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Solving Generalized groupings problems in Cellular manufacturing systems by genetic algorithms

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Abstract: *Cell formation problem consists of identifying machine groups and part families. Generalized grouping problem have more than one process plans and or process routes. In non-heierarchical methods all decisions are made simultaneously and in heierchical methods decisions are made in stages. Because of complexity of the generalized problem, solving large size problems using simultaneous approach becomes difficult. The grouping problem assumes a particular structure depending on the objectives and the constraints. The mathematical models of generalized grouping are found to be either NP-complete or hard to solve. Since even the relaxed version of grouping problem is NP-complete, it is unlikely that the optimal solution to the problem can be found efficiently. Genetic Algorithm is largely used for solving problems in cellular manufacturing. In this paper, a model is developed to solve the generalized grouping problem considering alternative process plans. Several design and manufacturing parameters such as production volume, process sequence, machine capacity, processing time, machine duplication, number of cells and cell size are considered. The objective function minimizes intercellular movements and number of exceptional elements. A procedure based on genetic algorithms to solve the problem in two phases has been demonstrated. In the first phase it finds the process routes and in the next it forms grouping of machines. The algorithm coded in C++ was tested on Windows workstation. The objective to form cells and part families was based on a double grouping (operations and machines). The final solution is a proposition of machine cells defining part families. The algorithm is really fast and allows trying different configurations for the set of data and different alternatives of the weights for all criteria. It can be useful in solving large size grouping problems.*

Key Word*: Cellular manufacturing, Genetic algorithms, alternative routes, generalized groupings*

I. Introduction

Cellular manufacturing systems are widely accepted as one of the major applications of group technology in manufacturing, for improving productivity in medium volume and medium variety production systems and acquiring flexibility in terms of frequent product changes. Cell manufacturing problem mainly involves identifying part families, formation of machine cells and assignment of parts to respective cells. The major benefits are reduced production lead time, reduced work-in-process, reduced setup time, reduced delivery time, reduced labor, reduced tooling, reduced rework, improved quality and subsequently reduced costs [1]. The major aim of this part-machine grouping is to form perfect part groups with similar design or processing requirements so that each part family can be processed within a single machine cell. Over the last two decades, since the introduction of group technology in manufacturing, large numbers of solution procedures have emerged for grouping problems. Extensive reviews of solution procedures are given [2], [3], [4]. These procedures can be divided into two categories. Methods based on production part characteristics such as part geometry, material, tolerance to identify part families. Methods based on production process, plans or routings. A process plan lists the sequence of specific machines or work centers corresponding to each operation of the part. The grouping problem assumes a particular structure depending on the objectives and the constraints. Simple grouping is to identify part families and machine cells so that each machine cell can process at least one part family. However this may not be true assumption and each part can have more than one process plans as well as operations required to make the part can be performed on alternate machines [5].

The grouping problem termed as generalized grouping is to select only one process route for each part and to identify the process route families and machine cells so that each machine cell can process at least one process route family. Two broad approaches of solving the grouping problems are present. In non-hierarchical approach, all decisions are made simultaneously and in hierarchical approach decisions are made in stages. Because of complexity of generalized problem, solving large size problems using simultaneous approach becomes difficult. While the problem solving turns out to be relatively easier with hierarchical approach, but it may lead to suboptimal solutions at later stage [6]. Mathematical programming approaches are applied to find optimal solutions to the problems related to cellular manufacturing systems. These formulations can provide optimal solutions, which can serve as basis to judge the goodness of industrial heuristics. Since even the relaxed version of grouping problem is NP-complete, it is unlikely that the optimal solution to the large problem can be found efficiently [7]. Metaheuristics provide solutions to the problems in reasonable time.

Genetic algorithm is extensively applied for combinatorial optimization problems. Genetic algorithm works with fixed number of solutions called as population and iteratively performs some steps until a pre specified termination condition is meeting. It evaluate each chromosome and based on its fitness populate a gene pool by applying reproduction, crossover and mutation operators [8].

In this paper, a model is developed to solve the generalized grouping problem. Several design and manufacturing parameters such as production volume, process sequence, machine capacity, processing time, machine duplication, number of cells and cell size are considered. The function minimizes intercellular movements and number of exceptional elements. A procedure based on genetic algorithms to solve the problem in two phases has been demonstrated. In the first phase, it finds the process routes randomly and in the next, it forms grouping of machines. It iteratively solves for better solution. The final solution is a proposition of machine cells defining part families. The algorithm is fast and allows trying different configurations for the set of data and alternative routes.

II. Prior work and studies

Despite the vast literature available for simple grouping, the generalized grouping problem has attracted relatively less attention from the researches. Kusiak [1] considered the grouping problem first in which each part has more than one process routes. A generalized grouping problem was termed and p-median model was used. Minimizing sum of similarity coefficient values around median process route within the family was objective function. Rajamani [5] proposed general integer linear and nonlinear programming formulations. The generalized grouping concept was made more generalized which considered each part has more than one process plans and each operation of a process plan can be performed on more than one machines. Shanker and Agrawal [9] considered maximizing association of part operations with machines. The problems are formulated as graph partitioning models that determine the groups either hierarchically or simultaneously and solve the operations by assignment problem. Zhao and Wu [10] used a genetic algorithm to solve a multi-objective cell formulation problem. User defined weights are used to convert multiple objectives into a single objective. The objectives considered are total number of exceptional elements total within cell load variation and inter cellular movements. Gravel at el [14] used alternate process plans for products and proposed double loop genetic algorithm to generate an efficiency frontier cell formation problems with two objectives viz. minimizing intercellular transfers and intracellular load balance among machines. Shanker and Vrat [7] applied a fuzzy programming approach.

Uddin and Shanker [11] have used genetic algorithm to minimize the total number of intercellular movement in the presence of multiple process plans for each part by simultaneous approach. Two interrelated problems were solved. One pertaining to the assignment of machines to cells and second to assignment of process plans are solved. Jaiswasl and Adil [12] used simulated annealing to minimize sum of cost of intercellular moves, machine investment and machine operating cost. Lei and Wu [13] considered Tabu search approach by similarity coefficient method and subsequently improved by Tabu search method. Most of the existing methods are integer programming as their optimization technique is NP-complete. Some of the models use heuristics to solve the problem but the drawback is that the convergence is not guaranteed towards the optimum.

In this paper, a model is developed to solve the cellular manufacturing problem using alternative process plans by two phase algorithm. As shown in Figure 1, number of part families is determined in first phase by assigning part routes to part families. Once the part route families are determined, machine cells are constructed.

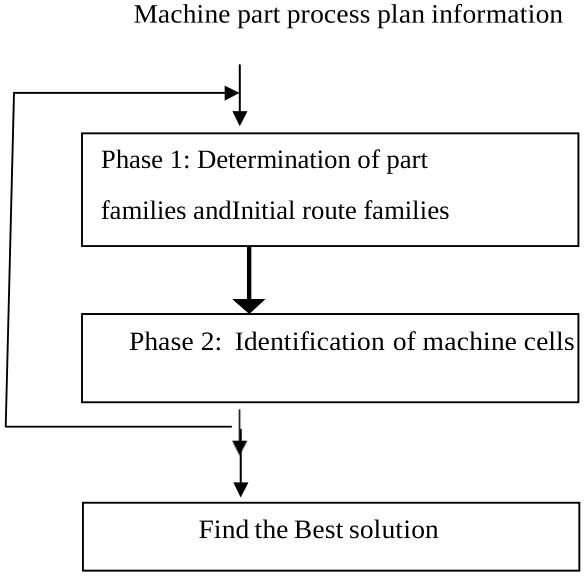

Figure 1. Two-phase algorithm

III. Model Developed

In this section, the notations and the mathematical model are presented.

3.1 Notation

Subscripts, parameters and sets

k	*part*
m	*machine type*
p	*process route*
c	*machine cell*
C	*Total number of machine cells to be formed*
K	*Total number of parts to be manufactured*
M	*Total number of machines*
PR(k)	*Set of process routes for part k*
R(kp)	*Set of machine types required to process part k using process route p*
TR(kp)	*Total number of machine types required to process part k using process route p=|R(kp)|*
T_{kpm}	*Time required on machine m to produce one unit of part k using process route p*
D_k	*Demand of part k*
B_m	*Time available on each machine of type m*
max_c	*Maximum number of machines allowed in cell c*
min_c	*Minimum number of machines allowed in cell c*

Decision variables

Y_{kp} = *1 if process route p is selected for part k or 0 otherwise*

Z_{mc}= *1 if machine m is assigned to cell c or 0 otherwise*

3.2 Mathematical model

The objective function and various constraints related to intercellular movements are presented below.

Minimize Z $= \sum_{c=1}^{C} \sum_{k=1}^{k} \sum_{p \in PR(k)}^{n}$ Ykpc (1)

Subject to

$\sum_{p \in PR(k)} Y_{kp} = 1$, k= 1….K (2)

$$\sum_{c=1}^{C} Zmc = 1 \,, \; m = 1 \ldots. M \qquad (3)$$
$$\sum_{m=1}^{M} Z\,\text{mc} \;\geq\; \text{Min}, \; c = 1 \ldots. C \qquad (4)$$
$$\sum_{m=1}^{M} Zmc \;\leq\; \text{Max}, \; c = 1 \ldots. C \qquad (5)$$
$$Ykp \sum_{m \in R(kp)} Zmc - TR(kp)Ykpc \;\leq 0 \,, \quad c= 1.. C, k=1.. K , \; \forall \; p \in PR(k) \qquad (6)$$
$$\sum_{k=1}^{K} \sum_{p \in PR(k)} dkYkpTkpm \;\leq bm \,, \qquad m= 1 .. M \qquad (7)$$
$$\text{Ykp} \in \{0,1\} \,, \; k= 1.. K \,, \forall \; p \in \Pr(k) \,, \qquad (8)$$
$$\text{Ykp} \in \{0,1\}, \; k= 1.. K \,, \forall \; p \in \Pr(k) \;, \; c= 1 .. C \qquad (9)$$
$$\text{Zmc} \in \{0,1\} \,, \; m = 1 .. M \,, \; c = 1 .. C \qquad (10)$$

The objective function (1) minimizes the intercellular movements by minimizing the number of visits of various parts from one cell to another for its processing. Constraint (2) selects only one process route for each part. Constraint (3) ensures that each machine is assigned to only one cell. Constraint (4) and (5) express the constraints on the minimum and maximum number of assignments of machines to a group, respectively. With the help of constraint (6) variable Ykpc is defined in such a way that this constraint aids the objective function by trying to assign, if possible, all the machines required by a process route to the same cell. In case this is not possible, this constraint will try to assign, as many machines required by a process route as possible to the same cell. Constraint (7) ensures that the total machining time required by all the selected process routes on any machine must not exceed its available capacity. Constraint (6) is non-linear and can be linearized by rule suggested by Glover and Wooley [17]. The rule is as follows. Replace each product term Ykp, Z mc by a continuous variable Vkpmc, which is required to satisfy the constraints (11) to (14).

$$\sum_{m \in R(kp)} Vkpmc - TR(kp)\; Ykpc \;\leq 0, \qquad k= 1 .. K, c= 1 .. C \,, \forall \; p \in PR(k) \qquad (11)$$
$$\text{TR(kp) Ykp} + \sum_{m \in R(kp)} Zmc - \sum_{m \in R(kp)} Vkpmc - TR(kp) \leq 0, \; k= 1 .. K, c= 1 .. C \,, \forall \; p \in PR(k) \qquad (12)$$
$$\text{-Ykp} - \text{Zmc} + 2 \text{ Vkpmc} \;\leq\; 0, \; k= 1 .. K, c= 1 .. C \,, \forall \; p \in PR(k) \,, \; \forall \; m \in R(kp) \qquad (13)$$
$$\text{Vkpmc} \;\geq\; 0, \; k= 1 .. K, c= 1 .. C \,, \forall \; p \in PR(k) \,, \; \forall \; m \in R(kp) \qquad (14)$$

IV. Genetic algorithm

In this section, we present the basis and detail the proposed genetic algorithm. The implementation of genetic algorithm requires an encoding mechanism to represent a solution as a chromosome. Evaluation function which will encoded chromosomes as an argument and return the relative fitness. A selection procedure set for reproduction. A cross over operator and a mutation function for bringing a variety and diversity in the population. Given an initial set of process routes the problem P1 improves the solution in phase 1. The result of solving P1 is input for the problem P2, which is solved. At each iteration, the proposed genetic algorithm is run for a fixed number of generations to solve the problem P1 and P2. The basic structure of the proposed algorithm to solve problems P1 and P2 is as follows.

The problem formulated in section 3 is a non-linear programming problem. There are three decision variables: Ykp, Ykpc and Zmc. It is evident that the values of Zmc define completely the configuration of machine cells, i.e. c= 1 ..C. Further, when machine cells have been formed. Ykp dictate Ykpc values as described below. If the process route p of part k visits any cell c for it is processing then Ykpc becomes '1' or '0' otherwise. Thus we decouple the problems P1 and P2 that are solved in succession to minimize Ykpc. Given initial set of process routes (one process route for each part), i.e. Ykp values, the problem become a simple grouping problem, the index p becomes constant (p*) for the problem P1.

$$P1\!: Minimize \; \sum_{c=1}^{C} \sum_{k=1}^{K} Y(kp*)c$$

Subject to (3) to (5) and modified (6a)

$$\sum_{m \in R(kp*)} Zmc - TR(kp*)Ykp*c \;\leq 0 \,, \quad c= 1.. C, k=1.. K \,, \qquad (6a)$$

The result of solving P1 is a set of Zmc values. The quantity Ykpc becomes a constant for particular Ykp for problem P2.

$$P2\!: Minimize \; \sum_{p=1}^{P} \sum_{k=1}^{K} \Big(\sum_{c=1}^{C} Ykpc\Big)\, Ykp$$

Subject to (2) and (7).

The result of solving P2 is a new set of values of Ykp. The problems P1 and P2 are solved iteratively until convergence is achieved. Implementation of Genetic algorithm requires an encoding mechanism to represent a solution as a chromosome. Evaluation functions which will take encoded chromosomes as an argument and return the relative fitness. A selection procedure for reproduction with two operators, i.e. crossover and mutation are implemented. By iterating the procedure for fixed number of cycles which fetch the best solution for the problem.

V. Numerical illustration

The genetic algorithm was coded in C++ programming language using simple array data structure. In order to test effectiveness of the present algorithm, some small data sets were selected. The results are compared with literature.

Parts and their Process Plan-----→

M	1	1	1	2	2	3	3	4	4	5	5
↓	1	2	3	1	2	1	2	1	2	1	2
1			1		1	1		1	1		1
2		1	1	1			1				
3	1			1	1				1	1	
4	1	1				1	1	1		1	

Table 1. Kusiak's original incidence matrix [1]

Parts and their Process Plan-----→

M	1	3	2	4	5
↓	2	2	2	2	2
2	1	1			
4	1	1			
1			1	1	1
3			1	1	

Table 2. Result by present model.

Parts and their Process Plan-----→

M	1	1	2	2	3	4	4	5	5	5	5	6	6	7	8	8	9	9	10	10
↓	1	2	1	2	1	1	2	1	2	3	4	1	2	1	1	2	1	2	1	2
1					1			1	1					1		1				
2	1	1	1	1		1	1					1			1	1	1	1		
3		1						1	1	1	1			1					1	
4			1	1	1	1	1	1		1	1	1	1		1	1	1		1	1

5	1		1			1			1		1				1			1		1
6	1	1	1	1			1						1		1	1	1	1		

Table 3.Sankaran and Kasilingam's incidence matrix [15]

Table 1 contains data sets which shows processing times of five parts and four machines. Table 2 shows two cells without any exceptional elements. Table 3 contains data sets which shows processing times of ten parts and six machines. Table 4 shows cells with two exceptional elements.

Parts and their Process Plan-----→

M	3	5	7	1 0	1	2	4	6	8	9
↓	1	1	1	2	1	1	1	1	2	2
1	1	1	1							
3		1	1							
2					1	1	1	1	1	1
4	1	1		1		1	1	1	1	
5				1	1	1	1		1	1
6					1	1			1	1

Table 4. Result by present model.

VI. Comparative Study

In order to test the effectiveness of the present algorithm, large size data sets were selected. A large size problem given by Nagi [16] was selected to solve. There are twenty machine types and twenty parts with total fifty one number of process routes. Results reported in literature shown in Table 5 are compared with obtained in Table 6.

Cell No.	Part no.	Route no.	Machine no.
1	18,19, 20	1,1,1	4,13,15
2	11,12,13	1,1,1	3,8,11,18
3	1,2,3,4,5	2,2,2,2,3	1,7,9,12
4	14,15,16,17	2,2,2,1	10,14,17,19
5	6,7,8,9,10	1,6,2,6,1	2,5,6,16,20

Table 5. Result by Nagi [16].

Cell No.	Part no.	Route no.	Machine no.
1	18,19, 20	1,1,1	4,13,15
2	11,12,13	3,3,3	3,8,11,20

3	1,2,3,4,5	2,2,2,2,1	1,7,9,12
4	14,15,16,17	2,2,2,1	10,14,17,19
5	6,7,8,9,10	1,5,2,4,1	2,5,6,16,18

Table 6. Result by present model.

VII. Conclusion

In this paper, a model is presented to solve the generalized group technology cell formation problem. It has multiple process routes for each part. Capacity of the machines and demand of each part has been formulated. The method selects the process route for minimizing the intercellular movements. A procedure based on genetic algorithm to solve the problem has been demonstrated by three problems selected from literature. The algorithm is quite effective to find global optimal solution within a reasonable time. The proposed model gives a good separable cell formation for medium and large sized problem also.

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