IIE Transactions (2002) **34**, 837–846

Multiple criteria approach and generation of efficient alternatives for machine-part family formation in group technology

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Received September 1998 and accepted August 2001

Multiple Criteria Decision-Making (MCDM) seeks to find one or several satisfactory alternatives among a set of possible alternatives. In this paper, for the first time, we develop a multiple criteria decision-making approach for solving the machine-part cell formation problem when there are conflicting objectives. The objectives are to: maximize the machine utilization rate (to have a higher productivity rate), minimize the number of duplicated machines (to have a lower cost and space requirement), and minimize the number of exceptional elements (to have a lower inter-flow traffic among cells). Our approach can be modified to consider other objectives as desired. To find the most preferred alternative to this problem, we develop an approach for generating all efficient (non-dominated) alternatives and then select the most preferred alternative from this set. Our approach consists of three steps: (i) generating a seed alternative for each given number of cells; (ii) generating all non-dominated alternatives for each given seed alternative; and (iii) evaluating all generated non-dominated alternatives to find the most preferred alternative. The relationships among alternatives and objectives are discussed. An example is solved to demonstrate the details of the proposed approach. Some experimental results solving several problems selected from the literature are also presented.

1. Introduction

Cellular manufacturing has been recognized as one of the most innovative approaches for improving productivity and flexibility under the many-products and low-volume production environment, as it tries to effectively transform batch-type production into line-type production. One of the first problems to be solved in the system design stage is the machine-part cell formation. According to similarities in design features or processing requirements, the parts are grouped into families, and machines into cells. Families of parts can then be processed in their corresponding machine cells.

Multiple Criteria Decision-Making (MCDM) seeks to find one or several satisfactory alternatives among a set of possible alternatives. Alternatives are judged by several criteria, which are conflicting in almost all real life decision problems. Many approaches have been proposed for solving MCDM problems. The most recently proposed interactive methods provide a desirable and flexible way to solve MCDM problems. By interaction with the decision-maker, preference information is captured and utilized to evaluate alternatives. The interactive procedures often involve eliminating undesirable alternatives so as to decrease the set of alternatives.

Several interactive methods have been proposed to screen the set of alternatives and to assess the decision-maker's preference information over criteria (Malakooti, 1988a; Davey and Olson, 1998; Karacapilidis and Pappis, 2000). The effort has been focussed on decreasing the set of alternatives and decreasing the number of questions posed to the decision-maker for assessing his/her preference information. In the case of large alternative sets and non-linear utility functions, it is still a very difficult if not impossible task to assess the decision-maker's preference information and find the best alternative. MCDM techniques are an integral piece in solving group technology problems.

Many manufacturing firms are considering using group technology and cellular manufacturing technology to increase their productivity and flexibility, and quicken their responses to market changes. The design of a cellular manufacturing system consists of three major stages: (i) economical and technical feasibility study; (ii) design of manufacturing systems; and (iii) systems implementation

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(Wemmerlov and Hyer, 1989). A Cellular Manufacturing System (CMS) can be designed by applying group technology and just-in-time concepts. One of the first problems to be solved in the system design stage is the machine-part cell formation. According to similarities in design features or processing requirements, parts are grouped into families, and machines into cells. Families of parts can then be completely processed in their corresponding machine cells. The design procedures based on design features of parts require a classification and coding system that is time-consuming and difficult to develop and implement. Most design methods use the processing requirement of parts to form machine-part cells (King and Nakornchai, 1982; Kusiak, 1987; Srinivasan *et al.*, 1990; Dahel and Smith, 1993).

The processing requirements of parts on machines can be represented in the form of a matrix $\{a_{ij}\}$ called the machine-part incidence matrix. The incidence matrix $\{a_{ij}\}$ has m rows representing machines and n columns representing parts. For an element a_{ij} in the incidence matrix

$$a_{ij} = \begin{cases} 1 & \text{if part } j \text{ requires an operation on machine } i, \\ 0 & \text{otherwise.} \end{cases}$$

The grouping of parts into families and machines into cells results in row and column exchanges of the incidence matrix. The hoped-for solution is a block-diagonal matrix. Figure 1(a) is an example of an initial machine-part incidence matrix with 10 machines and 15 parts. Figure 1(b) is the resultant matrix after grouping; there are three distinct machine-part cells. Part family 1, consisting of parts 2, 10, 11, 12, and 7, can be processed on Machine cell 1, which consists of machines 1, 7 and 10. Part family 2, consisting of parts 3, 5, 8, 13, and 15, can be processed on Machine cell 2, which consists of machines 2, 5, and 8. Part family 3, consisting of parts 1, 6, 9, 14, and 4, can be processed on Machine cell 3, which consists of machines 3, 4, 6 and 9.

The cells formed in the above example are mutually exclusive. But in most cases, the final grouped cells are not mutually exclusive. A few entries outside the diagonal blocks represent operations to be performed outside the assigned machine cells. These elements are called exceptional elements. The corresponding machine is called a bottleneck machine, and the corresponding part is called an exceptional part. Figure 2 shows the final clustering of a different problem with seven exceptional elements.

During the past two decades, many research papers have been published in the literature for machine-part cell formation. These methods are based on the following approaches:

1. Coding and classification (Xu and Wang, 1989; Bedworth *et al.*, 1991).

(a)

Machine \ Part	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
01		1								1	1	1			
02			1		1			1					1		1
03	1					1			1					1	
04	1			1					1					1	
05			1		1			1					1		1
06	1			1		1			1					1	
07		1					1			1	1	1			
08			1		1			1					1		1
09				1		1			1					1	
10		1					1			1	1	1			

(b)

Machine \ Part	2	10	11	12	7	3	5	8	13	15	1	6	9	14	4
01	1	1	1	1											
07	1	1	1	1	1										
10	1	1	1	1	1										
02						1	1	1	1	1					
05						1	1	1	1	1					
08						1	1	1	1	1					
03											1	1	1	1	
04											1		1	1	1
06											1	1	1	1	1
09												1	1	1	1

Fig. 1. (a) An initial incidence matrix with 15 parts and 10 machines; and (b) the expected final clustered matrix.

Machine \ Part	2	7	11	12	5	8	9	10	13	15	1	3	4	6	14
01	1	1	1	1											
06	1	1	1	1								1		1	
07	1		1	1											
02					1		1	1	1	1					
05						1	1	1	1	1					
10					1	1	1	1	1	1					
03		1				1			1		1	1		1	1
04											1	1	1	1	1
08											1	1	1	1	1
09	1			1								1	1	1	1

Fig. 2. The final clustered matrix of a system with seven exceptional elements.

2. Machine-part group analysis (Burbidge, 1971; King, 1980a,b; Chan and Milner, 1982; Chandrasekharan and Rajagopalan, 1986).
3. Similarity coefficients (Seifoddini, 1989; Askin *et al.*, 1991).
4. Knowledge-based (ElMaraghy *et al.*, 1988; Singh *et al.*, 1991).
5. Mathematical programming (Choobineh, 1988; Logendran, 1990; Rajamani *et al.*, 1992).
6. Fuzzy clustering (Li *et al.*, 1988; Xu and Wang, 1989).

Most of the methods developed in the literature are concerned with the machine-part cell formation while having a single objective function to optimize. After solving the cell formation problem, if there exist exceptional elements in the final cell structure, some of the methods suggest duplicating some of the bottleneck machines, or subcontracting exceptional parts in order to get a mutually exclusive cell structure. For some more recent developments and methods for machine-part formation see Pierreval and Plaquin (1998) and Onwubolu and Mutingi (2001). From the practical point of view, several issues, such as cost to duplicate machines, cost to transport parts, and machine utilization rate, should be taken into consideration while designing part/machine cells. There is a need for a systematic analysis for identifying different objectives and criteria for construction and evaluation of alternatives. The generalized P-median model is one of the very few methods that considers two objectives, production cost and the total sum of distance measures.

Recently, several significant contributions have been made to the field relating to group technology. Among these are artificial neural network approaches that can be used to solve group technology problems. Malakooti and Zhou (1998) develop a feedforward approach for the analysis and design of artificial neural networks. Methods for machine set-up optimization via artificial neural network approaches have been created as well (see Malakooti and Raman 2000a). Malakooti and Raman (2000b) also develop a clustering and multiple criteria approach for using nerual networks. Many advances have been made recently in the field of MCDM as well. Malakooti (2000) developed a method for solving MCDM problems using partial preference information. In related fields, multi-objective approaches to solving established problems have gained widespread support (see Malakooti and Al-alwani 2001; Malakooti and Subramanian 1999). Malakooti (1988b), presents a decision-making methodology that the decision-maker can use to identify and solve MCDM problems using the identified utility function.

In this paper, we propose a multiple criteria decision-making approach to investigate the machine-part cell structure formation when conflicting objectives are present. The approach includes three levels: forming one seed alternative for each possible number of cells; generating alternative cell structures for each possible number of cells; and selecting the best cell structure; the selection is based on maximizing the machine utilization rate, minimizing the number of duplicated machines, and minimizing the number of exceptional elements. The relationships among these objectives are investigated and experimental results are presented.

There are several techniques to assess weights of additive utility functions; these methods include ranking and rating criteria (objectives), (Steuer, 1986), weights derived from indifferent trade-offs (Keeney and Raiffa, 1976). Although in this paper, for the purpose of illustration, we use an additive utility function, one may use more complex utility functions that may be concave, convex, or other types (Malakooti and Zhou, 1994).

The rest of the paper is organized as follows. In Section 2, the multiple criteria approach is presented. In Section 3, an example is solved and the relationships among criteria are investigated. Section 4 provides the experimental results. Section 5 contains the conclusions. Table 3 contains the details of the experimental results.

2. The multiple criteria approach for cell formation

In practice, mutually independent machine-part cells do not exist for most problems (for more information about Group Technology see Chandrasekharan and Rajagopalan (1986); Malakooti and Yang, (1995)). This means that the corresponding exceptional parts need to be moved among different machine cells. In order to decrease this kind of intercell part flow, the corresponding bottleneck machines need to be duplicated. Duplicating machines can decrease intercell part flow but will increase the capital cost and may decrease the machine utilization rate. There is a trade-off among intercell part flow and capital cost, as well as other criteria such as machine utilization, cell utilization, machine loading, etc. Most of the methods require the number of cells, R, to be given (known) parameter. However in practical design, the number of cells is unknown and needs to be determined. In this paper, we propose an approach to identify the most preferred alternative. Clearly, to put all machines and parts into one single cell or to create a unique cell for each machine does not make any sense. We assume that the minimum number of machine-part cells $R_{\min}$ is two.

2.1. *Model formulation*

2.1.1. *Definitions*

1. An alternative a_i is a machine-part cell structure which can be represented as $\{(m_{ir}, p_{ir}),\ r = 1, 2, \ldots, R\}$, where m_{ir} is the index set of machines in cell r, p_{ir} is the index set of parts in cell r, and R is the number of cells.
2. $R_{\min}$ is the minimum possible number of cells and $R_{\max}$ the maximum possible number of cells.

3. The machine utilization rate (MU) can be computed;

$$MU = N1/\left(\sum_{r=1}^{R} m_r n_r\right),$$

where $N1$ is the total number of ones within the cells, R is the number of cells, m_r is the number of machines in the rth cell, and n_r is the number of components in the rth cell (Chandrasekharan and Rajagopalan, 1986). Generally speaking, the higher the MU, the better the machines are being utilized.

2.1.2. *The model*

2.1.2.1. The multiple criteria problem: Problem (P1): From the set of q alternatives (machine-part cell structures) $A = \{a_i, i = 1, 2, \ldots, q\}$, find the alternative that optimizes the following objectives:

min $f_1(a_i)$ = number of duplicated machines;
min $f_2(a_i)$ = number of exceptional elements;
max $f_3(a_i)$ = machine utilization rate,

where

$$a_i \in A.$$

We define the normalized values of $f_1(a_i)$, $f_2(a_i)$, and $f_3(a_i)$ as:

$$f_1^*(a_i) = (f_{1\max}(a_i) \times f_1(a_i))/(f_{1\max}(a_i) \times f_{1\min}(a_i)), \quad (1)$$

$$f_2^*(a_i) = (f_{2\max}(a_i) \times f_2(a_i))/f_{2\max}(a_i) \times f_{2\min}(a_i)), \quad (2)$$

$$f_3^*(a_i) = f_3(a_i). \quad (3)$$

Then the problem can be formulated as:

$$\max f_1^*(a_i),$$
$$\max f_2^*(a_i),$$
$$\max f_3^*(a_i),$$
$$a_i \in A.$$

We generate all non-dominated (or efficient) alternatives for each given value of cell numbers, R, i.e., solve the following problem for each R, where R is the number of cells, ranging from $R_{\min}$ to $R_{\max}$.

For each given value of number of cells (R), solve,

$$\max f_1^*(a_i),$$
$$\max f_2^*(a_i),$$
$$\max f_3^*(a_i),$$
$$a_i \in A.$$

The set of solutions to the above problem is discrete. One set of approaches for solving discrete multiple criteria decision making problems (Steuer, 1986; Malakooti, 1989; Malakooti and Zhou, 1994) are based on assuming that there exists a composite objective (so-called utility or value function) for a given decision-maker that can be assessed in order to rank alternatives and find the most preferred alternative. Efficiency or non-dominancy is a well-known definition that can be used to screen out alternatives that cannot be selected as the most preferred alternative. For the three objective problem assuming all objectives are to be maximized, the definition is as follows:

An alternative $a_i \in A$ is non-dominated if and only if there does not exist any other alternative $a_{i'} \in A$, such that $f_1^*(a_{i'}) \geq f_1^*(a_i)$, $f_2^*(a_{i'}) \geq f_2^*(a_i)$, and $f_3^*(a_{i'}) \geq f_3^*(a_i)$ where at least one of above inequalities is greater than (>).

For example, (2, 10, 6) dominates (2, 9, 6), but does not dominate (3, 8, 5); from these three alternatives, alternative (2, 9, 6) can be eliminated. In practice, there may exist many dominated alternatives that need not be generated or evaluated. In our Multiple Criteria Decision-Making (MCDM) approach to cell formation, we use the non-dominancy definition to avoid generating or evaluating useless alternatives.

2.1.2.2. The additive composite utility function: Problem (P2). Given that the composite utility function is additive, we propose to solve the MCDM cell selection problem as follows:

Step 1. For each given number of cells R, generate the set of non-dominated alternatives $A = \{a_i, \ i = 1, 2, \ldots, q\}$, find the most preferred alternative which maximizes the utility function for the first three objectives:

Maximize
$$U(a_i) = w_1 f_1^*(a_i) + w_2 f_2^*(a_i) + w_3 \, f_3^*(a_i),$$
$$a_i \in A,$$

where $w_1 + w_2 + w_3 = 1$ and w_1, w_2, $w_3 > 0$. w_1, w_2, and w_3 are known; they are the weights of importance given by the decision-maker for the first three objectives respectively.

Step 2. For each given R value, find the best alternative $a_i \in A$ such that $U(a_i) \geq U(a_{i'})$ for any $a_{i'} \in A$. Then for each given R, one best alternative is selected.

Step 3. Now the decision maker is presented with $R_{\max} - R_{\min}$ number of MCDM alternatives from which he or she should select the best one.

2.2. *A three-level approach to find the best alternative*

2.2.1. *Level 1*

For each given number of cells solve the family formation problem using one of the existing machine-part cell formation methods (Chandrasekharan and Rajagopalan 1986; Srinivasan *et al.*, 1990; Kusiak *et al.*, 1992). The generated alternative for each given R is called a seed alternative. We start the cell number at $R_{\min} = R = 2$ and increase R to $R + 1$ and solve the problem again, repeat this procedure until $R = R_{\max}$.

For a given R, we define an alternative to be a local non-dominated alternative if it is non-dominated with respect to a set of alternatives generated in the vicinity of the seed alternative. Clearly, the seed alternative is a local non-dominated alternative because the number of duplicated machines of the seed alternative is zero (which is the maximum value of f_1^*).

In our experiments, we used the neural network-based machine-part cell formation method (Malakooti and Yang, 1995) to form the seed alternatives for each cell; however, as stated before, any other family formation method can be used to generate the seed alternative.

2.2.2. *Level 2*

For the given R, generate a set of local non-dominated alternatives from the seed alternative using the following heuristic procedure:

Step 1. If there are no exceptional elements in the seed alternative, stop!
Step 2. Find the bottleneck machine j^* with the most exceptional elements.
Step 3. Find the corresponding machine-part cell C_r^* in which the most parts need to be processed on bottleneck machine j^*.
Step 4. Duplicate machine j^*, and put it in cell C_r^*; now a new local non-dominated alternative is generated.
Go to Step 1.

Using the above heuristic procedure, new alternatives are generated by duplicating one bottleneck machine (at a time) to decrease the number of exceptional elements. Although f_1^* of a new alternative decreases, the corresponding f_2^* increases. We conclude that the generated alternatives are always local non-dominated with respect to the two criteria f_1^* and f_2^*.

2.2.3. *Level 3*

Once all local non-dominated alternatives for all values of R are generated, we check the efficiency definition for all alternatives and remove all inefficient (or dominated) alternatives.

In this step, the decision-maker is asked to choose the best alternative for each given R, this selection can be achieved by direct paired comparison of alternatives or using the additive composite utility function (Problem (P2)). After identifying the best alternative for each given R, then the decision-maker is asked to choose the best alternative from this set of $R_{\max} - R_{\min}$ number of alternatives.

3. An example to explain the three-level MCDM approach and the relationships among criteria

In this section, we first solve an example problem in detail using the developed approach. We then investigate the relationship among the following criteria: the number of duplicated machines, the number of exceptional elements, and the machine utilization rate.

3.1. *An example*

The system has 10 machines and 15 parts. Figure 3 shows the incidence matrix. The number of cells are $R = 2$, 3, 4, and 5.

3.1.1. *Level 1*

For illustrative purposes let consider $R = 3$. To show the multi-criteria alternatives associated with $R = 3$, we first generate a seed alternative for solving the machine cell formation using any of the existing methods. As an example, we can use the Artificial Neural Network (ANN)-based method (Malakooti and Yang, 1995) to form the seed alternative. The following is a brief summary of the ANN-based method: input a pattern (a machine vector or a part vector) to the two-layer neural network; compute the distance between the input pattern and three cluster centers (weight vectors); the node with the shortest distance is the winning node and the input pattern belongs to the corresponding cluster; update the weight vector according to an update equation; repeat the steps until an error criterion is satisfied. The neural network clustered patterns corresponding to machines 01, 06, and 07 into cluster 1; patterns corresponding to machines 02, 05, and 10 into cluster 2; patterns corresponding to machines 03, 04, 08, and 09 into cluster 3.

Machine \ Part	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
01		1					1				1	1			
02					1				1	1			1		1
03	1		1			1	1	1					1	1	
04	1		1	1		1								1	
05								1	1	1			1		1
06		1	1			1	1				1	1			
07		1									1	1			
08	1		1	1		1								1	
09		1	1	1		1						1		1	
10					1			1	1	1			1		1

Fig. 3. A system with 10 machines and 15 parts.

Machine \ Part	2	7	11	12	5	8	9	10	13	15	1	3	4	6	14
01	1	1	1	1											
06	1	1	1	1								1		1	
07	1		1	1											
02					1		1	1	1	1					
05						1	1	1	1	1					
10					1	1	1	1	1	1					
03		1				1			1		1	1		1	1
04											1	1	1	1	1
08											1	1	1	1	1
09	1			1								1	1	1	1

Fig. 4. The seed alternative for cell number $R = 3$.

Machine \ Part	2	7	11	12	5	8	9	10	13	15	1	3	4	6	14
01	1	1	1	1											
06	1	1	1	1								1		1	
07	1		1	1											
02					1		1	1	1	1					
05						1	1	1	1	1					
10					1	1	1	1	1	1					
03'						1			1						
03		1									1	1		1	1
04											1	1	1	1	1
08											1	1	1	1	1
09	1			1								1	1	1	1

Fig. 5. The alternative generated from the seed alternative.

The procedure was repeated for part vectors. Figure 4 shows the final matrix by the ANN-based method. In this case $f_1 = 0$ (number of duplicated machines), $f_2 = 7$ (number of exceptional elements) and $f_3 = (11 + 16 + 18)/(4 \times 3 + 6 \times 3 + 5 \times 4) = 0.90$.

3.1.2. *Level 2*

Step 1. Are there any exceptional elements? Yes.

Step 2. Find the bottleneck machine j^* with the most exceptional elements. j^* = machine 03 (three exceptional elements).

Step 3. Find the corresponding machine-part cell C_r^* in which the most parts need to be processed on machine 03. $C_r^* = C_2$.

Step 4. Duplicate machine 03 and put it in cell C_2 to form a new alternative, $f_1 = 1$, $f_2 = 5$ and $f_3 = 0.84$.

Repeat Steps 1–4 until there are no exceptional elements in the incidence matrix. We can generate four alternatives.

For the given three cells ($R = 3$), the objective values of these alternatives are given in Table 1.

Using the same procedure, when we set the cell number $R = 2$, 4, and 5, we can generate corresponding seed alternatives and generate the sets of local non-dominated alternatives. Figure 6 shows the seed alternative for $R = 2$, Fig. 7 shows the seed alternative for $R = 4$, and Fig. 8 shows the seed alternative for $R = 5$. We do not increase the cell number beyond $R = 5$ because a cell with only one machine in it appears when $R = 5$ (see Fig. 8).

In Table 2, we list all 29 alternatives for this problem. We normalize the first three objective values using

Machine \ Part	5	8	9	10	13	15	1	3	4	6	14	2	7	11	12
02	1		1	1	1	1									
05		1	1	1	1	1									
10	1	1	1	1	1	1									
03		1			1		1	1		1	1		1		
04							1	1	1	1	1				
08							1	1	1	1	1				
09								1	1	1	1	1			1
01												1	1	1	1
06								1		1		1	1	1	1
07												1		1	1

Fig. 6. The seed alternative for $R = 2$.

Table 1. The objective values of all five alternatives when $R = 3$

	a_3	a_4	a_5	a_6	a_7
Number of duplicated machines: f_1	0	1	2	3	4
Number of exceptional elements: f_2	7	5	3	1	0
Machine utilization rate: f_3	0.90	0.84	0.80	0.78	0.75

Machine \ Part	2	7	11	12	5	8	9	10	13	15	1	3	14	4	6
01	1	1	1	1											
06	1	1	1	1								1			1
07	1		1	1											
02					1		1	1	1	1					
05						1	1	1	1	1					
10					1	1	1	1	1	1					
03		1				1			1		1	1	1		1
04											1	1	1	1	1
08											1	1	1	1	1
09	1			1								1	1	1	1

Fig. 7. The seed alternative a_0 for $R = 4$.

Machine \ Part	2	7	11	12	5	9	10	8	13	15	1	3	14	4	6
01	1	1	1	1											
06	1	1	1	1								1			1
07	1		1	1											
02					1	1	1								
05						1	1	1	1	1					
10					1	1	1	1	1	1					
03		1						1	1		1	1	1		1
04											1	1	1	1	1
08											1	1	1	1	1
09	1			1								1	1	1	1

Fig. 8. The seed alternative a_0 for $R = 5$.

Equations (1), (2) and (3). The normalized objective values are f_1^*, f_2^*, and f_3^* respectively. For each given R value, if the decision-maker's preference weights are known, the best alternative is the one with the highest utility value for that given number of cells (R). For the purpose of illustration, we show our results for two different sets of values of weights, which could represent the respective preferences of two different decision-makers. The two sets of weights are: $w_1 = w_2 = w_3 = 1/3$, and $w_1 = 0.2$, $w_2 = 0.4$, $w_3 = 0.4$, respectively. Then we calculate utility values corresponding to these two sets of weights. U_1 is the utility value corresponding to $w_1 = w_2 = w_3 = 1/3$, U_2 is the utility value corresponding to $w_1 = 0.2$, $w_2 = 0.4$, $w_3 = 0.4$.

Suppose that the decision-makers utility is U_1 i.e., $w_1 = w_2 = w_3 = 1/3$. For two cells, $R = 2$, either alternatives 1 or 2 are the best alternatives. For $R = 3$, alternative 3 is the best one; for $R = 4$, alternatives 9 or 10 are the best ones; and for $R = 5$, alternatives 20, 21, or 22 are the best ones. At this stage, the decision-maker is asked for paired comparison of above alternatives, that is finding the best one from the set of alternatives, 1, 2, 3, 9, 10, 20, 21, and 22.

For example, suppose that the decision-maker selects alternative 3 (a_3) which is associated with three cells ($R = 3$). See Fig. 9 for the alternative 3, a_3. For this alternative the number of duplicated machines is zero, the number of exceptional elements is seven, and the machine utilization rate is 0.90.

Now suppose that the decision-maker's weights of importance for objectives are: $w_1 = 0.2$, $w_2 = 0.4$, and $w_3 = 0.4$, and after the comparison of the best alternatives for different R values, the decision-maker selects alternative 6, a_6, as the best one, see Fig. 10 for details of this alternative. For this alternative the number of duplicated machines is three, the number of exceptional elements is one, and the machine utilization rate is 0.78.

We note that different decision-maker's may choose different values of R and assess different weight values for objectives than those given in these examples.

3.2. *Some observations about the relationships among criteria*

We now use the data obtained by solving the above example problem to demonstrate the relationships among criteria. We try to construct relationships for the following pairs of criteria: the machine utilization rate and the cell numbers, the number of exceptional elements and the cell numbers, the machine utilization rate and the number of duplicated machines, the number of exceptional elements and the number of duplicated machines.

The machine utilization rate (where no duplicated machines are allowed) increases when the number of cells increases. The number of exceptional elements (where no duplicated machines are allowed) increases when the number of cells increases. For a given number of cells, the machine utilization rate decreases when the number of duplicated machines increases. For a given number of cells, the number of exceptional elements decreases when the number of duplicated machines increases.

For a given (constant) number of duplicated machines, as R increases, the machine utilization also increases. Similarly, for a given machine utilization when R increases, the number of duplicated machines also increases. One can also conclude that, for a given R, as the number of exceptional elements increases, the machine utilization also increases.

4. Experimental results

To test our approach, we programmed it in the C language and ran it on an IBM/486 compatible PC. We collected

Table 2. The 29 alternatives generated by the developed procedure

	$R=2$		$R=3$					$R=4$			
	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	a_{11}
Number of duplicated machines: f_1	0	1	0	1	2	3	4	0	1	2	3
Number of exceptional elements: f_2	2	0	7	5	3	1	0	15	12	10	8
Machine utilization rate: f_3	0.59	0.57	0.90	0.84	0.80	0.78	0.75	0.93	0.93	0.93	0.90
Normalized value of f_1 using Equation (1): f_1^*	1.00	0.91	1.00	0.91	0.82	0.73	0.64	1.00	0.91	0.82	0.73
Normalized value of f_2 using Equation (2): f_2^*	0.90	1.00	0.65	0.75	0.85	0.95	1.00	0.25	0.40	0.50	0.60
Normalized value of f_3 using Equation (3): f_3^*	0.59	0.57	0.90	0.84	0.80	0.78	0.75	0.93	0.93	0.93	0.90
U_1 ($U_1 = 1/3(f_1^*) + 1/3(f_2^*) + 1/3(f_3^*)$)	0.83	0.83	0.85	0.83	0.82	0.82	0.80	0.73	0.75	0.75	0.74
U_2 ($U_2 = 0.2(f_1^*) + 0.4(f_2^*) + 0.4(f_3^*)$)	0.80	0.81	0.82	0.82	0.82	0.84	0.83	0.67	0.71	0.74	0.75

Machine \ Part	2	7	11	12	5	8	9	10	13	15	1	3	4	6	14
01	1	1	1	1											
06	1	1	1	1								1		1	
07	1		1	1											
02					1		1	1	1	1					
05						1	1	1	1	1					
10					1	1	1	1	1	1					
03		1				1			1		1	1		1	1
04											1	1	1	1	1
08											1	1	1	1	1
09	1			1								1	1	1	1

Fig. 9. The best machine-part cell structure for $w_1 = w_2 = w_3 = 1/3$.

Machine \ Part	2	7	11	12	5	8	9	10	13	15	1	3	4	6	14
01	1	1	1	1											
06	1	1	1	1											
07	1		1	1											
09'	1			1											
02					1		1	1	1	1					
05						1	1	1	1	1					
10					1	1	1	1	1	1					
03'						1			1						
06'												1		1	
03		1									1	1		1	1
04											1	1	1	1	1
08											1	1	1	1	1
09												1	1	1	1

Fig. 10. The best machine-part cell structure for $w_1 = 0.2$, $w_2 = 0.4$, and $w_3 = 0.4$.

eight problems from the literature and solved them using the developed approach. We summarize the experimental results in Table 3. For the purpose of the experiment, we chose two sets of preference weights: (i) $w_1 = w_2 = w_3 = 1/3$; and (ii) $w_1 = 0.2$, $w_2 = 0.4$, and $w_3 = 0.4$. We calculated utility values for these two sets of weights respectively. Then, the best alternatives corresponding to these two sets of weights were found. We also list the approximate computational time for each problem.

5. Conclusions

In this paper, we developed a multiple criteria decision-making approach to obtain the most preferred alternative for the machine-part cell formation problems when there exist conflicting objectives. We developed a three-level method. We first generate a seed machine-part cell alternative for a given number of cells. For this alternative, a set of non-dominated alternatives are generated. We considered the following objective functions: the number of duplicated machines; the number of exceptional elements; and the machine utilization rate. In this paper, we address three objectives; however, in practice one may choose two of these three objectives. Alternatively, one may consider more than three objectives; or develop one's own definition of such objectives. The contribution of this paper is the presentation of an algorithm that shows how to formulate and solve multi-objective cell formation problems by generating non-dominated alternatives. Thus, one can use or develop other objectives and still use our approach with the same principles for generating efficient (non-dominated) alternatives.

Number of cells																	
$R = 4$						$R = 5$											
a_{12}	a_{13}	a_{14}	a_{15}	a_{16}	a_{17}	a_{18}	a_{19}	a_{20}	a_{21}	a_{22}	a_{23}	a_{24}	a_{25}	a_{26}	a_{27}	a_{28}	a_{29}
4	5	6	7	8	9	0	1	2	3	4	5	6	7	8	9	10	11
6	4	3	2	1	0	20	17	14	12	10	8	6	4	3	2	1	0
0.88	0.83	0.79	0.78	0.77	0.75	0.97	0.97	0.97	0.97	0.95	0.93	0.90	0.88	0.87	0.86	0.83	0.79
0.64	0.55	0.45	0.36	0.27	0.18	1.00	0.91	0.82	0.73	0.64	0.55	0.45	0.36	0.27	0.18	0.09	0.00
0.70	0.80	0.85	0.90	0.95	1.00	0.00	0.15	0.30	0.40	0.50	0.60	0.70	0.80	0.85	0.90	0.95	1.00
0.88	0.83	0.79	0.78	0.77	0.75	0.97	0.97	0.97	0.97	0.95	0.93	0.90	0.88	0.87	0.86	0.83	0.79
0.74	0.73	0.70	0.68	0.66	0.64	0.66	0.68	0.70	0.70	0.70	0.69	0.68	0.68	0.66	0.65	0.62	0.60
0.76	0.76	0.75	0.74	0.74	0.74	0.59	0.63	0.67	0.69	0.71	0.72	0.73	0.73	0.74	0.74	0.73	0.72

Table 3. A summary of the experimental results

Problem number	*Number of parts*	*Number of machines*	*Number of alternatives*	*Number of efficient alternatives*	*Best alternative (1)*; R*	*Best alternative (2)*; R*	*Computation time (seconds)*
1	7	5	8	8	$a_{1;\,2}$	$a_{3;\,2}$	3
2	7	5	8	8	$a_{1;\,2}$	$a_{3;\,2}$	3
3	7	5	10	10	$a_{1;\,2}$	$a_{3;\,2}$	4
4	7	5	10	10	$a_{1;\,2}$	$a_{3;\,2}$	4
5	15	10	14	13	$a_{2;\,3}$	$a_{2;\,3}$	5
6	15	10	28	22	$a_{1;\,2}$	$a_{1;\,2}$	9
7	10	12	21	21	$a_{1;\,2}$	$a_{4;\,3}$	7
8	20	8	46	16	$a_{7;\,3}$	$a_{7;\,3}$	15

*(1)**: If $w_1 = w_2 = w_3 = 1/3$ and for given number of cells (R).
*(2)**: If $w_1 = 0.2$, $w_2 = 0.4$, and $w_3 = 0.4$ and for given number of cells (R).

We developed a systematic approach for generating non-dominated alternatives for each given number of cells. We demonstrated that all non-dominated alternatives can be generated by an enumeration method (i.e., generating of non-dominated alternatives for each and all of the cells).

We successfully solved and obtained the most preferred alternative for several well-known problems from the literature using our approach developed in this paper. We also investigated the relationships among the criteria for different alternatives.

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Contributed by the Computer Technologies and Information Systems Department.