Problem 3

The problem is shown in Table 6.8. This is the case of multiple routes, part volume (and single batch) and sequential CF problem.

Table 6.8 Eight parts and six machines for Problem 3

Parts	Part volume	Part route	Machines					
			M1	M2	M3	M4	M5	M6
P1	50	1	1	3		2		
		2		1	2		3	4
		3		2	1		3	4
P2	30	1			1		3	2
P3	20	1			1		2	3
P4	30	1	1			2		
		2	2	1		3		
P5	20	1		3	2		4	1
		2			1			2
P6	10	1	1	2	3			
		2	1	2				3
P7	15	1		3			1	2
		2			3		1	2
		3		1				2
P8	40	1		2		1		

A total number of 10 intercellular moves are produced by the proposed procedure. This is the same number of intercellular moves as reported by Yin and Yasuda (2002) and Alhourani (2013). A total number of 50 intercellular moves is generated using the algorithm of Gupta (1993). The Best route produced by proposed approach is P1(1)-P2(1)-P3(1)-P4(2)-P5(2)-P6(1)-P7(2)-P8(1). Tables 6.9 and 6.10 shows the solutions of Problem 3 using different approaches and the proposed GA.

Table 6.9 Solutions using different approaches for Problem 3

Approach	Reference	Machine cells		Number of intercellular moves
		I	II	
Similarity coefficient method (CLINK)	Gupta (1993)	M2,M3,M5,M6	M1,M4	50
Similarity coefficient method	Yin and Yasuda (2002)	M1,M2,M4	M3,M5,M6	10
Similarity coefficient method	Alhourani (2013)	M1,M2,M4	M3,M5,M6	10
Proposed GA		M1,M2,M4	M3,M5,M6	10

Table 6.10 Block diagonal solution of Problem 3 by the proposed GA

Parts	Part volume	Selected part route	Machine cell I			Machine cell II			Intercellular movements of each part
			M1	M2	M4	M3	M5	M6	
P1	50	1	1	3	2				--
P4	30	2	2	1	3				--
P6	10	1	1	2		3			10
P8	40	1		2	1				--
P2	30	1				1	3	2	--
P3	20	1				1	2	3	--
P5	20	2				1		2	--
P7	15	2				3	1	2	--

6.4.4 Problem 4

Table 6.11 Twenty parts and eight machines Problem 4

Part	Machines							
	M1	M2	M3	M4	M5	M6	M7	M8
P1					2	1		
P2	1		2					
P3	2	1		5			3	4
P4		1		2			3	4
P5					2	1		
P6		1		2	5		3	4
P7		4		2			3	1
P8	1		2					
P9	1		3			2		
P10				2	3	1		
P11	3		2				1	
P12					1	3	2	
P13	1		2					
P14	1	2	3					
P15				1	2			
P16	1		2					
P17	3		1		2			
P18		2		1			4	3
P19	1		2					
P20		2		1		3	4	5

The problem is presented in Table 6.11. This is the case of single route, unit volume part (and single batch) and sequential CF problem. Here, maximum permissible number of machines in a cell is given as five.

The proposed procedure produced the solution containing 2 machine cells and 13 intercellular moves and it is the same as the solution of Alhourani and Seifoddini (2007). Tables 6.12 and 6.13 show the solution of problem 4 produced by different approaches and the proposed GA.

Table 6.12 Solutions of Problem 4 using different approaches

Approach	Reference	Machine cells			Number of intercellular moves
		I	II	III	
Similarity coefficient method (CLINK)	Nair and Narendran (1998)	M1,M3	M5,M6	M2,M4,M7,M8	17
Considering machines as 'points' in multi-dimensional space	George et al. (2003)	M1,M3	M5,M6	M2,M4,M7,M8	16
CLASSPAVI	Raja and Anbumalar (2016)	M1,M3	M5,M6	M2,M4,M7,M8	16
Similarity coefficient method	Alhourani and Seifoddini (2007)	M1,M3,M5	M2,M4,M6,M7,M8		13
Proposed GA		M1,M3,M6	M2,M4,M5,M7,M8		13

Table 6.13 Solution of Problem 4 produced by the proposed GA

Part	Machine cell I			Machine cell II					Intercellular movements of each part
	M1	M3	M6	M2	M4	M5	M7	M8	
P1			1			2			1
P2	1	2							--
P5			1			2			1
P8	1	2							--
P9	1	3	2						--
P11	3	2					1		1
P13	1	2							--
P14	1	3		2					2
P16	1	2							--
P17	3	1				2			2
P19	1	2							--
P3	2			1	5		3	4	2
P4				1	2		3	4	--
P6				1	2	5	3	4	--
P7				4	2		3	1	--
P10			1		2	3			1
P12			3			1	2		1
P15					1	2			--
P18				2	1		4	3	--
P20			3	2	1		4	5	2

6.4.5 Problem 5

The problem is reported in Table 6.14. This is the case of multiple routes, unit volume part (and single batch) and sequential CF problem. Here, maximum permissible number of machines in a cell is five.

Table 6.14 Twelve parts and twelve machines CF Problem 5

Part	Routes	Machines											
		M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
P1	1			3		2	1		5			6	4
	2					4	3	5			1	2	
P2	1	4	2		3	5					1		
	2	2		4	1		5				3		
	3		2				3						1
P3	1		3			2			1				4
	2								2				1
P4	1		2		3					1			
	2		1	3				2		4			
P5	1	1	4		3		2		5				
P6	1		3	2		6			5			4	1
	2					3			4		2	1	
P7	1					4		2			1	3	
	2			1	2			4			3		
P8	1		2		3	1							
P9	1		5	4			1	2				3	
	2		1	2			4					3	
P10	1				1	3			2				
P11	1		2	1						4	3		5
P12	1		3				1	2					

A total number of 12 numbers of intercellular moves is produced by the proposed procedure. This is the best result compared with the existing algorithms. There is a substantial improvement in the CF problem. The best route produced by proposed approach is P1(2)-P2(3)-P3(2)-P4(1)-P5(1)-P6(2)-P7(1)-P8(1)-P9(1)-P10(1)-P11(1)-P12(1). Table 6.16 shows solution of problem 5 given by different approach. Tables 6.15 and 6.16 show the solutions given by different approaches and the produced by proposed GA for Problem 5.

Table 6.15 Solutions using different approaches for Problem 5

Approach	Reference	Machine cells			Number of intercellular moves
		I	II	III	
Simul. Annealing	Sofianopoulou (1997)	M2,M4,M7,M9,M10	M3,M5,M8,M11,M12	M1,M6	15
Branch and Bound	Spiliopoulos and Sofianopoulou (1998)	M1,M2,M4,M7,M10	M3,M5,M6,M8,M11	M9,M12	15
Simul. Annealing	Chen et al., (1995)	M4,M5,M7,M8,M10	M2,M3,M6,M11,M12	M1,M 9	17
Tabu Search	Sun et al., (1995)	M4,M5,M7,M10,M11	M2,M3,M6,M8,M12	M1,M9	19
Fussy Approach	Chu and Hayya (1991)	M1,M2,M4,M7,M9	M3,M6, M10,M11,M12	M5,M8	16
Simul. Annealing	Sofianopoulou (1999)	M1,M6,M7,M10,M11	M2,M3,M4,M9,M12	M5,M8	13
Similarity coefficient method	Alhourani (2013)	M2,M3,M4,M9,M12	M5,M6,M7,M8,M11	M1,M10	15
Similarity coefficient method	Yin and Yasuda (2002)	M2,M3,M4,M12	M5,M6,M7,M8,M11	M1,M9,M10	15
Proposed GA		M5,M6,M7,M10,M11	M2,M4,M8,M9,M12	M1,M3	12

Table 6.16 Solution of Problem 5 produced by the proposed GA

Part	Selected route	Machine cell I					Machine cell II					Machine cell III		Intercellular movements of each part
		M5	M6	M7	M10	M11	M2	M4	M8	M9	M12	M1	M3	
P1	2	4	3	5	1	2								-
P6	2	3			2	1			4					1
P7	1	4		2	1	3								-
P9	1		1	2		3	5						4	2
P12	1		1	2			3							1
P2	3		3				2				1			1
P3	2								2		1			-
P4	1						2	3		1				-
P5	1		2				4	3	5			1		2
P8	1	1					2	3						1
P10	1	3						1	2					1
P11	1				3		2			4	5		1	3

6.5 Conclusions

The objective of this study is to find the best route of parts as well as to minimize total number of intercellular movements in the entire system. In this study, a genetic algorithm is proposed to solve different standard benchmark cell formation problems. Computational results comparing the proposed algorithm with some well-known existing methods for 5 benchmark problems reveal that proposed algorithm gives solutions either better than or competitive with the existing algorithms.

Chapter 7

APPLICATION OF GA TO A REAL-LIFE CELL FORMATION PROBLEM

7.1 Introduction

In CMS, the CF usually seeks to obtain a solution of completely independent machine cells where, each machine cell assigns o an independent part family so that a cell can carry out all operations of that particular part family. However, in actual practice, it is sometimes difficult to execute all the operations of a part family following a particular machine cell. Therefore, the principal objective of the CF in CMS is to minimize intercellular movements of parts and to maximize utilization of machines (Logendran, 1990). Since the CF problem belongs to the class of NP- hard (Ballakur and Steudel, 1987), heuristic and metaheuristic approaches are mostly preferred to obtain optimal or near-optimal solution for this problem in reasonable computational times.

In the literature survey, we have seen that most of the cell formation methods have been applied for the problem of one process route, equal part volume and without sequence of processes (James et al., 2007; Ali et al., 2014; Laha and Hazarika, 2017 and Hazarika and Laha, 2015). However, in today's CMSs, parts with unequal part volume and process sequence pass through multiple routings (Kusiak, 1987).

In this chapter, a genetic algorithm approach is proposed for solving the CFP with alternative routings, operation sequences of the parts and unequal part volumes.

7.2 Problem description

A real-life CFP with alternative part routes and machines/or processes sequence taken from Kim et al. (2004) is shown in Table 7.1. The problem has uneven part volume (annual demand), single batch and machine process capacities.

For example, in Table 7.1, no operation is performed in machine M3 for the part P1 on route 2 and as a result, the processing time for the part P1 is zero. Similarly, the third operation is processed in machine M5 for the part P2 on route 3 and the corresponding processing time for the part P2 is four and so on. The part-machine incidence matrix and the processing time matrix are shown in Table 7.2 and Table 7.3 respectively. Empty elements means there is no operation.

Table 7.1 A CFP with alternative part routes

Part (annual demand)	Part route	Machine (processing time)									
		1	2	3	4	5	6	7	8	9	10
1(6)	1	0(0)	5(3)	3(4)	1(3)	0(0)	2(3)	0(0)	4(4)	0(0)	0(0)
	2	0(0)	0(0)	0(0)	1(4)	0(0)	2(3)	3(3)	4(4)	0(0)	0(0)
2(18)	1	0(0)	2(4)	0(0)	0(0)	3(3)	0(0)	0(0)	0(0)	1(4)	4(3)
	2	0(0)	0(0)	3(4)	0(0)	1(4)	0(0)	0(0)	0(0)	4(3)	2(3)
	3	0(0)	2(4)	1(4)	0(0)	3(4)	0(0)	5(4)	0(0)	0(0)	4(3)
3(20)	1	1(4)	0(0)	4(4)	2(3)	0(0)	3(3)	0(0)	5(4)	0(0)	0(0)
	2	0(0)	2(3)	3(3)	4(4)	0(0)	5(3)	1(4)	0(0)	0(0)	0(0)
4(14)	1	2(4)	0(0)	0(0)	3(4)	0(0)	4(4)	0(0)	1(4)	0(0)	0(0)
	2	1(4)	0(0)	0(0)	2(3)	0(0)	3(4)	4(4)	5(4)	0(0)	0(0)
	3	2(3)	0(0)	3(3)	0(0)	0(0)	4(4)	0(0)	0(0)	1(3)	0(0)
5(20)	1	0(0)	4(4)	2(4)	0(0)	5(3)	0(0)	0(0)	0(0)	3(3)	1(4)
	2	0(0)	1(4)	4(3)	0(0)	2(3)	0(0)	0(0)	0(0)	5(4)	3(3)
6(6)	1	0(0)	4(4)	2(4)	0(0)	0(0)	0(0)	0(0)	0(0)	3(3)	1(4)
	2	0(0)	4(4)	2(3)	0(0)	5(4)	0(0)	0(0)	0(0)	3(4)	1(3)
	3	0(0)	3(3)	1(3)	4(3)	0(0)	0(0)	0(0)	0(0)	2(4)	5(4)
7(18)	1	3(3)	0(0)	0(0)	0(0)	0(0)	5(4)	1(4)	2(4)	0(0)	4(3)
	2	1(1)	0(0)	4(4)	2(4)	0(0)	3(4)	0(0)	0(0)	0(0)	0(0)
8(14)	1	0(0)	0(0)	0(0)	0(0)	2(4)	5(4)	0(0)	4(3)	3(3)	1(3)
	2	0(0)	2(3)	5(3)	0(0)	3(4)	0(0)	0(0)	0(0)	1(3)	4(4)
	3	0(0)	1(3)	4(4)	0(0)	2(3)	3(3)	0(0)	0(0)	0(0)	0(0)
9(12)	1	3(4)	0(0)	0(0)	4(3)	0(0)	5(3)	1(3)	2(4)	0(0)	0(0)
	2	4(4)	0(0)	1(4)	0(0)	0(0)	0(0)	2(3)	2(3)	0(0)	0(0)
	3	0(0)	0(0)	1(4)	0(0)	0(0)	2(4)	3(4)	4(3)	0(0)	0(0)
10(6)	1	0(0)	5(4)	3(3)	0(0)	1(3)	4(3)	0(0)	0(0)	0(0)	2(3)
	2	0(0)	0(0)	3(3)	0(0)	0(0)	0(0)	0(0)	4(4)	1(4)	2(3)
Capacity limit		300	300	300	300	300	300	300	300	300	300

Table 7.2 Part-machine incidence matrix

Part (annual demand)	Part route	Machine									
		1	2	3	4	5	6	7	8	9	10
1(6)	1		5	3	1		2		4		
	2				1		2	3	4		
2(18)	1		2			3				1	4
	2			3		1				4	2
	3		2	1		3		5			4
3(20)	1	1		4	2		3		5		
	2		2	3	4		5	1			
4(14)	1	2			3		4		1		
	2	1			2		3	4	5		
	3	2		3			4			1	
5(20)	1		4	2		5				3	1
	2		1	4		2				5	3
6(6)	1		4	2						3	1
	2		4	2		5				3	1
	3		3	1	4					2	5
7(18)	1	3					5	1	2		4
	2	1		4	2		3				
8(14)	1					2	5		4	3	1
	2		2	5		3				1	4
	3		1	4		2	3				
9(12)	1	3			4		5	1	2		
	2	4		1				2	3		
	3			1			2	3	4		
10(6)	1		5	3		1	4				2
	2			3					4	1	2

Table 7.3 Processing time matrix

Part (annual demand)	Part route	Machine processing time									
		1	2	3	4	5	6	7	8	9	10
1(6)	1		18	24	18		18		24		
	2				24		18	18	24		
2(18)	1		72			54				72	54
	2			54		72				54	54
	3		72	72		72		72			54
3(20)	1	80		80	60		60		80		
	2		60	60	80		60	80			
4(14)	1	56			56		56		56		
	2	56			42		56	56	56		
	3	42		42			56			42	
5(20)	1		80	80		60				60	8
	2		80	60		60				80	60
6(6)	1		24	24						18	24
	2		24	18		24				24	18
	3		18	18	18					24	24
7(18)	1	54					72	72	72		54
	2	18		72	72		72				
8(14)	1					56	56		42	42	42
	2		42	42		56				42	56
	3		42	56		42	42				
9(12)	1	48			36		36	36	48		
	2	48		48				36	36		
	3			48			48	48	36		
10(6)	1		24	18		18	18				18
	2			18					24	24	18

Indices and parameters

i	Index for machines
j	Index for parts
r	Index for routes
R_j	Total number of routes of part *j*
k	Index for cells
N	Total number of cells
M	Total number of machines
P	Total number of parts
D_j	Demand rate of part *j*
L_k	Minimum number of machines in cell *k*
U_k	Maximum number of machines in cell *k*
t_{ijr}	Processing time of part *i* on machine *j* in route *r*
T_i	Allowable processing time of machine *i*

Decision variables

x_{ik} = 1 if machine *i* is assigned to cell *k*; otherwise 0

y_{rj} = 1 if route *r* of part *j* is assigned; otherwise 0

$\sigma_{j\,(kk')}$= 1 if successive operations of part *j* is done on cells *k* and *k′*; otherwise 0

Objective Function

The objective of the proposed approach is to minimize the intercellular movement of each part j (I_j) because of minimum intercellular movements (Z) and minimum cell load variation (T) of the system.

$$I_j = \sum_{r=1}^{R_j} \sum_{i=1}^{M} \sum_{k=1}^{N} D_j \, \sigma_{j\,(kk')} (1 - x_{ik})\, y_{rj} \tag{7.1}$$

$$Z = \sum_{j=1}^{P} I_j \tag{7.2}$$

$$T = max \sum_{k=1}^{N} \sum_{i=1}^{M} \sum_{j=1}^{P} \sum_{r=1}^{R_j} y_{rj}\, t_{ijr} - min \sum_{k=1}^{N} \sum_{i=1}^{M} \sum_{j=1}^{P} \sum_{r=1}^{R_j} y_{rj}\, t_{ijr} \tag{7.3}$$

Constraints

1. Assignment of one machine to only one cell

$$\sum_{k=1}^{N} x_{ik} = 1 \qquad \forall i \tag{7.4}$$

2. Lower bound and upper bound of a cell size

$$L_k \le \sum_{i=1}^{M} x_{ik} \le U_k \quad \forall k \tag{7.5}$$

3. Total processing time of machines for selected routes

$$\sum_{j=1}^{P} t_{ijr} \le T_i \quad \forall i, j \tag{7.6}$$

7.3 Genetic Algorithm

GA is a stochastic search based global optimization algorithm technique guided by natural evolution principle. It starts with a set of random solutions, called initial population. Then, it executes selection, reproduction, crossover and mutation sequentially for a fixed number of iterations. The basic steps of the GA are as follows:

Step 1: Generate the initial random populations.

Step 2: Evaluate the fitness of each individual population.

Step 3: Select or sort populations.

Step 4: Generate new set of population from the best individual by the crossover operator.

Step 5: Apply the mutation operator.

Step 6: Repeat Steps 2-5 for the maximum number of iterations as the stopping criterion.

Step 7: Obtain the best solution.

In the proposed GA, each individual of the initial population is encoded with integers and it varies from one to the maximum number of possible cells. The length of the chromosome is equal to the sum of the number of machines and jobs. For example, Fig. 7.1 shows a randomly generated solution or chromosome for three machine cells. Here, machines M2, M3, M5 and M10 are assigned to cell 1, machines M1, M7 and M8 to cell 2 and machines M4, M6 and M9 to cell 3.Similarly, parts P1, P3, P4, P7, and P10 are assigned to part family 1, parts P2, P5 and P6 to part family 2, and parts P8 and P9 to part family 3. Fig. 7.1 shows a randomly generated solution for 10 machines cell formation problem.

M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
2	1	2	1	1	3	2	2	3	1	1	2	1	1	2	2	1	3	3	1

Figure7.1 Randomly generated solution for 10 machines CFP

The fitness value for each chromosome in the population is computed based on the selection process to assess the high probability of selecting the candidate solution to the next iteration. The larger fitness value of an individual is having its higher probability of survival for the next generation. Each individual in the population is evaluated by the criteria of intercellular movements and cell load variation. In the selection process, we used the roulette-wheel procedure. In order to generate offspring from the population, we used single point crossover operator.

For the 10 parts, 10 machines CFP, crossover point of two selected chromosomes, say, parent 1 and parent 2 are taken at a randomly selected location and as a result, another two new chromosomes say, offspring1 and offspring 2 are generated. Fig. 7.2 shows two parent chromosomes and their crossover points, and Fig. 7.3 presents two offspring (offspring 1 and offspring 2) generated after the crossover of parent 1 and parent 2.

Parent 1	2	1	2	1	1	3	2	2	3	1	1	2	1	1	2	2	1	3	3	1

↑

Crossover point

↓

Parent 2	3	1	3	2	2	3	1	1	3	2	1	2	3	1	3	1	2	2	3	1

Fig. 7.2 Two parent chromosomes and their crossover points

Offspring 1	2	1	2	1	1	3	2	2	3	2	1	2	3	1	3	1	2	2	3	1
Offspring 2	3	1	3	2	2	3	1	1	3	1	1	2	1	1	2	2	1	3	3	1

Fig. 7.3 Two offspring generated after the crossover of parent 1 and parent 2

In order to illustrate the mutation operator, we consider a chromosome as shown in Fig. 7.4 and the mutation point is sixth gene. The new chromosome after the mutation operation is shown Fig. 7.5. To obtain the feasible optimum solution, we repeat steps 2-5 of the proposed GA for the maximum number of iterations.

2	1	2	1	1	3	2	2	3	2	1	2	3	1	3	1	2	2	3	1

↑

Mutation point

Fig. 7.4 A chromosome before mutation

2	1	2	1	1	3	2	2	3	1	1	2	3	1	3	1	2	2	3	1

↑

Mutation point

Fig. 7.5 The chromosome after mutation

Similar to other metaheuristics, the parameters play an important role in the performance of the proposed GA. Therefore, we conducted several preliminary computational experiments to ascertain the best parameter values of the proposed method. The selected parameters of the proposed GA are as follows:

- Crossover operator: Single point crossover
- Chromosome length: sum of number of machines and jobs
- Selection: Rank-based roulette wheel selection
- Population size: 25
- Probability of mutation: 0.015
- Number of generations: 2500
- Number of selected chromosomes: 5
- Number of trails: 10

7.4 Computational Results

The benchmark problem taken from Kim et al. (2004) is shown in Table 7.1 and the corresponding part-machine incidence matrix and the processing time are given in Tables 7.2-7.3. The proposed method was coded in MATLAB R2010a and executed on a processor with Intel Core i5 CPU with 8 GB RAM at 3.30 GHz speed.

The solution for the cell formation with the best routes and cell load variations for processing times of the proposed GA is given in Table 7.4. Here, we consider the same weight factor to minimize both intercellular movement of parts and cell load variation.

Total intercellular movements of parts = 40+18+14+6 = **78**

Maximum cell load variation = 298-122 = **176min**.

The computational time is **0.755526** seconds.

Table 7.4 Best routes with processing times

Parts	Routes	Machine cell 1					Machine cell 1					Intercellular movement for annual demand of each parts
		1	4	6	7	8	2	3	5	9	10	
1(6)	2	0(0)	1(4)	2(3)	3(3)	4(4)	0(0)	0(0)	0(0)	0(0)	0(0)	
3(20)	2	0(0)	4(4)	5(3)	1(4)	0(0)	2(3)	3(3)	0(0)	0(0)	0(0)	40
4(14)	2	1(4)	2(3)	3(4)	4(4)	5(4)	0(0)	0(0)	0(0)	0(0)	0(0)	
7(18)	2	1(1)	2(4)	3(4)	0(0)	0(0)	0(0)	4(4)	0(0)	0(0)	0(0)	18
9(12)	1	3(4)	4(3)	5(3)	1(3)	2(4)	0(0)	0(0)	0(0)	0(0)	0(0)	
2(18)	2	0(0)	0(0)	0(0)	0(0)	0(0)	0(0)	3(4)	1(4)	4(3)	2(3)	
5(20)	2	0(0)	0(0)	0(0)	0(0)	0(0)	1(4)	4(3)	2(3)	5(4)	3(3)	
6(6)	2	0(0)	0(0)	0(0)	0(0)	0(0)	4(4)	2(3)	5(4)	3(4)	1(3)	
8(14)	1	0(0)	0(0)	5(4)	0(0)	4(3)	0(0)	0(0)	2(4)	3(3)	1(3)	14
10(6)	2	0(0)	0(0)	0(0)	0(0)	4(4)	0(0)	3(3)	0(0)	1(4)	2(3)	6
Machine load		**122**	254	**298**	190	194	164	282	212	224	192	

To compare the performance of the proposed method with the existing methods in terms of the intercellular movements and cell load variation along with the computational time, we considered two algorithms of Zhao and Wu (2000) and Kim et al., (2004). The comparative computational results are shown in Table 7.5.

Table 7.5 Comparative computational results

Algorithms generated by	Total intercellular movements	Maximum cell load variation	Computational time in seconds
Kim et al., (2004)	88	118	0.03
Zhao and Wu, (2000)	82	112	519.4
The proposed method	**78**	176	0.755

From the results of Table 7.5, it reveals that the proposed approach gives better solutions than the existing algorithms in terms of total intercellular movements in reasonable computational times. However, in terms of cell load variation, the proposed approach performs inferior to the existing algorithms. Therefore, we recommend that the proposed method is more efficient compared to the existing algorithms in respect of minimum intercellular movements and computational efforts.

7.5 Conclusions

Recently, metaheuristic algorithms are being successfully used to solve cellular manufacturing system problems because it is difficult to generate optimal solutions, especially for large-sized cell formation problems in reasonable computational times using exact optimization and heuristic methods. This chapter considers the part-machine cell formation problem with the objective of minimizing intercellular movements of parts and cell load variation in alternative routes of parts and sequence of processes. In this study, a genetic algorithm is presented to solve this problem. Computational results comparing with the well-known algorithms reveal that the proposed heuristic produces best solution among the existing algorithms.

Chapter 8

CONCLUSIONS, LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

8.1 Conclusions

In this research work, we have proposed a heuristic approach based on Euclidean distance matrix for the cell formation problem with the objective of maximizing the grouping efficacy. The problem deals with the cell formation with single routing with no process sequences to maximize grouping efficacy and the cell utilization. In this work, we used Euclidean distance matrix to cluster machines for machine cells and parts for part families. The computational results reveal that the proposed heuristic significantly outperforms the existing well-known heuristics for a set of benchmark problems. In the same problem, we have presented a genetic algorithm based heuristic for the cell formation problem with the objective of minimizing exceptional elements as well as void elements simultaneously to maximize the grouping efficacy. Empirical results on multiple benchmark problem instances of various sizes have shown that the proposed method in terms of grouping efficacy are either better than or competitive with the existing metaheuristic algorithms.

In this research work, we have also considered the cell formation problem with multiple routings with process sequences and part volumes. In this case, the objective function is to minimize total inter-cellular movement of parts. We have presented a heuristic approach based on Euclidean distance matrix for the cell formation in multiple routes, process sequential and parts volume (including batch size and number of batches) with the objective of minimum intercellular movement of parts. We computed the Euclidean distances of machines for processing parts along with the part volume, batch size, and number of batches and the corresponding clustering is done by single linkage clustering method for minimum Euclidean distance. The computational results demonstrate that the proposed heuristic performs well in comparison with the existing heuristics. In the research work considering the same problem, we proposed a genetic algorithm to determine the optimum route of parts as well as to minimize total number of intercellular movements in the entire system. The computational results based on a set of benchmark problems have shown that the proposed genetic algorithm performs best among the existing metaheuristic algorithms in respect of both the solution quality and computational times.

8.2 Limitations of this research

There are some limitations of this research worth to mention.

1. The impact of the variation in the number of parts and machines on the performance of the proposed methods has not been analyzed in details.

2. The compared algorithms have not been coded. A detailed coding of these methods would have helped in achieving a better comparison of execution time.

3. We have considered a single criterion such as grouping efficacy and number of intercellular movements in the cell formation problems. Multi-objective cell formation problems can be used.

4. In this research, we have addressed only deterministic cell formation problems, whereas, stochastic based cell formation problems can be applied.

8.3 Future research directions

Several issues are worthy of future research suggestions.

1. Modification of the proposed methods may be applied to the cell formation problem with multi-objectives.
2. The proposed algorithms can be suitably modified for applying to other cellular manufacturing environment, like solving cell formation problem to minimize the number of voids and exceptional elements in a three dimensional (cubic) machine–part–worker incidence matrix.
3. It would be useful to develop effective optimization methods for other important issues in cellular manufacturing systems like cell scheduling and lot sizing.
4. As an alternative to the proposed metaheuristic algorithm, some newer soft computing methods have also great potential for developing efficient and effective arrangement of cells and part families in the cellular manufacturing system.

Appendix

Problem No.2 (7×5)

	M1	M3	M2	M5	M4
P2	1	1			
P4	1	1		1	
P7	1	1			
P3			1	1	1
P5			1	1	
P1		1			1
P6				1	1

Problem No. 16 (24×18)

	M3	M4	M5	M6	M11	M12	M15	M1	M2	M8	M10	M13	M16	M17	M9	M18	M7	M14
P2	1	1	1								1						1	
P5	1	1	1	1													1	
P8	1	1	1	1								1						
P9	1	1	1	1								1						
P12	1	1	1								1						1	
P15	1	1	1	1			1											
P17	1	1	1	1			1											
P7					1	1	1											
P13						1	1	1										
P14					1	1						1						
P18					1	1	1											1
P21					1	1												1
P10			1	1				1		1								
P23			1	1				1	1	1								
P19						1					1	1						
P22		1				1						1						
P4			1							1			1	1				
P1							1								1			
P3					1					1					1			
P24			1		1					1					1			
P11			1													1		
P16			1													1		
P6		1				1											1	
P20										1								1

Problem No. 18 (23×20)

	M1	M3	M5	M6	M12	M13	M18	M4	M8	M14	M20	M2	M11	M19	M9	M15	M7	M10	M17	M16
P1	1	1	1	1	1	1	1	1	1	1				1		1				
P2		1		1	1										1			1		
P10	1		1	1	1	1	1								1					
P11	1	1	1		1															
P15	1	1	1	1	1	1	1		1	1	1	1								
P3	1							1	1		1									
P12								1	1	1	1					1				
P16									1	1	1							1		
P22	1	1		1				1	1	1	1				1	1		1		
P5												1	1	1	1					1
P18		1			1	1									1	1			1	1
P19															1	1			1	
P21	1							1							1	1				
P23	1							1							1	1				
P7		1											1		1		1	1	1	1
P8																	1	1		
P9																	1	1		
P17																		1		
P4			1			1														
P6																		1	1	
P13									1			1							1	
P14												1								1
P20					1	1														1

Problem No. 20 (35×20)

	M2	M4	M13	M14	M18	M11	M12	M15	M16	M19	M5	M6	M9	M10	M20	M3	M7	M8	M17	M1
P2	1	1	1	1	1															
P7		1		1	1												1			
P10	1			1																
P12	1	1	1	1	1				1								1			
P13	1	1	1	1	1															
P24	1	1	1	1	1												1			1
P27		1		1																
P31	1			1	1											1	1			
P4						1	1	1	1	1										
P6						1	1	1	1											1
P9						1	1	1	1	1								1		
P11						1	1	1		1										1
P21						1	1	1		1										
P28								1		1										
P30								1	1	1		1					1			1
P33						1	1													
P8												1	1	1	1					
P14											1	1	1	1	1					1
P19	1											1	1	1	1		1			
P22												1		1			1			
P23											1		1		1		1	1		1
P26									1		1			1	1		1			
P1																1	1	1	1	1
P3																1	1		1	
P5											1					1	1	1	1	
P15																1	1	1	1	1
P17											1						1	1	1	
P20					1												1	1	1	1
P29																1	1			
P35													1					1	1	
P16														1						
P18	1			1					1											1
P25												1							1	1
P32									1	1			1				1			1
P34																				1

Problem No. 21 (40×24)

	M6	M8	M18	M2	M15	M19	M4	M7	M14	M21	M23	M24	M3	M20	M1	M17	M5	M11	M10	M12	M13	M22	M9	M16
P4		1	1																	1				
P5		1	1		1												1							
P18	1		1																	1				
P26	1	1			1														1					1
P30	1	1	1																			1		
P38	1	1					1																	
P13				1		1		1																
P14				1	1	1			1															
P27			1		1	1														1				
P36				1		1											1							
P11			1				1		1					1										
P25								1	1					1										
P28							1	1																
P3										1	1	1												
P32								1			1	1												1
P2												1	1	1										
P12											1		1	1			1				1		1	
P15													1	1				1						
P23													1	1				1						
P34		1										1	1	1										
P7																1								
P9						1				1					1				1					
P17															1	1					1			
P31					1									1	1	1								
P10	1									1							1	1						
P22				1													1	1		1				
P35						1											1				1			
P20																1			1	1				
P24													1						1	1				
P1										1											1	1		
P16		1							1												1	1		
P6																			1				1	
P29																1							1	
P33				1						1					1								1	
P39		1																					1	1
P40						1		1															1	
P8							1																	1
P19														1	1									1
P21							1																	1
P37					1																			1

Problem No. 22 (40×24)

	M6	M8	M18	M3	M20	M2	M19	M4	M16	M5	M11	M10	M12	M13	M22	M1	M21	M23	M24	M17	M9	M7	M14	M15
P4		1	1										1											
P5		1	1							1														1
P18	1		1										1											
P26	1	1							1			1												1
P30	1	1	1												1									
P38	1	1						1																
P2				1	1														1					
P12				1	1					1				1				1			1			
P15				1	1						1													
P23				1	1						1													
P34		1		1	1														1					
P13						1	1											1				1		
P14						1	1																1	1
P36						1	1			1														
P8								1	1															
P19					1				1							1								
P21								1	1															
P10	1									1	1						1							
P22						1				1	1		1											
P35							1			1				1										
P20												1	1							1				
P24				1								1	1											
P1														1	1		1							1
P16		1												1	1								1	
P9							1					1				1	1							
P33						1										1	1				1			
P3																	1	1	1					
P32									1									1	1			1		
P7																				1				
P17														1		1				1				
P31					1											1				1				
P6																					1			
P29																				1	1			
P39		1							1												1			
P28								1														1		
P40							1														1	1		
P11			1		1			1															1	
P25					1																	1	1	
P27			1				1						1											1
P37									1															1

Problem No. 25 (46×28)

	M18	M22	M23	M26	M27	M28	M1	M8	M9	M10	M15	M11	M12	M13	M14	M24	M3	M4	M5	M19	M20	M21	M6	M7	M16	M17	M25	M2
P17	1			1				1									1						1					
P1								1	1	1	1	1			1					1								
P2							1	1	1	1	1	1																1
P3		1						1		1	1									1								
P4			1				1	1	1	1																		
P5			1					1	1	1										1								
P7							1	1	1													1						
P12							1	1		1															1			
P15								1	1	1							1	1										
P16								1	1	1							1						1					
P24								1	1		1			1		1	1	1										
P39									1			1	1	1	1													
P40									1			1	1	1													1	
P41								1				1		1	1													
P42													1	1		1						1						
P43												1		1		1												
P14					1			1	1								1	1	1									
P18						1		1									1	1	1									
P19	1									1							1	1	1									
P20	1							1									1	1	1									
P21	1																1	1	1				1					
P22					1											1	1	1	1									
P23								1								1	1	1	1									
P25												1				1	1	1	1		1		1					
P28																	1	1	1					1				
P30									1								1	1						1				
P31				1													1	1					1					
P6								1	1											1		1						
P8								1												1	1	1						
P9								1	1											1	1							
P10																				1	1	1				1		
P11		1																		1		1						
P32		1																			1	1						
P33															1							1						
P36																		1			1							
P13								1	1			1		1			1						1	1				
P26					1			1									1						1	1				
P27													1			1	1						1	1				
P29																	1		1				1	1				
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P45									1			1													1	1		
P34												1					1										1	
P35																	1						1				1	
P46								1								1											1	
P38							1																		1			1

Problem No. 27 (50×30)

	M1	M4	M11	M13	M18	M20	M22	M6	M8	M12	M25	M27	M29	M19	M21	M23	M2	M5	M9	M14	M16	M3	M10	M24	M30	M15	M17	M7	M28	M26
P1	1	1	1	1														1	1											
P18	1	1	1																				1							
P28					1	1								1																
P30					1		1								1															
P32						1	1								1															
P34					1		1							1																
P35						1	1									1														
P36					1	1									1															
P37					1	1	1																							
P5	1			1				1	1																					
P7		1	1						1	1								1					1							
P13								1	1																			1		
P14								1	1	1																				
P15								1	1	1																				
P16								1	1	1																				
P40												1	1												1					
P41											1	1	1																	
P45											1		1																1	
P49											1	1																		1
P50											1		1																	
P29						1								1		1														
P31														1	1	1														
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P38														1	1	1														
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P6	1			1															1			1	1							
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P12									1																			1		
P43																													1	1
P47												1																	1	
P46																									1					1

Problem No. 28 (90×36)

	9	11	17	19	21	24	12	31	33	34	35	36	3	14	16	7	25	27	5	15	30	26	28	2	10	20	29	4	1	13	22	6	8	18	23	32
8		1		1	1	1															1										1					
15		1	1	1		1																									1					
21		1	1	1	1	1															1										1					
22		1	1	1	1	1															1										1					
40	1	1	1	1	1	1							1																							
51		1	1	1																																
56	1	1	1		1								1																							
62		1		1											1																					
64	1	1	1		1								1																							
68		1	1	1																																
73		1	1	1	1																				1											
76	1	1	1	1	1	1																														
77	1		1	1		1								1												1			1							
88			1	1	1									1						1						1										
90			1	1	1	1								1								1		1		1										
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4																						1														1

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