Capacitated Cellular Manufacturing System Design: A Genetic Algorithm Approach

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Abstract

In this study, a genetic algorithm approach is proposed to solve the capacitated cellular manufacturing system (CMS) design problem. The problem is observed in both machine and labor-intensive cells where cells are utilized based on the operation times and customer demand. The objective is to design a CMS with product families that are formed with most possible like products. Suer et al. (2010) proposed a modified capacitated p-median mathematical model to the problem. In this study, genetic algorithm is proposed to deal with larger problems by varying the number of cells per family restriction. Suer et al.'s mathematical model and proposed genetic algorithm are compared. GA found optimal solution in small problems in all replications and near-optimal solution in moderate to big sized problems with high frequency. In terms of execution times, significant reductions are achieved with GA on moderate to big sized problems.

1. Introduction

Manufacturing system design has been a challenging issue where various approaches have been proposed in literature and implemented in manufacturing industries. Cellular manufacturing system (CMS) design gained popularity due to the increase in product variety and fluctuation in customer demand. Cellular manufacturing is an application of group technology to manufacturing systems. A typical cellular manufacturing system consists of manufacturing cells which are responsible for manufacturing of similar products with one-piece-flow principle. A manufacturing cell is small manufacturing unit designed to have people, dissimilar equipment and machines together to produce like products with lower lead times, work-in-process inventory (WIP), setup times, workforce (Wemmerlov U. and Johnson D. J. 1997). Unit-peace flow principle and manufacturing products as families in cells bring such advantages, there are few disadvantages of using cellular manufacturing philosophy such as being less flexible to rapid changes in job mix and demand volumes (Satoglu and Suresh 2009).

Manufacturing cells can be classified as machine-intensive cell and labor-intensive. In a machine-intensive manufacturing cell, operator involvement for an operation is usually limited and the machine has the major impact on the operation performance in other words processing time, e.g. milling with CNC. The operator usually performs loading the raw material, unloading the finished good and quality control. On the other hand, in labor-intensive manufacturing cells, the operation is mainly carried out by the operator due to the necessity of continuous operator involvement in operation, e.g. jewelry manufacturing.

There are several approaches proposed in literature to deal with the cell formation problem (e.g. coding and classification systems, part-machine group analysis based clustering, similarity coefficient-based clustering, mathematical programming and graph theoretic methods) (Singh

and Rajamani 1996). In solving cell formation problem with the assistance of similarity coefficient, identification of product similarity is one of the most important steps in cellular manufacturing system design since it has crucial impact on the overall manufacturing system performance. Majority of works in literature evaluate product similarity based on the process route similarity. Jaccard's similarity coefficient is found as the most stable similarity coefficient which performs well with the most of the cell formation problems (Y. Yin and K. Yasuda 2005). Various cell formation approaches have been proposed in literature. Most of the studies used mathematical optimization to find the best configuration of product families and cells. The rest of the studies includes simulation, heuristics and metaheuristics as the cell formation approach. In one of the earliest works, Purcheck (1974) employed linear programming. Kusiak (1987) developed the p-median linear programming model which forms the product families and cells simultaneously based on similarity coefficients. Akturk and Turkcan (2000) proposed an integrated algorithm which solves the machine - cell and part-family formation problem simultaneously along with an efficiency measure of cell formation with monetary terms. Albadawi, Bashir and Mingyuan (2005) developed a two-phase mathematical model. Machine-cell formation is identified via applying factor analysis and the assignment of products to the machine cells and a case study is provided. For a comprehensive review of similarity coefficient based methods, see Yong Yin and Kazuhiko Yasuda (2006).

In addition to mathematical optimization, metaheuristics have been proposed due to the NP-Hard nature of cell formation problems. Such metaheuristics as Genetic Algorithms (GA), Simulated Annealing (SA) and Tabu Search (TS) are widely applied to the cell formation problem. Moon, Gen and Suer (1999) developed a GA based model for minimizing additional capital investment in manufacturing cell design. Asokan, Prabhakaran and Kumar (2001)

proposed both GA and SA in order to minimize the total moves and cell load variation. Suer, Pena and Vazques (2003) worked on the deterministic CMS design problem to minimize the total machine investment cost. An evolutionary algorithm is developed and applied to three different problems with seven different cost schemes. Cao and Chen (2004) proposed an integrated approach for manufacturing cell formation with fixed charge cost, which includes a mixed integer non-linear programming model and a TS algorithm for the NP-Hard problems. Jayaswal and Adil (2004) developed a model and solution methodology comprised of simulated annealing and local search heuristics for the problem of cell formation to minimize the sum of costs of inter-cell moves, machine investment and machine operating costs. Solimanpur, Vrat and Shankar (2004) applied a multi-objective integer programming model and a GA with multiple fitness functions to the design of cellular manufacturing systems with independent cells.

Majority of the works in literature takes the cell formation problem as grouping product families based on the operational route-based similarities. However, while product similarity is being used as metric to form product families, demand volumes thus capacity requirements are usually neglected. In this study, capacity utilization is considered in addition to product similarity. The problem studied is explained in detail in the next section.

2. Problem Statement

The original problem is obtained from a jewelry company. There are thirty products and eighteen machines. Each product is processed on consecutive machines depending on the process route. Since process routes represent unidirectional flow, the type of cell configuration is flow shop. The machine with the maximum processing time among all machines on a route is considered to be the bottleneck machine.

Table 1. Incidence Matrix

	Machines																		
Parts	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**Annual Demand**
1	15	19	17	16														19	1631
2	15	16	17	15	18		19		18									19	727
3	16	18	15	17				20		18	17							20	2297
4					19		18		20	20								20	1046
5	18	17	15	18				17				15						19	1181
6				16		20			19			16		16		19		20	2005
7	15	17	20								18		20				20	20	1683
8	16			17	20	16			17									20	2371
9	16	17	17								18		15					19	1398
10				15		18				17								20	1320
11	19	16	15								19		18					20	2464
12	16	18	17	19				19										20	1441
13				16	17	16				15								17	2185
14	16	19	15	18	17	16			17				15			16		19	1971
15	15	16									17		16					17	877
16				18		15			19									20	884
17	16	17	15	15					15			15	19					20	1172
18							19	19	15	17				19				20	1266
19	18	19	15	18		20			16							17		20	2324
20	18	18	17								19		19					20	523
21	19	18	17								16		18		18			20	975
22				16		16						15						17	1443
23	18	15	19	15														20	777
24	16	17	19								18	20						20	2294
25	17	18	16	19				18				19		16				20	1165
26	17	16	17	15								17	18					18	916
27	18	20	17			17					20							20	902
28				19		17				19								19	2260
29	19	16	20													19		20	724
30				16				16								17		17	1166

Cells are assumed as independent from each other (dedicated to one product family) and inter-cell movement of products is not allowed. Such restrictions have been also observed in manufacturing systems such as pharmaceutical, medical device and food manufacturing. In some of these industries, independent cell configuration is a requirement since the potential product mix-up may cause serious health and hygiene problems. Each dedicated cell is responsible for

the production of only one family and each product can only be assigned to one family. Machine setup times are insignificant, they are assumed to be zero in this study. The single-piece flow is adapted for moving products in all cells. Annual cell capacity is taken as 2000 hours (50 weeks/yr * 40 hours/week). The annual demand and processing time for each product are known and constant. The product-machine matrix for the 30 parts is shown in Table 1. The objective is to design a cellular manufacturing system with the minimum number of cells such that the total similarity is maximized.

3. Methodology

In a deterministic case, annual demand, processing times and therefore capacity requirements are known exactly. Suer et al. (2010) developed the capacitated P-Median model to address the cell utilization and similarity trade-off for the deterministic CMS design. The hierarchical framework used includes the identification of similarities and determination of capacity requirements and solution with the deterministic capacitated p-median mathematical model. In this study, a Genetic Algorithm is developed and compared with mathematical model.

3.1. Identification of Similarities and Capacity Requirements

The similarity matrix is constructed based on the similarity coefficients. The similarity coefficient for each pair of products is calculated via the suggested equation by Suer et al. (Suer, Huang, and Sripathi 2010) as shown in Equation 1 which is basically the ratio of the common number of machines to the total number of machines required to produce pairs of *i* and *j*.

$$MS_{ij} = \frac{The\ number\ of\ common\ machines\ required\ to\ produce\ both\ \ parts\ i\ and\ j}{The\ total\ number\ of\ machines\ required\ to\ produce\ either\ i\ or\ j} \quad (1)$$

Once similarities are calculated, the capacity requirements are obtained via Equation 2, where PT_i is the processing time in minutes, AD_i is annual demand in units and ACR_i is the annual capacity requirement for the product *i* in hours.

$$ACR_i = \frac{AD_i * PT_i}{60} \quad (2)$$

3.2. Deterministic Capacitated P-Median Model

The deterministic model uses two types of information, namely: capacity requirements and machine similarity coefficients. Product families and cells are formed based on available cell capacity and similarity of products. The indices, parameters and decision variables are listed as follows.

Indices:

i Product index

j Product index and family/cell index

Parameters:

S_{ij} Similarity coefficient between product *i* and *j*

CR_i Percentage of capacity requirement for product *i*

n Number of products

TU Upper limit for cell capacity

Decision Variables:

X_{ij} 1, if product *i* is assigned to family *j* ; 0, otherwise

Objective Function:

$$\max Z = \sum_{i=1}^{n}\sum_{j=1}^{n} S_{ij} * X_{ij} - \sum_{j=1}^{n} X_{jj} \quad (3)$$

Subject to:

$$\sum_{i=1}^{n} CR_i * X_{ij} \leq TU \qquad j = 1, \dots, n \quad (4)$$

$$\sum_{j=1}^{n} X_{ij} = 1 \qquad i = 1, \dots, n \quad (5)$$

$$X_{ij} \leq X_{jj} \qquad j = 1, \dots, n \; and \; i = 1, \dots, n \quad (6)$$

$$X_{ij} \in [0,1];\; X_{ij} \; integer \quad (7)$$

The objective function is to maximize the total similarity. Equation 4 restricts the cell utilization up to the cell capacity. Equation 5 guarantees that each product is assigned to at most one cell. Equation 6 forces the assignment of each product to only one of the cells that are opened. Equation 7 shows that the product assignment decision variable is binary thus no inter-cell movement is allowed.

3.3 Genetic Algorithms

Due to the NP-Hard nature of the cell formation problem, a Genetic Algorithms (GA) is developed. GA is usually used for solving large size problems where mathematical models encounter computational and memory issues. The general framework of GA is shown in Figure 1. This framework also represents one generation of a replication.

A typical GA consists of following steps (Süer, Mese, and Eğilmez 2011):

1. Initial population of n chromosomes is formed randomly.
2. Chromosome pairs are matched as mates (Mating)
3. The crossover and mutation operations are performed to generate offspring.

4. For selection, parents are added to the selection pool along with offspring.
5. The next generation is selected from this pool based on their fitness function values.
6. These steps are repeated until the number of the generations specified by the user is reached.
7. Finally, the best chromosome obtained during the entire evolutionary process is taken as the final solution.

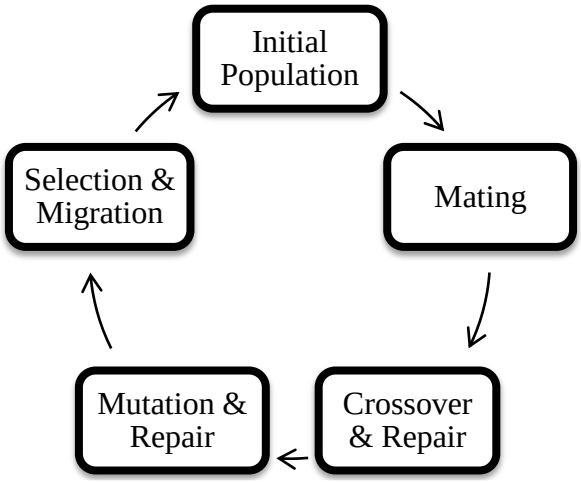

Figure 1. Illustration of one generation

3.3.1. Example Problem:

A 10-product example problem is derived from 30-product dataset to illustrate the methodology. The annual demand, bottleneck machine processing time and capacity requirements are given in Table 2.

Table 2. Example Problem Data

Parts	Annual Demand	Bottleneck Machine Processing Time	Capacity Requirement
1	1631	19	516.5
2	727	19	230.2

3	2297	20	765.7
4	1046	20	348.7
5	1181	19	374.0
6	2005	20	668.3
7	1683	20	561.0
8	2371	20	790.3
9	1398	19	442.7
10	1320	20	440.0

3.3.2. Chromosome Representation

An example chromosome for a 10-part cell formation problem is given in Figures 4 and 5. The typical chromosome carries only the product number information at first as shown in Figure 2. Once the product numbers are randomly assigned to genes, cells are formed just considering the available capacity. Cell capacity is considered as 2000 hours for the example given below. As long as a cell is not over utilized, products are kept assigning to corresponding cell from the first gene on the left most side to through the chromosome. If overutilization occurs, a new cell is opened.

Products are assigned to cells as shown in Figure 3, based on the capacity availability. Cell capacity is taken as 2000 hours and the cumulative capacity allocation of 3 cells are shown in Table 3. Products are formed into 3 cells. Once the chromosome is built, the next step is the calculation of fitness function.

Chromosome	**2**	**1**	**4**	**3**	**5**	**8**	**7**	**9**	**6**	**10**

Figure 2. Chromosome representation after product number assignment

Cell No	**1**				**2**			**3**		
Chromosome	2,1	1,1	4,1	3,1	5,2	8,2	7,2	9,3	6,3	10,3

Figure 3. Final chromosome representation after cell allocation
Table 3. Product-cell formation

Product	Capacity Requirement	Cumulative Capacity Requirement	Cell Number
2	230.2	230.2	**Family 1 Assigned to Cell 1**
1	516.5	746.7	
4	348.7	1095.4	
3	765.7	1861.0	
5	374.0	374.0	**Family 2 Assigned to Cell 2**
8	790.3	1164.3	
7	561.0	1725.3	
9	442.7	442.7	**Family 3 Assigned to Cell 3**
6	668.3	1111.0	
10	440.0	1551.0	

3.3.3. Fitness Function Calculation and Mating

Fitness function of a chromosome is obtained via summing the pair-wise similarities of products that are allocated into the same cell. Once total cell similarities are calculated, the fitness function is obtained via summing all the cell similarities up. For example, the total similarity of cell 1 is obtained via summing the pair-wise similarities of products that are assigned to a cell. After all of the chromosomes' fitness functions are calculated in the initial population, mating is applied by randomly choosing pairs from the population.

3.3.4. Crossover and Mutation

In crossover operation, a random number is drawn between 1 and the maximum number of cells. Based on the number, the cells that crossover operation is to be applied are determined. The cells which crossover is not applied are kept the same. On the other hand, selected cells are swapped between the pairs of chromosome and then a repair operation is applied. The repair operation is simply replacing the duplicate products with the ones which are not assigned from left to right. Once the repair is finished, new cell number allocation is applied from left to right. In mutation operation, simply a random number is generated for each gene. If the random number is less than

the mutation probability, then the corresponding gene (product number) is replaced with another randomly picked product.

3.3.5. Selection

After a generation (one cycle of GA) is finished, a selection pool is obtained which consists all of the off-spring and parents. The best chromosome is selected as best-so-far solution and kept. On the other hand, a predetermined portion of existing generation is selected from the selection pool for the next generation and remaining portion is randomly generated. For example, assume that *p* is the desired percentage of migration; best *p* % of pool is going to be kept for the further generations. P is basically an experimentation parameter.

4. Experimentation and Results

In the experimentation, three datasets are used, namely: cell formation with 10, 20 and 30 products. The 10 and 20-product datasets are built by taking first 10 and 20 products from the 30-product dataset. All datasets are solved with both Suer et al.'s (2010) mathematical model and the proposed GA.

4.1. Cell Formation Results

The capacity requirements or the 10-Product problem is given in Table 2. For the10-Product problem, products are formed into three cells with the deterministic model as Cell 1: {1, 2, 5, 10}, Cell 2: {4, 6, 8} and Cell 3: {3, 7, 9}. The total similarity is found as 3.857. Moreover, there are 6 cells formed with 20 products and 9 cells formed for the 30 products. The cell formation and total similarity results obtained with mathematical model are shown in Table 4.

Table 4. Results of Cell Formation with Deterministic Mathematical Model

Problem Size	**10 Products**	**20 Products**	**30 Products**
The Number of Cells	3	6	9

The Optimal Solution (Total similarity)	3.857	9.699	16.397
Family Formation	Cell 1: [1, 2, 5, 10]	Cell 1: [1, 2, 5, 11]	Cell 1: [7, 9, 15, 20, 21]
	Cell 2: [4, 6, 8]	Cell 2: [3, 10, 13]	Cell 2: [10, 13, 28]
	Cell 3: [3, 7, 9]	Cell 3: [14, 17, 19]	Cell 3: [11, 24, 27]
		Cell 4: [6, 8, 16]	Cell 4: [2, 14, 19]
		Cell 5: [4, 18]	Cell 5: [8, 16, 22, 30]
		Cell 6: [7, 9, 12, 15, 20]	Cell 6: [4, 6, 18]
			Cell 7: [1, 3, 23, 29]
			Cell 9: [5, 12, 17, 25, 26]

4.2. Comparison with GA

The motivation of this study is to develop an alternative metaheuristics for the capacitated cell formation problem. A Genetic Algorithm software is developed with Java. To evaluate the performance of the proposed GA, it is compared with the mathematical model developed by Suer et al.'s (2010). The experimentation parameters used are shown in Table 5. Ten replications are made for each problem size. Initial population sizes of 100, 1000 and the number of generations of 50, 500 and 1000 are used for the 10, 20 and 30-Product problems, respectively. The crossover and mutation probabilities are kept as 0.7 and 0.1 and a selection rate of 10 % is used.

Table 5. Experimentation Parameters Used

Problem Size	**10**	**20**	**30**
The number of replications	10	10	10
The number of generations	50	500	1000
Initial Population	100	1000	1000
Probability of Crossover	0.7	0.7	0.7
Probability of Mutation	0.1	0.1	0.1
Selection Rate	10%	10%	10%

The results of comparison are shown in Table 6. GA found the optimal solution with 100%, 80% and 70% frequencies for 10, 20 and 30-product problems. The average gap between the optimal solution and the solution obtained from GA is less than 0.5% for all problems. The maximum

gap between GA's result and the optimal solution is obtained as less than 2.5%. In terms of solution times, GA works more efficient than mathematical model. The pattern of behavior that of GA shows is shown in Figure 4, where the results of 30 parts with 70% frequency on 10 replications are illustrated.

Table 6. Comparison of GA with Mathematical Model

Problem Size[1]	**10**	**20**	**30**
The Optimal Solution (Total Similarity)	3.857	9.699	16.397
Frequency of Optimal Solution	100%	80%	70%
The Average Gap	0.00%	0.32%	0.45%
The Maximum Gap	0.00%	2.02%	2.44%
The Minimum Gap	0.00%	0.00%	0.00%
Exe. Time of Mathematical Model (Sec.)	6	73	109
Average Exe. Time of GA (Sec.)	0.7	6.71	11.3

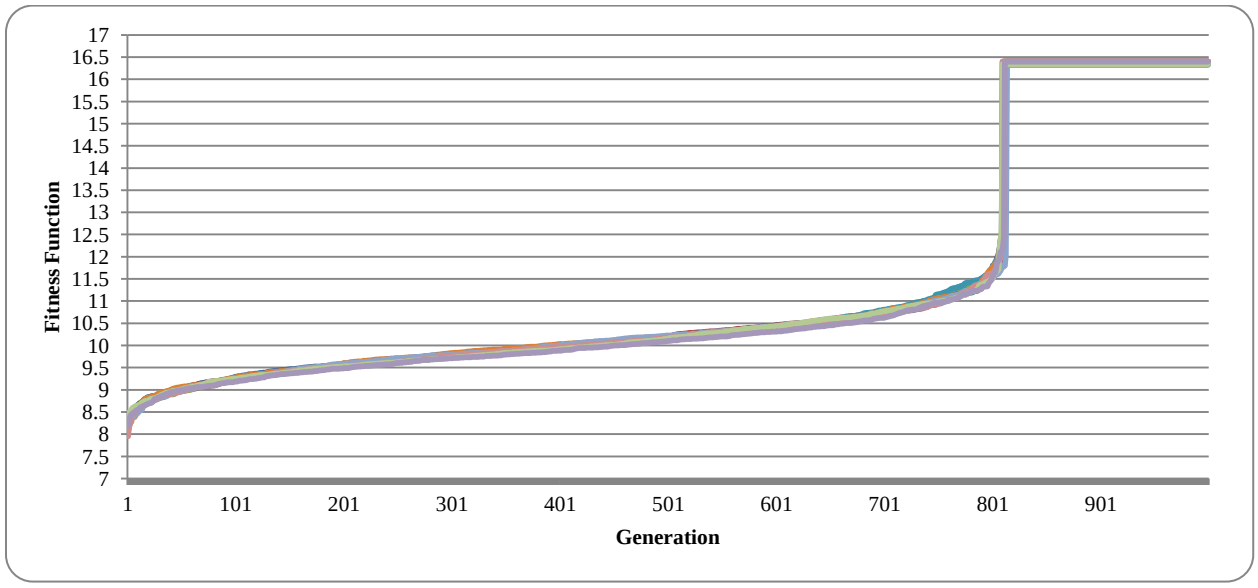

Figure 4. GA's pattern of behavior

5. Conclusion

In this study, capacitated cell formation problem is addressed. A genetic algorithm is developed as alternative to mathematical model provided by Suer et al. (2010). In the small problem, GA

found the optimal solution in all replications. In medium and large sized problems, GA found a solution that is on the average less than 0.5 % far from the optimal solution while keeping the execution time significantly lower. The maximum gap between the results of GA and mathematical model is found as 2.44% of the optimal solution. In conclusion, the proposed GA performed as good as the mathematical model with the small sized problem (100% frequency) and provided the optimal solution with high frequencies (80% and 70%) with the medium and large datasets, respectively. Experimentation with different parameters, addition of cost to model and allowance of inter-cell movement are some of the directions that current research is planned to continue.

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