PRABHA - A New Heuristic Approach For Machine Cell Formation Under Dynamic Production Environments

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Abstract

Over the past three decades, Cellular Manufacturing Systems (CMS) have attracted a lot of attention from manufacturers because of its positive impacts on analysis of batch-type production and also a wide range of potential application areas. Machine cell formation and part family creation are two important tasks of cellular manufacturing systems. Most of the current CMS design methods have been developed for a static production environment. This paper addresses the problem of machine cell formation and part family formation for a dynamic production requirement with the objective of minimizing the material handling cost, penalty for cell load variation and the machine relocation cost. The parameters considered include demand of parts in different period, routing sequences, processing time and machine capacities. In this work a new heuristic approach named PRABHA is proposed for machine cell formation and the part family formation. The computational results of the proposed heuristics approach were obtained and compared with the Genetic Algorithm approach and it was found that the proposed heuristics PRABHA outperforms the Genetic Algorithm.

Keywords

Cellular Manufacturing System, Dynamic Production Requirement, Heuristic Approach, Genetic Algorithms.

Introduction

Shorter product life cycles, unpredictable patterns of demand and customized products have forced the manufacturing firms to manage their business activities more efficiently and effectively in order to adapt to changing requirements. Traditional manufacturing systems, such as job shops and flow lines, cannot handle such environments. Cellular manufacturing system (CMS), which incorporates the flexibility of job shops and the high production rate of flow lines, has been viewed a promising alternative for such cases to meet the today's customer needs. The basic concept of CMS is to break up a complex manufacturing facility into several groups of machines called machine cells. Each group is dedicated to processing of a group of parts called part family. Therefore, each part type is produced ideally in a single cell, leading to simplified material flow and easier production scheduling.

Most of the current cellular manufacturing system design methods have been developed for a single-period planning horizon (static). They assume that problem data (e.g. product mix and demand) is constant for the entire planning horizon. Product mix refers to a set of part types to be produced, and product demand is the quantity of each part type to be manufactured. However, in practice, world product mix and product demand fluctuate in which case the planning horizon can be divided into smaller periods based on product mix and demand requirements.

In this work, a new heuristic method is developed and proposed to design the CMS under dynamic production requirements. The computational results of the proposed heuristics are compared with that of Genetic Algorithm approach and it was found that the proposed heuristics outperforms the Genetic Algorithm.

Literature Review

Though the CMS provide many benefits, design of cellular manufacturing systems is a complex, multi-criteria and multi-step process. Cell formation procedures can be broadly divided into three classes.

1. Visual inspection
2. Part Coding Analysis (PCA)
3. Production Flow Analysis (PFA)

Visual inspection is the least sophisticated, least expensive and least accurate method. It involves part-family formation by visually observing the part geometries. Part Coding Analysis uses a coding system to assign numerical weights to part characteristic and identifies part families using some classification scheme. PCA-based systems are traditionally design-oriented. Some PCA-based systems, for example Opitz (1970), incorporate production-based codes as supplemental codes, which can be used for production planning. MICLASS and CODE are some of the coding systems, which are widely recognized. The drawback in this method is that a particular coding system may not suit all manufacturing organization. PFA, developed by Burbidge (1963) is an approach for identifying the part families and corresponding machine cells based on manufacturing data such as production methods, part routing information and process plans. In recent days, there are many methods for designing machine cells and majority of the existing procedures follow the PFA approach.

In the past three decades many studies have been carried out on Cellular Manufacturing system design. The existing CMS design methods can be further classified into the following categories: array based cluster, similarity co-efficient, graph partitioning, mathematical programming, heuristic search, and AI-based approaches.

Array-based clustering, developed by McAuley (1972), is the most commonly used clustering technique. These techniques try to allocate machines to groups and parts to families by appropriately rearranging the order of rows and columns to find a block diagonal form of the machine-part incident matrix.

The similarity co-efficient approach requires identification of measures of similarity between machines, tools and design features. These similarity measures are used to form part families and machine groups based on methods such as single linkage cluster analysis, average linkage method, etc. McAuley (1972) used single linkage cluster analysis, Seifoddini and Wolf (1986) proposed a production data based similarity coefficient and developed a heuristic procedure and Kusiak (1987) used the P-median model for cell formation. Prabhakaran (2001) proposed a combined dissimilarity coefficient measure between machines for the machine cell formation.

Graph partitioning approaches treat the machines and/or parts as nodes and the processing of parts as arcs connecting these nodes. These models aim at obtaining disconnected sub graphs from a machine-machine or machine-part graph to identify manufacturing cells and allocate parts to cells. Rajagopalan and Batra (1975) have developed a graph-partitioning algorithm using cliques of machine graphs as a means of grouping machines. Srinivasan (1994) proposed an approach using minimum spanning tree on distance matrix established between machines and between components.

Mathematical programming approaches are widely employed in the design of CMS, since they are capable of incorporating certain design requirements in the design procedure. Boctor

(1991) demonstrated the use of linear programming for cell formation problem. Srinivasan et al (1990) presented an assignment model by using a similarity coefficient matrix as the input. A dynamic programming model was developed by Steudel and Ballakur (1987).

In recent times, meta-heuristic search approaches such as simulated annealing, genetic algorithms and tabu search, have been introduced in designing CMS as alternatives to mathematical programming approaches when computational time is prohibitive and/or linear objectives cannot be formulated (Brown and Sumichrast 2001, Lorena and Furtado 2001, Mak et al 2000, Prabhaharan et al. 2005, Muruganandam et al. 2005, Logendran, et al. 1994 and Asokan, Prabhakaran and Satheesh 2001).

AI-based approaches such as expert systems and neural networks, have been employed for designing CMSs because of their attractiveness in terms of computational time and ability to capture and employ design knowledge. Both heuristic search and AI-based approaches are relatively new in this area.

To evaluate the CMS design, many performance measures were presented in the literature like total bond energy, percentage of exceptional elements, machine utilization, grouping efficiency, grouping efficacy, total cell load variation, total inter and intracellular moves, machine relocation cost (Mc Cormick et al. 1972, King 1980, Chan and Milner 1982, Chandrasekharan and Rajagopalan 1986, Sureshkumar and Chandrasekaran 1990, Venugopal and Narendran 1992, Logendran 1991 and Anan Mungwattana 2000). Inter and intracellular moves, cell load variations and machine relocation are the mostly cited performance measures. In this work, a combined objective function is formulated to take advantage of the measures.

Most of the current cellular manufacturing system design methods have been developed for a static production requirement (Boctor 1991, Logendran et al. 1994). Several approaches in different research areas, such as dynamic plant layouts (Montreuil and Laforge, 1992, Wilhelm et al., 1998), flexible plant layouts (Yang and Peters, 1998), and dynamic cellular manufacturing (Chen, 1998, Wilhelm et al., 1998), have been proposed to deal with these dynamic production requirements. Chen (1998) developed a mathematical programming model for a system reconfiguration in a dynamic cellular manufacturing environment. Song and Hitomi (1996) developed a methodology to design flexible manufacturing cells. Wilhelm et al. (1998) proposed a multi–period formation of the part family and machine cell formation problem. Harhalakis, et al. (1990) presented an approach to obtain robust CMS designs with satisfactory performance over a certain range of a demand variation. Anan Mungwatanna (2000) presented a CMS model by assuming routing flexibility in dynamic and stochastic production requirements. In this work a new heuristic PRABHA is developed and proposed. The computational results of the proposed heuristics are compared with the Genetic Algorithm approach.

Problem Formulation

Many performance measures have been proposed in the literature to evaluate the solutions of the machine grouping problems. Inter and intercellular moves, cell load variations and machine relocation cost are the most cited performance measures. Logendran and Ramakrishna (1993) and Wicks (1995) used intercellular moves to minimize the material handling cost. In addition to the intercellular moves Logendran and Ramakrishna (1993) added minimization of intracellular moves as an additional objective. Venugopal and Narendran (1992) used total cell load variations as a measure to minimize the material flow problems. Machine relocation cost is also an essential factor to be considered for dynamic CMS and it was used by Wicks (1995) and Anan Mungwattana (2000). To utilize the benefits of these measures a combined objective function is formed and the function is used to evaluate the solutions of the proposed heuristic for the dynamic production requirements.

Solutions of the cell formation problems are evaluated based on the performance measures. In this work the solutions are evaluated based on a combined objective function formed to take advantage of the individual objectives. The combined objective function formed is the total cost which is shown below.

$$\text{Total Cost (OV)} = \beta_M \lambda_M + \beta_R \lambda_R + \beta_L \lambda_L \tag{1}$$

Where

β_M – Material handling cost per move

β_R – Cost per relocation

β_L – Penalty cost for cell load variation

λ_M – Total moves

λ_R – Number of Relocations

λ_L – Cell Load Variation

Material handling cost

Material handling cost is the cost of transferring parts either between machines or between cells when it is not produced completely in a single cell. The total cost of handling is the product of handling cost per move and total moves. The cost of handling per move is assumed as constant and is taken as $10 in this work. Total move is the sum of inter and intra cell moves. Inter and intra cell moves proposed by Logendran and Ramakrishna (1993) was calculated using the equation 2.

$$Total\ moves(\lambda_M) = \theta_1 \sum_{i=1}^{p} \sum_{i=1}^{k-1} {}_{k=1}\left| C_k - C_{k+1} \right| + \theta_2 \sum_{i=1}^{p} m_i \tag{2}$$

Where,

C_k Cell number in which operation 'k' is performed

C_{k+1} Cell number in which operation 'k+1' is performed

k_i Total number of operations to be performed on part 'i'

C Total number of cells

p Total number of parts

m_i Total number of intra cell moves performed by part 'i'

θ_1, θ_2 Weights attribute to the intercell and intracell moves are 0.7 and 0.3 respectively.

Penalty for cell load variation

Minimum cell load variation would aid the smooth flow of materials inside each cell and reduce the work-in-progress (WIP) within each cell. Increase in cell load variation will affect the smooth flow for material. This will increase the work in process inventory and the lead time. By taking in to account of the above factors a penalty cost in introduced. The penalty cost is assumed to be constant and is taken as $ 20 in this work. The total cell load variation proposed by Venugopal and Narendran (1992) is calculated using the equation 3.

$$cell\ load\ variation(\lambda_L) = \sum_{i=1}^{m} \sum_{l=1}^{c} x_{il} \sum_{j=1}^{p} \left(w_{ij} - m_{ij} \right)^2 \tag{3}$$

Where,

$$w_{ij} = \left(\frac{t_{ij} * N_j}{T_i} \right) \tag{4}$$

$$m_{lj} = \frac{\sum_{i=1}^{m} \left(x_{il} * w_{ij} \right)}{\sum_{i=1}^{m} x_{il}} \tag{5}$$

m Total number of machines

C Total number of cells

p Total number of parts

w_{ij} Workload induced by part 'j' on machine 'i'

t_{ij} Processing time (hour/piece) of part ‘j’ on machine ‘i’
T_i Available time on machine i in a given period of time
N_j Demand of part ‘j’ in a given period of time
x_{il} Cell membership index, where $x_{il}=1$ if the i^{th} machine is in cell 1, and 0 otherwise.
m_{lj} Average cell load induced by part ‘j’ on cell ‘l’

Machine Relocation Cost

When a new cellular manufacturing system is designed for the first period, relocation of machines will not be taken into account. But during the design of CMS for the next considered period, the existing layout has to be modified based on the new design and the machines have to be relocated. Number of relocation is also an important factor to take decision, whether to relocate the machine or not, to minimize the relocation cost. Relocation cost is the product of number of relocations and cost per relocation. In this work, the cost per relocation is assumed to be constant and is taken as $ 1000 per relocation. Number of relocations used by Wicks (1995) and Anan Mungwattana (2000) was calculated using the equation 6.

$$\text{Number of Relocations}\left(\lambda_{\mathrm{R}}\right)=\sum_{h=1}^{H}\sum_{c=1}^{C}\left(K_{ch}^{+}+K_{ch}^{-}\right) \qquad (6)$$

Where

H – Number of period

C – Total number of cells

K_{ch}^{+} - Number of machines added to the cell ‘c’ in the period ‘h’

K_{ch}^{-} - Number of machines deleted from the cell ‘c’ in the period ‘h’

Assumptions

The above mentioned objective function was evaluated with the following assumptions.

1. The product mix and demand for each part type in each period are known
2. The capacity of each machine type is known
3. Parts are moved between cells and machines in batches
4. The material handling cost per batch is known and is constant
5. The cost per relocation is known and is constant for all machines
6. Penalty cost for the cell load variation is known and is constant
7. Design of CMS for the first period is considered as new design

Following are the constraints.

1. Each cell should contain minimum of two machines.
2. Multiple copies of machines should not be assigned

Proposed Heuristic - PRABHA

In this work a new heuristic method is developed and proposed to solve the cell formation problem. The step by step procedure of the proposed heuristic is given the figure 1 and the steps are explained with a numerical illustration.

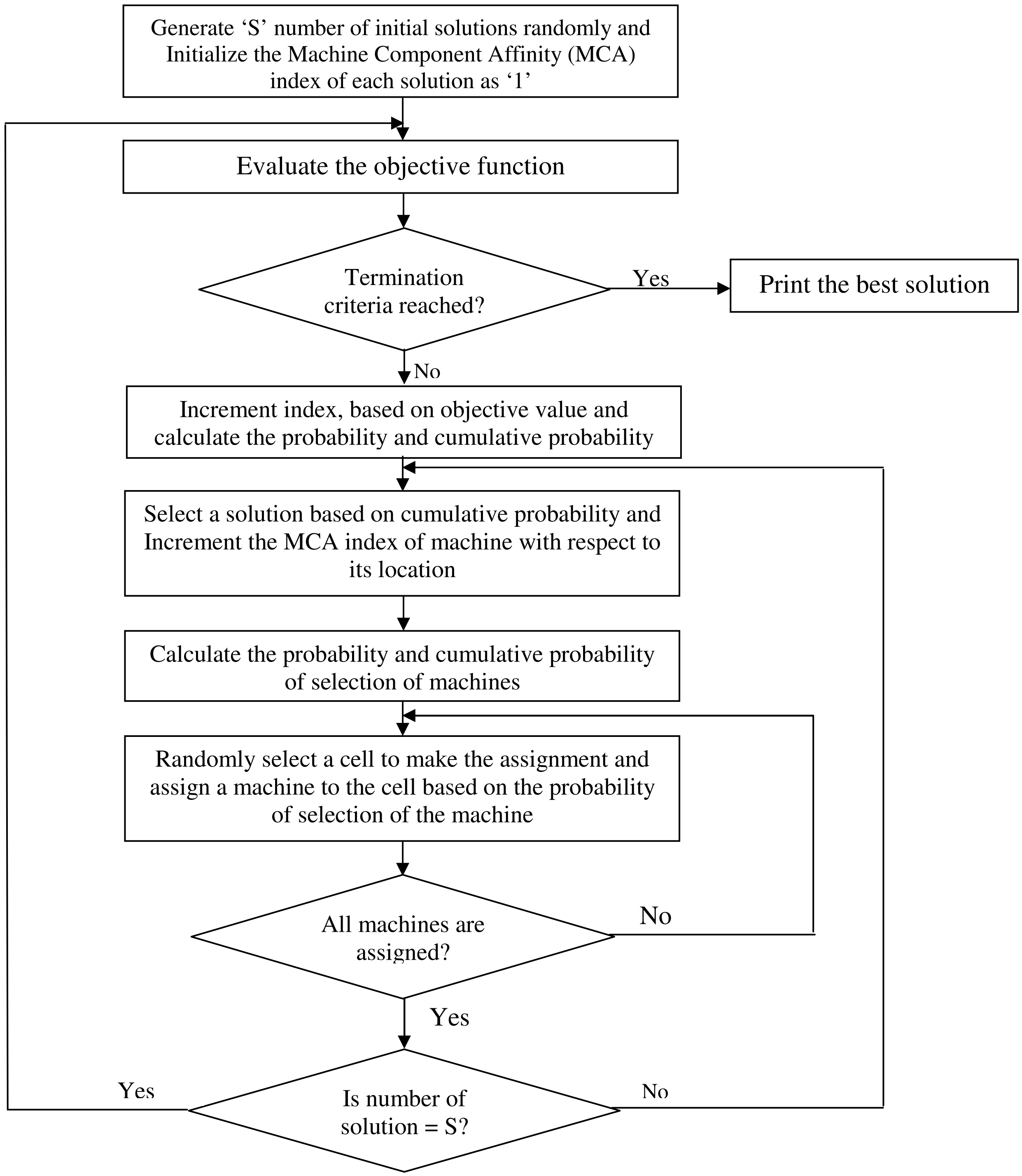
Generate 'S' number of initial solutions randomly and Initialize the Machine Component Affinity (MCA) index of each solution as '1'
Evaluate the objective function
Termination criteria reached?
Yes
Print the best solution
No
Increment index, based on objective value and calculate the probability and cumulative probability
Select a solution based on cumulative probability and Increment the MCA index of machine with respect to its location
Calculate the probability and cumulative probability of selection of machines
Randomly select a cell to make the assignment and assign a machine to the cell based on the probability of selection of the machine
All machines are assigned?
No
Yes
Is number of solution = S?
Yes
No

Figure 1: Flow Chart of PRABHA

The proposed method selects the machines and their locations based on a probability of assignment. For the construction of new solutions, it selects the set of solutions randomly. Instead of using Machine - Cell combination, (1) by considering the Project-Group combination this can be applied to assignment problems, (2) by considering City- City combination this can be applied to traveling sales man problems and also (3) by considering Job-Job combination this can be adapted to solve the sequencing problems. The adaptive behavior of the method can be used to solve many real life problems with small changes in the indexes and function evaluations. In this heuristic, the randomized method of constructing the solutions explores almost all the feasible solution in the search space. Based on the above characteristics of the proposed heuristic approach, it is entitled as PRABHA (Probabilistic, Randomized and Adaptive Based Heuristic Approach)

Numerical Illustration

A problem with 10 machines and 18 parts is considered to illustrate the proposed method. The parameters considered includes, demand of parts in different period, routing sequences, processing time and machine capacities. The production data and machine availability details for the selected problem are given in the Table 1 and Table 2.

Table 1: Production Data

art **o.**	**Routing Sequence (Machine Numbers)**	**Corresponding Unit Operation Time (min)**	**Demand (Nos.)**	
			Period 1	**P eriod 2**
	8 6 8 10 4	2 3 1 4 2	16 0	0
	7 9 2	2 3 6	31 0	2 55
	6 5	1 4	28	2

			0	40
	3 1 3	2 2 5	26 5	0
	5 6 7 10	4 2 1 5	80	1 50
	7 9 7 8	2 4 1 2	12 5	0
	7 9	4 1	36 0	4 50
	3 4 1 6	4 2 3 2	24 0	1 20
	2 7	3 2	17 5	2 35
0	2 7 9 5	5 3 1 1	95	2 5
1	10 8 5	1 2 2	10 0	0
2	1 3 10	1 3 3	23 0	4 25
3	8 10 5 6	2 3 1 2	28 5	0
4	9 2 7	3 2 1	31 5	0
5	6 8 10	2 1 2	50	0
6	4 3	2 4	27 5	1 50
7	6 5	3 5	26 0	2 60
8	4 3 1	2 6 4	15 0	4 55

Table 2: Machine Availability

Machine No.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**1 0**
Availability Time (min)	1 500	1 900	1 600	1 000	1 500	1 700	1 500	1 400	1 200	1 500

6.1 Initialization

In the initialization phase, the solutions are generated randomly and the constraint of minimum of two machines in a cell has been ensured. Number of cells is assumed as 2.

Table 3: Machine Cell Details

Soluti	Cell 1	Cell 2
1	1 3 4 6 8 10	2 5 7 9
2	1 3 4 7 8 9 10	2 5 6
3	1 3 4 5 6 7 8	2 9 10
4	1 3 5 8 10	2 4 6 7 9
5	1 3 7	2 4 5 6 8 9 10
6	1 3 6 10	2 4 5 7 8 9
7	1 3 4 8 10	2 5 6 7 9
8	1 3 4 5 6 7 8	2 9 10
9	1 2 5 9 10	3 4 6 7 8
1	1 2 3 7 8	4 5 6 9 10
1	1 3 4 6 8 10	2 5 7 9
1	1 3 4 7 8 9 10	2 5 6
1	1 3 4 5 6 7 8	2 9 10
1	1 3 4 6 8 10	2 5 7 9
1	1 3 7	2 4 5 6 8 9 10
1	1 3 4 6 8 10	2 5 7 9
1	1 3 4 7 8 9 10	2 5 6
1	1 3 7	2 4 5 6 8 9 10
1	1 3 4 6 8 10	2 5 7 9
2	1 3 7	2 4 5 6 8 9 10

6.2 Evaluation of Objective Function

Objective function is evaluated for the first period without considering relocation. Best objective value and corresponding machine cell combinations are selected. MCA index for all set of solutions will be initialized as 1. To strengthen the quality of the best solution, an increment is given to the MCA index value of all the solutions are calculated using the equation 7. The final MCA index is calculated using equation 8.

Increment to MCA Index, $\Delta MCA_{i=1}^{S} = \dfrac{OV_{Best}}{OV_{i=1}^{S}}$ (7)

Where

ΔMCA_i	Increment in MCA Index of solution 'i'
OV_{Best}	Best Objective Value
OV_i	Objective Value of the solution 'i'

Final MCA Index = $MCA_i + \Delta MCA_i$ (8)

Where

MCA_i – MCA index of the solution 'i'

The probability of selection of the solutions and the cumulative probability of selection of the solutions will be calculated and it is shown in Table 4. The solution having highest MCA index should be selected often to construct the new solution. To maximize the probability of selection of the best solution, a probability of selection is calculated as shown below.

$$P_s = \frac{MCA_i}{\sum_{i=1}^{S} MCA_i} \quad (9)$$

Where

P_s	–	Probability of selection
MCA_i	–	MCA index of the solution i
S	–	Number of solutions generated

Table 4: Objective Value, MCA Index and Probability of Selection of Five Solutions

Solutions	**Objective Value**	**CA Index**	**Increment**	**inal Index**	**Probability of Selection**	**Cumulative Probability**
1	11.22	.00	1.00	.00	0.22	0.22
2	12.27	.00	0.91	.91	0.21	0.42
3	15.04	.00	0.75	.75	0.19	0.61
4	13.77	.00	0.82	.82	0.20	0.81
5	13.96	.00	0.80	.80	0.19	1.00

6.3 Constructing New Solutions

A random number is generated from 0 to 1 and the tag point in the cumulative probability with in which it falls is located and the corresponding solution is selected for the construction of new solution. For example, if the generated random number is 0.21, the selected solution will be 1. If the generated random number is 0.34, the selected solution set will be 2.

For the selected solution, the increment to the index and the final indexes are calculated using the equation 7, 8 and is shown in Table 5. For example, if the selected solution is 1, the cell 1 contains the machines 1, 3, 4, 6, 8 and 10 and the cell 2 contains the machines 2, 5, 7 and 9.

For cell 1, if a machine is in cell 1, increment to MCA index will be 1. If a machine is in cell 2, the increment to MCA index will be 0. For cell 2, if a machine is in cell 1, increment to MCA index will be 0. If a machine is in cell 2, the increment to MCA index will be 1.

Probability of selection of the machine is calculated using the equation 9 and the cumulative probability of selection of the machines corresponds to the cells will be calculated and shown in Table 5. For example, the final MCA index for Machine 1 with Cell 1 is 2. The probability of machine 1 being assigned to the cell 1 will be 0.13. The final MCA index for Machine 1 with Cell 2 is 1. The probability of machine 1 being assigned to the cell 2 will be 0.07. From the above values it is understood that the probability of selection will be more for higher MCA index.

Table 5: MCA Index and Probability of Selection of Machines to Cells for Solution 1

Machine	Initial MCA Index		Increment in index		Final MCA Index		Probability of Selection		Cumulative Probability	
	Cell 1	Cell 2	Cell 1	Cell 2	Cell 1	Cell 2	Cell 1	Cell 2	Cell 1	Cell 2
1	.00	1.00	.00	.00	.00	.00	.13	.07	.13	.07
2	.00	1.00	.00	.00	.00	.00	.06	.14	.19	.21
3	.00	1.00	.00	.00	.00	.00	.13	.07	.31	.29
4	.00	1.00	.00	.00	.00	.00	.13	.07	.44	.36
5	.00	1.00	.00	.00	.00	.00	.06	.14	.50	.50
6	.00	1.00	.00	.00	.00	.00	.13	.07	.63	.57
7	.00	1.00	.00	.00	.00	.00	.06	.14	.69	.71
8	.00	1.00	.00	.00	.00	.00	.13	.07	.81	.79
9	.00	1.00	.00	.00	.00	.00	.06	.14	.88	.93

10	.00	1.00	.00	.00	.00	.00	.13	.07	.00	.00

Assign the machines to the cell based on the probability of selection of machines. A random number is generated between 1 and maximum number of cells to select the cell to which the assignment will be made (In this illustration it is 2). If the random number generated is 2, the assignment will be made to the cell 2. Another random number is generated between 0 and 1 and the tag point in the cumulative probability is located in the selected cell column and the machine to be assigned to the cell is selected. If the random number generated is 0.542, the selected machine will be 5 (Refer Table 5). Assignment of the selected machine will be made to the selected cell.

The above said procedure will be continued until all the machines are assigned to the cells, which gives the first solution for the next iteration. Multiple copies of machines should be avoided and the constraint of minimum two machines in a cell should be ensured. If the new solution satisfies the constraints accept the solution, otherwise the source solution will be retained for the next iteration.

A solution from the Table 4 is selected to construct the new solution for the next iteration. This procedure is repeated until 'S' numbers of solutions are obtained. After all the solutions are generated, the objective function is evaluated for the new solutions and the best solution is selected. If the termination criteria satisfied, print the global best solution for the first period, otherwise repeat the procedure until the termination criteria reached. In this work the termination criteria was considered as 1000 iterations.

6.4 Solution for the Next Period

The above said same procedure is repeated for the second period based on the production data. But during the function evaluation the relocation cost should also be considered and a best solution for the second period is obtained.

Genetic Algorithms

Genetic algorithms are inspired by Darwin's theory about evolution. Genetic Algorithms were invented by John Holland and developed by him and his students and colleagues. Genetic algorithm is a search and optimization procedure that arrives at an optimal solution by generating a rich child from a parent mating pool. It mimics the principles of natural genetics to arrive at the optimal solution. GA operates on the principle of the ‘survival of the fittest’ where weak individuals die before reproducing, while stronger ones survive and bear many offspring and breed children who often inherit the qualities that enabled their parents to survive.

From most of the literatures like Venugopal and Narendran (1992) and Mak et al. (2000) it was found that the performance of GA is good in machine cell formation in cellular manufacturing. Genetic Algorithm start with a set of solutions (represented by chromosomes) called population. Solutions from one population are taken and used to form a new population. This is motivated by a hope, that the new population will be better than the old one. Following is the basic structure of a genetic algorithm

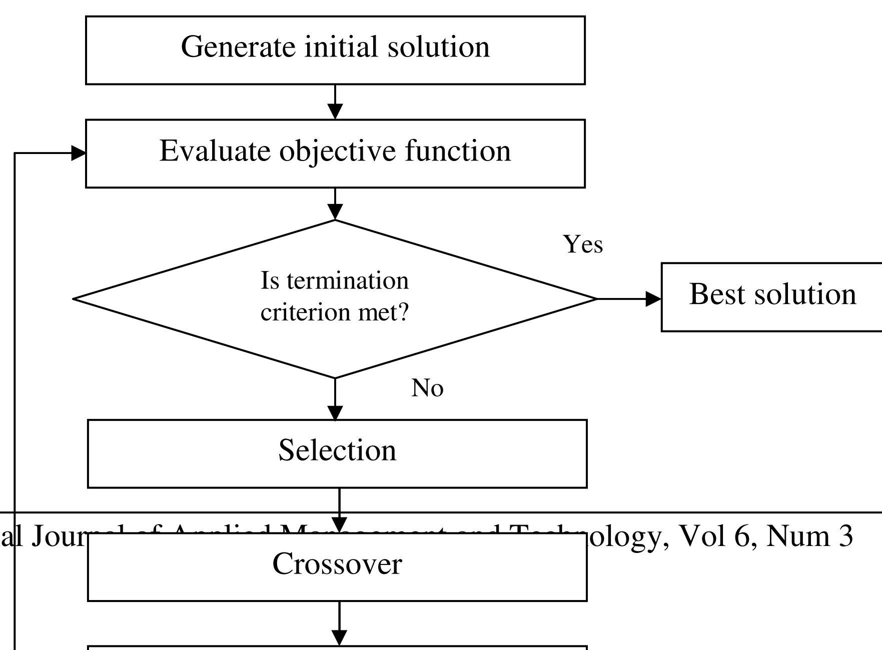

Figure 2: Flowchart of Genetic Algorithm

The bits or the genes in the chromosomes can be represented as binary, real integer numbers, or a combination of characters. In this work, the integer coding method used by Prabhaharan et al. (2005) is adapted to indicate the chromosomes. Value of the gene represents a cell number, and the positioning of a gene in the chromosomes represents the machine number.

For example,

2 1 3 3 2 1 3 2

The position of a number indicates which machine is in which cell. Here, the genes 2, 1, 3 etc. represents the cell number and corresponds to machines 1, 2, 3 etc. These numbers indicate that the number of cells considered is 3. The length of the chromosomes represents the number of machines considered in the problem and here in this case the length of chromosomes is 8.

7.1 GA parameters

Crossover probability says how often will be crossover performed. If there is no crossover, offspring is exact copy of parents. If there is a crossover, offspring is made from parts of parents' chromosome. Crossover is made in hope that new chromosomes will have good parts of old chromosomes and maybe the new chromosomes will be better. However it is good to leave some part of population survive to next generation. In this work, crossover probability is taken as 0.90. Single point crossover is used in this work.

Mutation probability says how often will be parts of chromosome mutated. If there is no mutation, offspring is taken after crossover (or copy) without any change. If mutation is performed, part of chromosome is changed. Mutation is made to prevent falling GA into local extreme, but it should not occur very often, because then GA will in fact change to random search. In this work, mutation probability is taken as 0.05. Swap operator is used for mutation.

Population size says how many chromosomes are in population (in one generation). If there are too few chromosomes, GA has a few possibilities to perform crossover and only a small part of search space is explored. On the other hand, if there are too many chromosomes, GA slows down. Population size is taken as 20 in this work.

Termination Criterion determines when the search process should end and in this work, it is considered as 1000 iterations.

Results and Discussion

In this work the cellular manufacturing system was designed for the dynamic production requirement. The parameters considered for the cell formation are: routing sequences, processing time, demand for the part, machine availability, material handling cost, machine relocation cost and penalty for cell load variation.

To validate the work, the problems were selected from Anan Mungwattana (2000) and the results were obtained. Results of the solution methodologies were shown in the Table 5.

Table 6: Comparison of results

P roblem	o of Cells	Individual Cost				Cumulative Cost	
		Period 1		Period 2			
		A	P RABHA	G A	P RABHA	G A	P RABHA

		70.14	37 0.14	4 13.73	41 3.73	7 83.87	78 3.87
P		60.43	34 9.17	8 375.77	13 98.28	8 736.20	17 47.45
1		44.30	34 2.98	4 368.37	23 81.45	4 712.67	27 24.43
		44.07	33 9.23	5 366.49	53 65.31	5 710.56	57 04.54
		70.81	36 0.13	3 87.10	39 4.30	7 57.91	75 4.43
P		43.46	34 0.84	2 378.66	23 64.12	2 722.12	27 04.96
2		35.71	33 3.63	3 356.15	33 58.04	3 691.86	36 91.67
		32.11	33 0.74	3 342.66	43 59.72	3 674.77	46 90.46
		24.99	32 4.99	3 343.42	36 2.08	3 668.41	68 7.07
P		13.20	30 8.44	1 339.55	23 36.59	1 652.75	26 45.03
3		10.34	30 2.21	4 326.58	33 23.27	4 636.92	36 25.48
			29	6	43	6	46

		97.64	4.13	323.03	11.44	620.67	05.57
		61.58	16 1.58	1 61.61	16 1.61	3 23.19	32 3.19
P 4		61.44	16 1.34	1 161.45	16 1.37	1 322.89	32 2.71
		61.24	16 1.23	3 161.23	11 61.23	3 322.47	13 22.46
		17.74	21 7.74	2 17.63	21 7.63	4 35.37	43 5.37
P		17.83	21 7.51	2 217.83	12 17.45	2 435.66	14 34.96
5		17.41	21 7.36	4 217.55	22 17.46	4 434.96	24 34.82
		17.29	21 7.30	4 217.25	42 17.58	4 434.54	44 34.88

From the above observations it is observed that the new heuristic approach PRABHA proposed in this work out performs the genetic algorithm. For the first period considered, the performance of GA and PRABHA will be close together. When problem is complicated by considering machine relocation the new heuristic PRABHA yields better results than GA.

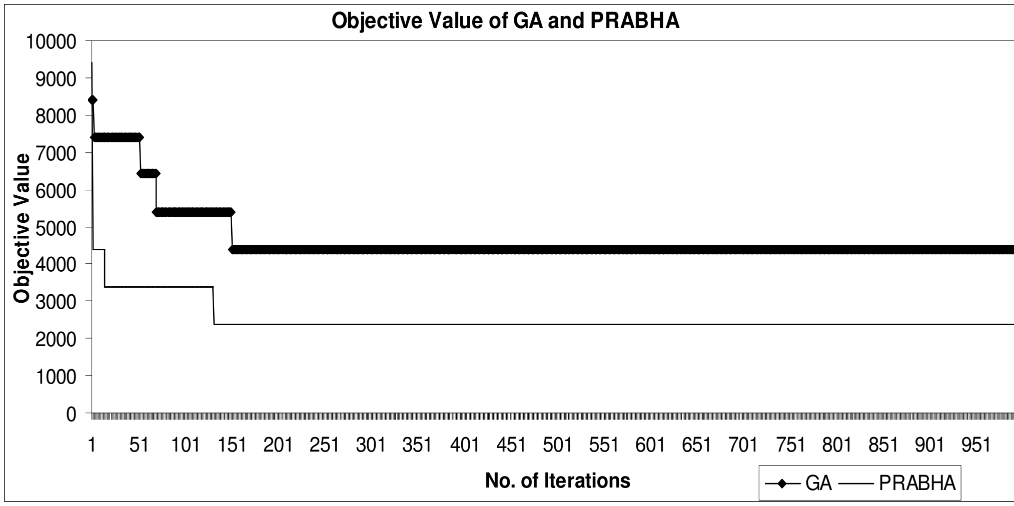

Figure 3: Evolution of Best Solution

Figure 3 represents a single typical experiment; we can see the key difference between PRABHA and Genetic Algorithm. PRABHA quickly finds good results and holds steady. Even after 1000 iteration, the GA does not reach the optimal solution. Overall, the behavior of PRABHA could be described as faster and steadier.

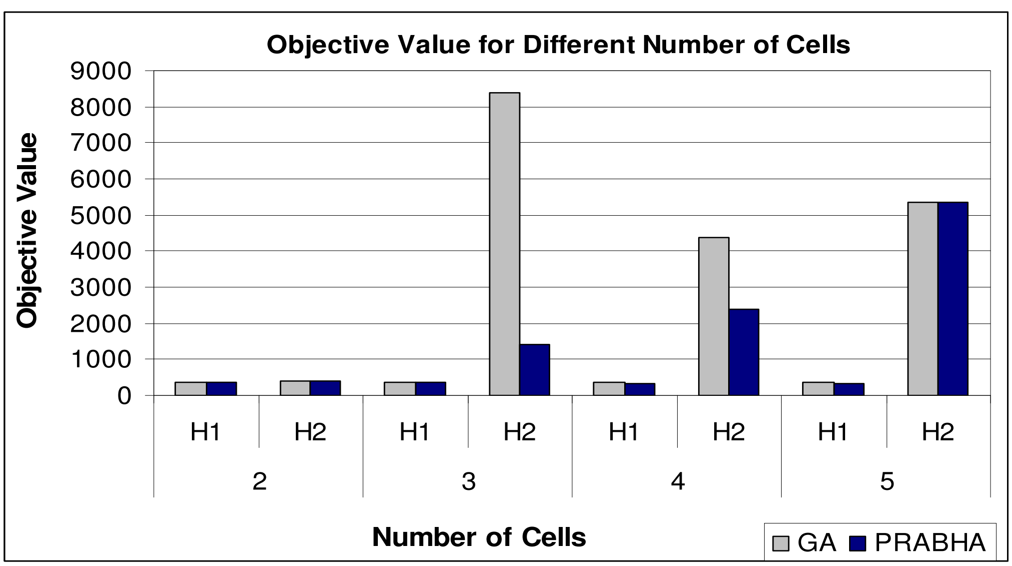

Figure 4: Solution Quality for different Number of Cells

Problem 1 was solved for different number of cells using both GA and PRABHA approach and the result are shown in Figure 4. From the results it is observed that for minimum number of cells, the performance of GA and PRABHA is found to be closer to each other. When problem is complicated by increasing the number of cells, the new heuristic PRABHA then yields better results than GA. Thus the overall performance of the PRABHA presented in this work is found to be superior to that of GA.

Conclusion

The purpose of this work is to propose a new heuristic search approach PRABHA and to compare the performance of it with the well known Meta-heuristic approach Genetic Algorithm, to solve the problem of designing cellular manufacturing systems. The study considers realistic aspects such as workload on each machine induced by the various parts, the sequence of operations, unit operation times on each machine, production volume, etc. The results from the experimental study can be summarized as follows.

1. The new heuristic approach PRABHA proposed in this work out performs the genetic algorithm.
2. PRABHA quickly finds good results and holds steady. Overall, the behavior of PRABHA could be described as faster and steadier.
3. When complex problem ie. more number of cells, machines and parts, is to be handled, the new heuristic PRABHA turns out to be better than GA.
4. Thus the overall performance of the PRABHA presented in this work is found to be superior to that of GA.

More often, this approach is preferred for solving cell formation problem. However, it can be extended to assignment problems by considering the Project-Group combination in place of Machine - Cell combination, to TSP problems by considering City-City combination in place of Machine - Cell combination and to sequencing problems by considering Job-Job combination.

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