Hybrid Approach of Genetic Algorithm in Case of Planning a Cellular Manufacturing System

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Abstract: One important issue regarding the implementation of cellular manufacturing systems relates to deciding whether to convert an existing job shop into a cellular manufacturing system comprehensively in a single go, or in stages by forming cells one after the other taking the advantage of the experiences of implementation. In this paper two heuristic methods based on multi-stage programming and genetic algorithm are proposed for cell formation. The results show that the multi-stage programming solves small problems faster than exact algorithms such as branch and bound. A heuristic procedure based on genetic algorithm is developed on the multi-stage programming to test larger problem sizes.

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1 Introduction

Cellular manufacturing is an application of flexible manufacturing system. It is the result of a direct application of the group technology philosophy.

The essential problem in Planning of a cellular manufacturing system (CMS) is determination of machine-groups and part families popularly known as the machine cell formation (MCF), or also known as machine-component grouping (MCG) problem. Mahesh and Srinivasan [7] clustered a number of techniques and provided an overview of various algorithms that forms cells comprehensively in total. As pointed out by Mahesh and Srinivasan [7], Wemmerlov and Johnson [10] and several others, all the above methods aim at creating a comprehensive CMS in total in a single go. In practice, however, from the viewpoints of planning and implementation and also for capital investment reasons, it would be desirable to move progressively towards conversion of the existing system into cells one after the other.

Adil and Ghosh [1] developed a mathematical model which forms cells based on greedy random adaptive search procedures.

Balakrishnan and Cheng [2] proposed a model which considers cell formation over a multi-period planning horizon with demand and resource uncertainties. In this study, cell formation has been done where at each period the cell configuration can be changed; however, planning, implementation or capital investment issues have not been addressed. Many researchers have tried to compare CM, hybrid CM and job shop together ([9], [17], [24]).

In this paper a new nonlinear integer programming model is designed to convert an existing functional layout to a cellular manufacturing system. Two methods based on multi-stage programming and genetic algorithm (GA) are applied for solving the model.

The rest of the paper is organized as follows. Section 2 introduces the problem; this is done by giving problem description, assumptions, notations and a new mathematical model. Our proposed algorithm based on multi-stage programming approach, genetic algorithm are designed in Section 3, 4 respectively. In Section 5, some experimentations and comparison are shown. Finally, Section 6 presents conclusions.

2 Problem Formulation

2.1 Problem description

We focus on cell formation decisions. Hence, here a functional layout is considered in the beginning of the planning horizon with the planning horizon being composed of multi periods. N parts are considered with each part visiting shops based on its requirements. Generally M machines are available in shops. The objective is to decide the number of cells formed in a period, and the assignment of machines to cells such that the total cost is minimized. The total cost consists of intra-cell and inter-cell material handling, intra-shop material handling, inter-shop material handling and material handling between cell and shop costs.

Assumptions

1. The demand for each part type in each period is known.
2. The number of cells formed in each period is limited.
3. Each cell consists of a minimum and maximum number of machines.
4. The unit cost of inter-cell movements, intra-cell movements and movements between cell and shop are known and constant over time.
5. The number of machines available is known and constant over time.

Notations

The following notations are used throughout the paper:

c	index for cells
u , t	indices for periods
m	index for machines
p	index for parts
s	index for shops
α	intra-cell material handling cost
β	inter-cell material handling cost
γ	cost of material handling between cell and shop
ω	inter-shop material handling cost
D_{pt}	demand for product p in period t
LB	minimum number of machines to be assigned to a cell
UB	maximum number of machines to be assigned to a cell
C_{max}	maximum number of cells can be formed in a period
M	Number of machines
S	Number of shops in the beginning of planning horizon
P	Number of parts
T	Number of periods
$\lvert k_j \rvert$	Number of members of set k_j

$$X_{cu} = \begin{cases} 1 & \text{If cell } c \text{ is formed in period } u \\ 0 & \text{otherwise} \end{cases}$$

$$Y_{mcu} = \begin{cases} 1 & \text{If machine } m \text{ is assigned to cell } c \text{ in period } u \\ 0 & \text{otherwise} \end{cases}$$

$$Z_{pm} = \begin{cases} 1 & \text{If part } p \text{ needs machine } m \\ 0 & \text{otherwise} \end{cases}$$

$$B_{pcu} = \begin{cases} 1 & \text{If part } p \text{ visits cell } c \text{ in period } u \\ 0 & \text{otherwise} \end{cases}$$

$$\delta_{pt} = \begin{cases} 1 & \text{If part } p \text{ visits a cell in period } t \\ 0 & \text{otherwise} \end{cases}$$

$$K_{mst} = \begin{cases} 1 & \text{If machine } m \text{ belongs to shop } s \text{ in period } t \\ 0 & \text{Otherwise} \end{cases}$$

$$\lambda_{pt} = \begin{cases} 1 & \text{If part } p \text{ visits a shop in period } t \\ 0 & \text{otherwise} \end{cases}$$

$$\varsigma_{pst} = \begin{cases} 1 & \text{If part } p \text{ visits shop } s \text{ in period } t \\ 0 & \text{otherwise} \end{cases}$$

2.2 Mathematical model

The objective function and constraints can be formulated as follows:

$$\text{Min } \psi(Y_{mcu}, X_{cu}, B_{pcu}, \delta_{pt}, K_{mst}, \varsigma_{pst}, \lambda_{pt}) =$$

$$\sum_{t=1}^{T}\sum_{u=1}^{t}\sum_{c=1}^{c_{\max}} \alpha . X_{cu} . \sum_{p=1}^{P} D_{pt} . [\sum_{m=1}^{M} (Y_{mcu} . Z_{pm}) - B_{pcu}]$$

$$+ \sum_{t=1}^{T}\sum_{p=1}^{P} \beta . D_{pt} . \sum_{u=1}^{t} [\sum_{c=1}^{c_{\max}} (X_{cu} . B_{pcu}) - \delta_{pt}] +$$

$$\sum_{t=1}^{T}\sum_{p=1}^{P} \gamma . \lambda_{pt} . \delta_{pt} . D_{pt} +$$

$$\sum_{t=1}^{T}\sum_{p=1}^{P} \omega . D_{pt} [\sum_{s=1}^{S} \varsigma_{pst} - \lambda_{pt}], \quad (1)$$

where

$$X_{cu} \geq X_{(c+1)u} \quad (2)$$

$$(1 - B_{pcu}) . \sum_{m-1}^{M} Y_{mcu} . Z_{pm} = 0 \quad (3)$$

$$\sum_{m=1}^{M} Y_{mcu} . Z_{pm} \geq B_{pcu} \quad (4)$$

$$(1 - K_{msu}) . K_{ms(u+1)} = 0 \quad (5)$$

$$K_{msu} - K_{msu} . K_{ms(u+1)} - \sum_{c=1}^{C_{\max}} Y_{mc(u+1)} = 0 \quad (6)$$

$$(1 - \lambda_{pt}) . \sum_{s=1}^{S}\sum_{m=1}^{M} K_{mst} . Z_{pm} = 0 \quad (7)$$

$$\sum_{s=1}^{S}\sum_{m=1}^{M} K_{mst} Z_{pm} \geq \lambda_{pt} \quad (8)$$

$$(1-\delta_{pt}).\sum_{c=1}^{C_{max}} B_{pcu} = 0 \quad (9)$$

$$\sum_{c=1}^{C_{max}} B_{pcu} \geq \delta_{pt} \quad (10)$$

$$\sum_{c=1}^{C_{max}} Y_{mcu} \leq 1 \quad (11)$$

$$(1-X_{cu}).\sum_{m=1}^{M} Y_{mcu} = 0 \quad (12)$$

$$\sum_{m=1}^{M} Y_{mcu} \geq X_{cu} \quad (13)$$

$$(1-\zeta_{pst}).\sum_{m-1}^{M} K_{mst}.Z_{pm} = 0 \quad (14)$$

$$\sum_{m-1}^{M} K_{mst}.Z_{pm} \geq \zeta_{pst}. \quad (15)$$

The objective function (1) represents the total cost. The total cost consists the costs of intra-cell material handling (first term in *objective function 1*), inter-cell material handling (second term), material handling between cell and shop (third term) and inter-shop material handling (fourth term). Eq. (2) ensures the order of cell formation in a period. Eqs. (3) and (4) show that part *p* visits cell *c*, when at least one of the required machines to process the part is allocated to the cell. Eq. (5) is to ensure that a machine could belong to a shop if it was in that shop in preceding period. Eq. (6) represents that a machine can be allocated only to a cell or a shop in each period. Eqs. (7) and (8) show that part *p* visits shop *s* when at least one of the required machines to process the part is allocated to this shop. Eqs. (9) and (10) ensure that a part moves inter-cell if the part visits more than one cell in a period. Eq. (11) ensures that each machine can be allocated to at most one cell in each period. Eqs. (12) and (13) ensure that a cell is formed in a period if at least one machine is allocated to the cell. Eqs. (14) and (15) show that part *p* visits shop *s*, when at least one of the required machines to process the part is allocated to the shop.

3 Multi-stage programming

Multi-stage programming is a powerful optimization technique that is particularly applicable to many complex problems requiring a sequence of interrelated decisions. Here our proposed algorithm is based on a multi-stage approach. Therefore, before applying the algorithm, the number of cells, formed in each period, and the initial location of each machine should be known. We apply a forward recursive approach to solve the problem.

The recursive relation defining the dynamic step is given by the following equation:

$$F_{k=\{k_1,k_2,..,k_j\}}(i,j) = \min\begin{Bmatrix} F_{\{k_1,k_2,..,k_{j-h}\}}(i-1, j-h) + \\ \psi(\mathrm{Y_{mci}}, \mathrm{X_{ci}}, \mathrm{B_{pci}}, , \mathrm{K_{msi}}, \lambda_{\mathrm{pi}}) \end{Bmatrix}, \quad (16)$$

$0 \leq h \leq C_{max}$,

$i = 1,2,..,T$,

$j = 0,1,...,i*c$,

$LB \leq |k_j| \leq UB$,

$X = (Y_{mcu}, X_{cu}, B_{pcu}, \delta_{pt}, K_{mst}, \lambda_{pt})$,

where $F_{\{k_1,k_2,..,k_j\}}(i,j)$ means the minimum total cost from period 1 to period *i*, when *j* cells are formed, and k_j shows the machines in cell *j*. $\psi(X)$ is the value of objective function based on the objective function (1) in current period and *X* is the vector of update values of decision variables in the period. k = ϕ means that no cells is formed. The optimum solution is achieved as follows:

$$\psi^* = \min\begin{pmatrix} F(T, j) \\ j = 0,1,2,.., \min(T \times C, \frac{M}{LB}) \end{pmatrix} \quad (17)$$

Algorithm

Here, the steps of algorithm based on multi-stage programming are proposed.

Step 1. Setting the initial value of decision variables

According to the initial layout, in which all machines are assigned to shops before planning, no cells are formed. The decision variable values are set as follow:

$X_{cu} = 0$ *for c = 1,2..,C_{max} and u =1,2,..,T*

$Y_{mcu} = 0$ *for m = 1,2,..,M , c = 1,2,..,C_{max} and u =1,2,..,T*

$B_{pcu} = 0$ *for p = 1,2,..,P , c =1,2,..,C_{max} and u =1,2,..,T*

$\delta_{pt} = 0$ *for p = 1,2,..,P , t = 1,2,..,T*

If machine *m* belongs to shop *s* in initial layout.

$$K_{ms0} = \begin{cases} 1 \\ 0 \end{cases} \quad \text{otherwise}$$

$K_{mst} = 0$ *for m =1,2,..,m , s =1,2,..,S and t =1,2,..,T*

$\lambda_{pt} = 0$ *for p = 1,2,..,P , t =1,2,..,T*

Set *t=1*

Step 2. Combination of machines

Here, all feasible sets of machines are constituted. A set of machines includes at least *LB* and at last *UB* machines and is feasible if the machines, belonging to the set has not been assigned to any cell in previous periods and belongs to the remaining shops.

A machine can be assigned to no cell and remain in the shop and remainder shop is such a cell.

Step 3. Cell formation

Here, a set of machines is assigned to a cell. When the cell is formed in the current period, the related variables will be updated according to the following rules. Each cell contains a feasible set of machines.

Rule 1: In period *t* a machine can be assigned to a cell if it has not been assigned to any cell in this and previous periods. In other worlds the machine should belong to reminder shop before period t.

Rule 2: If machine *m* is assigned to cell *c* in period *t* then the decision variables are set as follow:

$Y_{mct} = 1$ and $Y_{mcu} = 0$ *for u = t+1, t+2, ..., T and c= 1,2,..,*C_{max}.

$K_{mst} = 0$ *for s= 1,2,..,S and t= t,t+1,..,T.*

Rule 3: If machine *m* belongs to cell *c* in period *t* ($Y_{mct} = 1$) and part *p* needs machine *m* then $B_{pcu} = 1$ and $\delta_{pt} = 1$.

Rule 4: If machine *m* belongs to shop *s* in period *t* ($K_{mst} = 1$) and part *p* needs machine *m* then $\lambda_{pt} = 1$.

Rule 5: In period *t* a machine cannot be assigned to a cell and a shop at the same time. In other words, in each period the following relation should be satisfied:

$K_{mst} \times Y_{mct} = 0$.

Step 4. Completion a solution, when a solution is completed, all machines in the period are assigned to a cell or remainder shop.

Step 5. Calculate the objective function with update variables.

Step 6. Using the recursive relation (16) and the value obtained in Step 5, use a multi-stage programming to obtain a value for the current solution.

Step 7. For all possible solutions in the current period repeat steps 3-6.

Step 8. Set *t= t+1*

Step 9. If $t \leq T$ then go to step 2 else go to step 10.

Step 10. Determine the best programming.

4 Genetic algorithm

4.1 GA approach

In this section a genetic algorithm for solving the problm is introduces. The components of genetic algorithm are selected based on Jans and Degraeve [6] study which review metaheuristic algorithm in a dynamic environment. The proposed GA consists of following steps:

4.1.1 Representation

In the increment cell formation problem, each solution is presented by a $T \times M$ matrix which rows show periods and columns show machines. The values of cells are set between zero and C_{max}, each value demonstrates the position of a machine in a period.

Table 1. Problem representation-chromosome

	M1	**M2**	**M3**	**M4**	**M5**	**M6**
P1	**0**	**0**	**0**	**0**	**0**	**0**
P2	**0**	**1**	**0**	**0**	**1**	**0**
P3	**2**	**1**	**2**	**3**	**1**	**3**
P4	**2**	**1**	**2**	**3**	**1**	**3**

6 Machines

4 Periods

4.1.2 Initialization and evaluation

The initialization process is executed with a randomly generated solution space. An initial population size (*popsize*) is set 50. The objective function is transformed fitness function infinite cost is attached to this for infeasible solution. (Dellaert et al. [4]):

$$f^i(t) = \begin{cases} f^i_{\max} - g^i(t) & when \quad g^i(t) < f^i_{\max} \\ 0 & if\ otherwise \end{cases}$$

Where $f^i(t)$ is the fitness value of *solution i,* $g^i(t)$ is the objective function with penalty cost and $f^i_{\max}$ is the largest objeve function value in the current solution.

4.1.3 Selection strategy

In this study, we use the roulette wheel and elitist as selection strategies.

4.1.4 Genetic operators: crossover and mutation

Here, the one column cross-over (Dellaert and Jeunet [3]) the matrixes of the two parents are cut in two at some random point and are recombined into one new solution. The crossover operator is given in Fig.1

	M_1	M_2	M_3	M_4	M_5	M_6
P_1	0	0	0	0	0	0
P_2	0	1	0	0	1	0
P_3	2	1	2	3	1	3
P_4	2	1	2	3	1	3

	M_1	M_2	M_3	M_4	M_5	M_6
	1	0	0	1	0	0
	1	2	2	1	0	0
	1	2	2	1	0	0
	1	2	2	1	3	3

	M_1	M_2	M_3	M_4	M_5	M_6
P_1	0	0	0	0	0	0
P_2	0	1	0	0	0	0
P_3	2	1	2	0	0	0
P_4	2	1	2	3	3	3

Figure 1. Crossover operator

The mutation operator changes the value of a cell randomly, for example Fig.2 shows the mutation operator.

	M_1	M_2	M_3	M_4	M_5	M_6
P_1	0	0	0	0	0	0
P_2	0	1	0	0	0	0
P_3	2	1	2	3	0	0
P_4	2	1	2	3	3	3

	M_1	M_2	M_3	M_4	M_5	M_6
P_1	0	0	0	0	0	0
P_2	0	1	0	0	0	0
P_3	2	1	2	3	0	0
P_4	2	1	2	3	3	3

Figure 2. Mutation operator

5 Some experiments and comparisons

In this section a number of numerical examples are solved using the multi-stage programming and genetic algorithm. Results along with the computational times and quality solutions are compared with branch and bound algorithm. The results are shown in Fig. 3.

6 Conclusion

This paper addresses a nonlinear programming model for Planning a cellular manufacturing system. The proposed algorithms based on multi-stage programming approach and genetic algorithm are applied to 20 experimental data.

The multi-stage method provides the optimal solutions in lesser number of iterations and number of levels for small size problems and hence the computational time is the least. For large size problems genetic algorithm is applied which produce good solutions in a reasonable time. Thus the proposed methods have the advantage of fast and accurate computations and have the ability to handle large-scale industrial problems.

Example	Number of Parts	Number of Machines	Number of Periods	C_{max}	Multistage Programming		Genetic Algorithm	
					Best solution	Computational time	Best solution	Computational time
1	4	4	2	2	3050	0:0:10	3050	0:0:0
2	6	6	3	2	19560	0:0:50	19560	0:0:1
3	6	8	3	2	30284	0:1:00	30284	0:0:5
4	6	10	3	2	43452	0:5:00	43452	0:1:0
5	6	10	3	3	35641	0:8:00	35641	0:0:48
6	6	10	3	4	28377	0:7:00	28377	0:0:59
7	8	10	4	3	78743	0:9:00	78743	0:1:30
8	8	10	4	4	66858	0:10:20	66858	0:1:57
9	10	10	4	4	85070	0:6:30	87624	0:2:08
10	10	12	4	3	129144	0:7:25	129177	0:2:18
11	10	12	4	4	110646	0:30:56	110646	0:2:25
12	10	12	5	3	156921	0:45:35	156921	0:2:35
13	10	15	5	3	232758	1:0:34	229798	0:2:22
14	10	15	5	4	367189	1:35:25	367189	0:2:59
15	10	20	5	4	252894	2:5:45	274937	0:3:00
15	10	20	8	4	528386	2:35:33	542615	0:2:31
17	15	20	8	4	—	—	949276	0:4:45
18	20	20	8	4	—	—	1129510	0:5:56
19	20	20	10	4	—	—	1921456	0:7:12
20	20	30	10	4	—	—	2134862	0:8:0

Figure 3. Comparative analysis (Computational time (hour : minute : second))

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