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Multi-Objective Cellular Manufacturing System under Machines with Different Life-Cycle using Genetic Algorithm

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***Abstract*—**In this paper a multi-objective nonlinear programming model of cellular manufacturing system is presented which minimize the intercell movements and maximize the sum of reliability of cells. We present a genetic approach for finding efficient solutions to the problem of cell formation for products having multiple routings. These methods find the non-dominated solutions and according to decision makers prefer, the best solution will be chosen.

***Keywords*—**Cellular Manufacturing, Genetic Algorithm, Multi-objective, Life-Cycle.

I. Introduction

DUE to the present competitive market, and rapid variation of customer's need, companies need to produce a large variety of products in small lot sizes at a competitive price just in time.

Managers who are faced with this rapid variation should change their strategy based on mass or batch production (job shop or flow shop) to flexible manufacturing systems. Mass production includes a small variety of parts with high volume of demand but batch production consists of a large variety of parts with low volume of demand. At the present, companies need to be flexible such as job shop and produce on time such as flow shop. Hence group technology is an alternative to overcome these difficulties and it is a good strategy to cope with the challenges of todays global environmental. Cellular manufacturing systems (CMS) are the result of direct application of group technology philosophy. Parts whit similar processing requirements such as machines, tools, route and/or geometrical shapes are classified to part families. Machine cells contain groups of functionally dissimilar machine types; each machine cell processes a part family.

The advantage of CMS has been addressed by numerous researchers such as reduction of set up times, reduction of material handling costs, reduction of in-process inventory, and reduction of cycle times, improvement of shop floor control and improvement of production efficiency. There have been many efforts towards the design of manufacturing cells based on the selection of part families and machine groups, considering only a single criterion such as follow:

1. Minimizing inter-cell movements
2. Maximizing parts and/or machines similarities (or minimizing dissimilarities)
3. Obtaining the block diagonal form of the part-machine incidence matrix
4. Minimizing cell load unbalances
5. Minimizing number of exceptional elements

There has been pressure on the manufacturing industries in the global market competition to consider more than one criterion such as minimizing material handling cost, shorter delivery time, shorter setup time and etc.

In this paper, we consider the bi-criterion, multiple route cell formation problems via an implementation of a genetic algorithm. The two criteria that we consider are minimization of intercell movements and maximization sum of reliability of cells. The method that we propose seeks to generate efficient solutions and according to the decision maker prefers, the best solution will be selected.

II. The Multi-Objective Cell Formation Problem

A. Back Ground Information on Multi-Objective Optimization

A general multi-objective optimization problem can be defined as follows [15]

Min/max $y = f(x) = (f_1(x), f_2(x) \dots f_n(x))$

Subject to

$x = (x_1, x_2, \dots, x_n) \in X$

$y = (y_1, y_2 \dots y_n) \in Y$

Where **x** is the decision vector, **y** is the objective vector, **X** is the parameter space and **Y** is the objective space.

A single solution (a decision vector) that results in an optimal objective vector does not generally exist for the general multi-objective optimization problem. Instead, there exists a set of Pareto-optimal decision vectors that form the Pareto set of solutions. A decision vector constitutes a Pareto-optimal solution if there is no other decision vector for the problem considered that provides a better performance than

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(dominates) this solution with respect to all objectives considered. Formally, a decision vector a is said to dominate decision vector b if and only if (assuming a minimization problem and without loss of generality).

$$\forall i \in \{1,2,\ldots,n\}: \quad f_i(a) \le f_i(b) \quad \vee \quad \exists i \in \{1,2,\ldots,n\}: \quad f_i(a) \prec f_i(b).$$

The aim of multi-objective optimization methods is to find a set of non-dominated solutions that provide a reasonable approximation of the Pareto set of solutions.

It should be noted that the non-dominated set of solutions produced by multi-objective optimization methods does not necessarily correspond to the actual Pareto set of solutions, which, for most real-life cases of multi-objective optimization, is not known in advance. It is the task of the decision maker to choose a non-dominated solution that fits best his/her considerations by considering all potential trade-offs.

B. Problem Description and Literature Review

One of the areas of production research that has attracted considerable attention over the last decades is Cellular Manufacturing (CM). CM is the application of an organizational approach called Group Technology (GT) [2] at the shop floor production level. The aim of CM is to bring the benefits of mass production lines to the job-shop manufacturing environment. Theoretically, this can be achieved by grouping together machines into cells that process specific product families.

CM has been shown to provide considerable cost benefits to practical manufacturing environments [14]. Despite the advent of new production design techniques such as Just in Time (JIT) systems and Agile manufacturing, CM is still considered to be a useful design principle since its application requires limited capital investment. The cell-formation problem is the central problem during the design of a new CM production system. It aims to find a grouping of machines into cells and parts into associated families that optimizes a single or a number of desired objectives. The cell-formation problem is a difficult NP-hard [8] grouping problem that has attracted considerable research attention over the last decades, at least for the single-objective case [11], [3]. However, Wemmerlov and Johnson [14] report that realistic cell-design processes are multi-objective in nature, involving a number of conflicting objectives. The inefficiency of traditional optimization methods in the solution of non-trivial instances of multi-objective problems means that there has been little research on the solution of the multi-objective version of the cell-formation problem.

Formally, the multi-objective cell-formation problem can be described as follows.

Given a number of parts and a number of machines necessary for the manufacturing of parts, a grouping of machines into cells and parts into associated families needs to be identified that will simultaneously optimize a number of conflicting objectives based on the principles of cellular manufacturing.

The cell-formation problem, even in its simplest form, is a difficult combinatorial grouping problem. Lee and Garcia-Diaz [9] indicate that the number of non-empty partitions of n objects becomes impossible to enumerate as the size of the problem increases, especially if the size of partitions is not pre-specified.

The existence of multiple objectives increases the complexity of the problem, limiting the use of traditional optimization methodologies to small-sized instances. In addition, these methodologies (analytic and heuristics) do not provide a natural mechanism for the simultaneous generation of multiple solutions. The reviews of Mansouri et al. [10] and Dimopoulos [4] clearly indicate that the majority of reported applications attempt to overcome this deficit by aggregating all objectives considered into a single objective using weighting schemes. While this mechanism allows existing methodologies that have been designed for the solution of single-objective cell-formation problems to be used in multi-objective problem instances, they do not provide the basis for an informed choice to the decision maker

Typical examples of this approach are the mathematical programming methodologies of Wei and Gaither [13], Boctor [1] and Ho and Moodie [7].

In this paper we treat the case where each part has more than one process plan and where each solution is evaluated according to two objective functions. The first seeks to reduce the intercell movements. The second seeks to increase sum of reliability of cells.

Among the factors influencing the performance of CMS are the structure of the machine–part matrix, the stability of the product mix in the manufacturing system, and the reliability of the machines in manufacturing cells [12]. Reliability plays an important role in the overall performance of CMS. Traditionally, cell formation and work allocation are performed assuming all the machines to be 100% reliable, which is never the case. Machine failures cause the greatest impact on due date and other performance criteria even if there is the option of rerouting the parts to alternative workstations. Machines are a major component of CMS and often it is not possible to handle machine breakdowns as quickly as the production requirements dictate. In addition, the disturbances caused by these breakdowns lead to scheduling problems, which decrease the productivity of the entire manufacturing operations. This issue points out an important need for the consideration of machine reliability in the design process of CMS, especially in light of the increasing complexity of such systems in recent years.

III. Modeling the Problem via Genetic Algorithm

Genetic algorithms are powerful and broadly applicable stochastic search and optimization technique based on principles from evolution theory. The usual form of genetic algorithm was described by Goldberg [5]. Genetic algorithms are stochastic search techniques based on the mechanism of natural selection and natural genetics. Genetic algorithms, differing from conventional search techniques, start with an initial set of random solutions called *population*. Each

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individual in population is called a chromosome, representing a solution to be the problem at hand. The chromosomes evolve through successive iterations, called *generation*. The chromosomes are evaluated using some measures of fitness. The enumeration procedure is capable of solving only small and medium-sized problems. We introduce, in this section, a GA which was proved to be an efficient technique for solving large cell formation problems. The suggested GA finds efficiency frontier for the bi-objective model. In this paper we have two types of chromosome, the machine-cell and part-route chromosomes. The machine-cell chromosome is of dimension m and each gene indicates whether or not a machine belongs to a given cell. The part-route chromosome is of dimension n and shows which routing is used for each part.

A numerical example of these representations is given in Table I. The first machine-cell chromosome of Table I states that the solution has 5 cell which represented by 7, 1, 3,4 and 5, also cell 1 will be composed of machines 3 , 8 and 12-13, the second cell indicated by "3" will contain machines 4-7 and 14-15, and so on. Furthermore, the first part-route chromosome says that part 1 uses the third routing, part 2 uses the second routing and part 3 uses the second routing, and so on.

TABLE I
CELLULAR AND PART-ROUTINGS CONFIGURATION

Machine-cell chromosome	Part-route chromosome
771333317451133	322133213121333313111221122122
652222812111566	113231213323111123113331222333

The initial populations are generated randomly and should respect a minimum *diversity threshold*, as suggested by Grefensette [6]. The minimum threshold was fixed at 0.9. The *parent population* selected with normalization method, in this method individuals of the population are chosen which their fitness are not less than average fitness of the population. Then individuals selected from parent population randomly for creation of a new generation. The next generation produced with the following operations:

(A). Crossover: An exchange between portions of two chromosomes.

(B). Mutation: A random modification of chromosomes.

(C). Reproduction: copying chromosomes according to the fitness function.

The crossover method, sometime called the one-point method, consists in replacing a section of the first chromosome by the corresponding section of the second. To determine the part of the first chromosome that should be kept, we use a random number (from 1-30 for the part-route chromosome and from 1-15 for the machine-cell chromosome). In the example of Table II, a machine-cell crossover, the number 6 was selected. The six first genes of this chromosome are kept and the chromosome completed with the 9 last genes of the second chromosome.

TABLE II
CROSSOVER METHOD ILLUSTRATED

Chromosome 1	Chromosome 2	Crossover
771333317451133	652222812111566	771333812111566

The mutation method consists in selecting one chromosome from parent population then two random genes are selected and replaced. And finally in reproduction the best chromosomes according to fitness function are copied in the next generation. We also use *improvement* methods in our algorithm, the local improvement for the part-route chromosome is as follow, in a 30 gene chromosome the procedure consists of subdividing each part-route chromosome into six blocks of five genes, in making a random selection of one of these blocks, and of modifying each gene in two different cycle ways as illustrated in Table III. This procedure is repeated three times. The six new chromosomes that are so created are evaluated and if one of them is superior to the initial chromosome, it will replace that chromosome.

TABLE III
EXAMPLE OF THE IMPROVEMENT METHOD

Selected block	Transformation 1	Transformation 2
23212	31323	12131

After some experimentation, the sizes of the population of machine-cell and part-route chromosome were fixed at 100 also 85% of the next generation is made from crossover, 10% with mutation and 5% with reproduction.

We use the following notation:

i index of the machines (i=1, …,m)

j index of the parts (j=1,…,n)

k index of the cells (k=1,…,c)

l index of the routes (l=1,…,r)

N_j demand for part j in the time horizon considered.

X_{ik} incidence matrix indicating if machine i is in cell k, x_{ik} = 1 if machine i is in cell k, and = 0 otherwise,

r_{jl} incidence matrix specifying the routing used for part j r_{jl} = 1 if part j used route l and = 0 otherwise.

r_i' reliability of machine i .

R_k' reliability of cell k .

Y_{il} incidence matrix indicating if machine i is on route l.

Z_{jk} incidence matrix assign part j to cell k.

r_{ik}' reliability of part j in cell k.

The functions considered are as follows:

Minimization of the intercell movements

$$\text{Min } F_1 = \sum_{j=1}^{n} N_j . [\ \sum_{k=1}^{C} Z_{jk} - 1\ ]$$

$$\sum_{i=1}^{m}\sum_{l=1}^{r}(r_{jl}.y_{il}.x_{ik})\begin{cases} \succ 0 & Z_{jk} = 1 \\ = 0 & Z_{jk} = 0 \end{cases}$$

Maximizing sum of reliability of cells

$$\text{Max } F_2 = \sum_{k=1}^{c} R_k^{'}$$

$$R_k^{'} = \min_j \frac{N_j . r_{jk}^{'}}{\sum_{j=1}^{n} N_j}$$

$$r_{jk}^{'} = \begin{cases} 1 & if \quad x_{ik}.r_{jl}.y_{il}.r_i^{'} = 0 \\ x_{ik}.r_{jl}.y_{il}.r_i^{'} & otherwise \end{cases}$$

These are the constraints:

Each machine may belong to only one cell.

$$\sum_{k=1}^{c} x_{ik} = 1 \text{ For i =1,2,…,m}$$

Each part may use only one route.

$$\sum_{l=1}^{r} r_{jl} = 1 \text{ For j = 1,2,…,n}$$

IV. NUMERICAL EXAMPLE

A numerical example of this problem which contains 15 machines, 30 parts and 3 routes is considered in this problem.

To implement the described procedure, we coded the algorithm in Borland Delphi, Version 7 for Windows XP. Computations were carried out using Intel Pentium Pro 200 MHz computer. In Table IV we find the workload required for each machine i and each part j. The demand for each part is given in Table V and reliability of machines are generated in random mode as follow,

7%,40%,63%,17%,55%,11%,44%,66%,6%,31%,82%,7%,7%,44% and 4%

Table VI presents the results obtained using the weighted-sum approach. The 10 results were obtained by systematically varying the weights (w_1, w_2) over the interval [0, 1] by increments of 0.1. Note that Table VI contain some results that do not efficient solutions. As we have pointed out, this occurs because the genetic heuristic does not guarantee a truly optimal solution at each iteration of the method proposed. These non-efficient solutions would, of course, be eliminated before presenting the results to a decision-maker.

V. CONCLUSION

In this paper we propose a new approach to the machine cell formation problem when the parts may follow alternative routes with the multi-objective of minimizing intercell movements and maximizing the reliability. An efficient genetic algorithm was implemented to solve the model. The computational experiences carried out show that the proposed approach can handle medium to large size problems with reasonable computing effort.

TABLE VI

No	F_1	F_2	Machine-cell chromosome	Part-route chromosome
1	0	0.2903	5 5 5 5 5 5 5 5 5 5 5 5 5 5 5	23322213313122332123123121111
2	604	0.3325	3 3 3 3 3 3 4 3 3 3 3 3 3 4 9	32122231222123231323322311221
3	152	0.3476	3 3 3 3 3 3 3 3 3 3 3 3 3 14 2	33321221222122211121232121223
4	437	0.3519	3 3 3 8 3 3 3 3 3 3 3 3 3 4 6	33321233221133112323222131231
5	1219	0.4031	1 1 1 1 1 1 1 1 1 1 6 1 1 6 5	32322232213133231111313111313
6	2864	0.4045	1 1 1 1 1 3 1 1 7 1 8 1 3 1 3	33321232211113131121212312131
7	1521	0.4043	1 1 1 1 1 1 1 1 1 7 7 1 1 11 1	33131122213132233111333221222
8	313	0.4051	1 1 1 1 1 1 1 1 1 1 1 1 2 1 1	22321121211223121211313121211
9	313	0.4056	1 1 1 1 1 1 1 1 1 1 1 1 3 1 3	32321231321223221111123111213
10	313	0.4056	1 1 1 1 1 1 1 1 1 1 1 1 5 1 3	32322213231223121222112331211
11	11911	0.4058	3 1 2 6 1 3 1 5 2 2 9 1 4 2 1	23213232222222133111223221322

RESULTS OF EXPERIMENT

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TABLE IV

(A) MACHINE – PART WORKLOADS FOR THE FIRST ROUTING

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1		1.2	0.3			0.8	0.4					0.8		0.7	1.1				1.0			0.9	0.5			0.2	1.1			0.4
2							0.8	1.0			0.2		1.2		0.8	0.7		0.3	1.0				1.1				0.8		0.5	0.6
3		0.8	1.1	0.2	1.1	1.2			0.7		0.8			0.8	0.8									0.6	0.4			1.0	0.9	
4	0.3	0.2	0.2			0.8		0.5	0.4	1.0				1.1			0.9		1.2	0.6		0.7	0.9		0.7				0.5	
5					1.1	0.8				0.6	0.7				0.9				0.7	0.3	0.6								0.8	
6	1.2	0.8	0.7	0.5			1.1	0.6											1.1		0.7		0.2	1.0	0.6		0.8			
7				0.4	0.3		1.0		1.0	0.3	1.1	0.4	0.7			0.9					0.8		0.9	0.9				0.9		
8	1.0	1.1	1.1		1.1		0.7							0.7		0.2	0.8	0.6			0.5		1.0					0.2		
9	1.0	0.8		0.9		0.9		0.7			0.3	0.6				1.0			0.5		0.3	0.4		0.2		0.6	0.4		0.9	
10				0.6									0.8	1.0		0.4						0.3		0.4	1.2				1.1	1.0
11	0.2															0.8														
12	1.0			0.6	0.7		0.8	0.3		0.6				0.4	0.3					0.4	1.0			0.8	0.7		0.2			0.6
13					0.9						0.3	0.7	1.0		0.3							0.9								
14			1.1			0.5						1.0	0.8					0.9		0.9		0.6					0.5			0.4
15								0.8	0.5																	0.8				0.7

(B) MACHINE – PART WORKLOADS FOR THE SECOND ROUTING

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1			0.7	0.3	0.8	0.6			0.3	1.0	0.7		0.9	0.8		1.1		0.4	0.8									0.6	0.7	1.1
2										0.5	0.9		0.4					0.9	0.4	1.1		0.6				1.1	0.4			0.6
3				0.3	1.2	0.5	0.7	0.8				0.8				0.5	0.4				1.0	0.2		0.6	0.8	0.3		0.4		
4	0.9			1.1			0.3				1.0	1.1	0.2				0.4						0.6	0.6			1.2	0.8	0.7	
5		0.7	1.0					1.1	0.6		0.9	0.5		0.4	1.1		0.3						0.3		0.3	0.4	0.7		0.2	
6			0.7	1.0							0.3		0.3	0.9	1.0			0.2		1.0		0.8	0.3	0.7		0.9				
7	1.0	1.2				0.9		0.6		0.4		0.6		1.1	0.2				0.4					1.1					0.6	0.3
8								0.4	1.0				1.0				0.3	0.3				0.4		0.8			0.2			0.6
9								0.6	0.5			1.0	1.1					1.0					0.7				1.2		1.0	0.8
10			0.3								0.5					0.8		0.2	0.4		1.1		1.1	0.8	0.6	0.8		0.9		
11								1.1	1.0	0.7					0.4		0.5			0.5								0.7		
12					0.5				1.1					1.0	0.8											0.3		0.8	0.8	
13				1.1		1.0						0.3							0.7	0.3		0.6								
14										0.6				0.9		1.1						0.8								
15	0.6				0.6	0.9									0.5				0.3	0.5					0.3					

(C) MACHINE – PART WORKLOADS FOR THE THIRD ROUTING

1			0.5		0.6			1.0	0.5				0.5		1.2	0.4	0.6		1.1			0.7	1.1					1.2	0.4	0.3
2		1.2				0.6	0.6				0.8	0.5	0.2	0.7	0.9	0.9	0.8	0.7		0.9				0.4						
3					0.4	0.9	0.7	0.7						0.9	0.7	0.6	0.5	0.5			0.7		0.9		0.9					
4	0.5	0.4		0.3						1.1				0.6	0.8					1.1	1.1	1.2		0.6						0.8
5		1.2										0.7		0.7		0.3						1.0	1.2	0.4		0.5		0.4		
6			0.8			0.5		0.9		0.7			0.5		0.9				0.8	1.1			0.3				1.2	0.3		1.0
7			0.5	0.3	0.3										1.1						1.0					0.3		0.5		
8					0.4	1.1	0.5				1.0	0.8	0.6	0.8			0.7	0.5	0.4		0.8	1.0			0.7					
9							0.8	1.0	0.4		0.9			0.9		0.9	0.8						0.5	1.1					0.5	
10	0.7		0.7	0.4	1.0		0.4		0.2	0.6	0.3							0.5	0.8						0.7		0.4	0.3	1.0	
11	0.4		0.4			0.6		0.9	0.5			0.4					1.0			0.6		0.6	1.1	0.5	1.2					0.6
12		0.6			0.7		0.3		0.5	0.5	0.2					1.0				0.4	0.4			0.7		0.2		1.0	0.9	
13		0.3		0.3						0.3	0.4		0.4													1.0	1.1			
14			1.0	0.5				0.7					0.8						0.9		0.6	0.9			0.5	1.0				
15		0.4		0.4						1.0																	0.8		1.1	

TABLE V
DEMAND FOR EACH PART

Part	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Demand	155	150	148	160	144	158	152	155	164	148	140	144	145	162	170
Part	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Demand	140	156	132	172	164	144	158	155	152	140	166	148	145	144	170