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Original Article

Effective fuzzy multi–objective model based on perfect grouping for manufacturing cell formation with setup cost constrained of machine duplication

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Abstract

At present, methods for solving the manufacturing cell formation with the assignment of duplicated machines contain many steps. Firstly, part families and machine cells are determined. Then, the incidence matrix of the cell formation is re-considered for machine duplications to reduce the interaction between cells with the restriction of cost. These ways are difficult and complicated. Besides, consideration of machine setup cost should be done simultaneously with the decision making. In this paper, an effective lexicographic fuzzy multi–objective optimization model for manufacturing cell formation with a setup cost constrained of machine duplication is presented. Based on the perfect grouping concept, two crucial performance measures called exceptional elements and void elements are utilized in the proposed model. Lexicographic fuzzy goal programming is applied to solve this multi–objective model with setup cost constraint. So, the decision maker can easily solve the manufacturing cell formation and control the setup cost of machine duplication, simultaneously.

Keywords: manufacturing cell formation, machine duplication, setup cost constrained, perfect grouping concept, lexicographic fuzzy goal programming

1. Introduction

One of the most important problems in cellular manufacturing systems (CMS) is the manufacturing cell formation problem. It is an application of group technology (GT). It faces classifying parts into part families and grouping machines into machine cells (Chandrasekharan and Rajagopalan, 1987; Chu and Hayya, 1991). In the part-family classifying, similar geometries, functions, materials and/or production processes are commonly considered (Wei and Kern, 1989). Whereas in the machine-cell grouping, necessary machines involving each part family are assigned to the manufacturing cells (Chu and Hayya, 1991; Kusiak and Cho, 1992; Mahdavi *et al.*, 2010a). This kind of problem is known as NP-complete (Wang, 1998; Wang, 2003; Fallahalipour *et al.*, 2011; Arkat *et al.*, 2012; Nouri and Hong, 2013).

The cellular layout in CMS is one of the key elements of lean production (Russell and Taylor, 2006). It is more advantageous comparing to process and product layouts. In process layout, moving and carrying in-process parts from one machine center to another are needed. So, waste of transporting parts is high especially for large batch sizes. Whereas, fast changes in product life cycle and the development of production system require layouts re–arrangement in product layout. Conversely, necessary machines of each product group are already set in the cell of cellular layout. So, setup and rearrangement of machines during the production period are needless. All products can be processed within their own manufacturing cell. Moreover, new products can be assigned to the cell which the necessary machines are already orga-

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nized. The flexibility of the cellular layout is proper for the modern manufacturing system.

Various methods for solving the manufacturing cell formation have been proposed (Papaioannou and Wilson, 2010). Basically, rearranging the rows and columns of the incidence matrix is the fundamental idea for solving this problem. The well-known matrix rearrangement methods are the bound energy (BE) algorithm and rank order cluster (ROC) algorithm (King, 1980; Chandrasekharan and Rajagopalan, 1987; Wei and Kern, 1989; Boctor, 1991; Song and Hitomi, 1992). However, solving the manufacturing cell formation problem using these methods is complicated and difficult, particularly in a real-world large-scale problem because a decision maker (DM) has to face the vast incidence matrix. Moreover, the number of cells is a result obtained by this kind of method so it cannot be controlled (Kusiak, 1985).

A more efficient method introduced by Kusiak (1987) called *p*-median based on a similarity between any two parts is a well-known mathematical method (Boctor, 1991; Song and Hitomi, 1992; Wang and Roze, 1994; Wang, 1998). This method can get the cell formation solution satisfyingly. Nevertheless, the *p*-median method requires two solving processes, which are part-family and machine-cell. Numerous mathematical programming approaches have also been proposed. The optimal solution can be guaranteed (Tsai and Lee, 2006; Mahdavi *et al*., 2007; Paydar and Sahebjamnia, 2009; Mahdavi *et al*., 2010b; Elbenani and Ferland, 2012).

Compromised metaheuristic methods also have been presented to solve this kind of problem (Carrie, 1973; Boctor, 1991; Adenso-Diaz *et al*., 2001; Adenso-Diaz *et al*., 2005; Dimopoulos, 2006; Fallahalipour *et al*., 2011; Xing *et al*., 2009; Tavakkoli-Moghaddam *et al*., 2011; Chattopadhyay *et al*., 2012; Tavakkoli-Moghaddam *et al*., 2012; Nouri and Hong, 2013). Many research papers have applied the notable metaheuristic algorithms such as genetic algorithm (GA) (Onwubolu and Mutingi, 2001; Wu *et al*., 2006; Mahdavi *et al*., 2009; Arkat *et al*., 2011), Simulated Annealing (SA) (Safaei *et al*., 2008; Tavakkoli-Moghaddam *et al*., 2008; Wu *et al*., 2008; Fallahalipour *et al*., 2011; Dalfard, 2013) and evolutionary algorithm (EA) (Dimopoulos and Zalzala, 2000; Goncalves and Resende, 2004). The advantage of these metaheuristic approaches is that acceptable solutions can be easily obtained by avoiding the complexity in solving such multivariate data of the manufacturing cell formation problem. However, the efficient solutions of these metaheuristic methods are not always guaranteed. So, more effective methods for solving the manufacturing cell formation problem are still needed (Nunkaew and Phruksaphanrat, 2011a, 2011b).

Normally, in the conventional methods, each machine has been assigned to only one machine cell (Mahdavi *et al*., 2007; Paydar and Sahebjamnia, 2009; Elbenani and Ferland, 2012). So, parts may need to be operated by the machine outside the cell. This interaction between two machine cells is regularly unavoidable in the solutions of manufacturing cell formation. This interaction can be shown by "exceptional elements" in the incidence matrix (Boctor, 1991; Wang and Roze, 1997). These unwanted elements may result in an increase of material handling, scheduling complication, cost of moving parts between cells and decreasing of operating quality. To solve such problem, assigning duplicated machines is needed to eliminate transferring parts between cells with the additional cost of machine setup. Assigning the duplicated machines has been suggested in many researches (Seifoddini and Wolfe, 1986; Wang and Roze, 1997; Nunkaew and Phruksaphanrat, 2012, 2013a). However, in the duplication process outlined in most of the research work and manufacturing systems (assignment of the duplicated machines to the appropriate machine cells) the DM has to reassign the duplicated machines after the manufacturing cell formation process (Seifoddini and Wolfe, 1986; Seifoddini, 1989; Wu, 1998; Botolini *et al*., 2011). This assignment creates an inconvenience, especially for huge practical cell formation problems. Besides, the consideration of machine setup cost should be done concurrently in the decision making of the DM.

Therefore, the lexicographic fuzzy multi–objective optimization (LFMO) model for solving the manufacturing cell formation with the assignment of duplicated machine and the consideration of machine setup cost is proposed in this paper based on *perfect grouping concept*. Consideration of exceptional elements and void elements are included in the proposed mathematical model. Moreover, the financial consideration of machine setup cost is also included.

2. Manufacturing Cell Formation and Machine Duplication

The manufacturing cell formation is concerned with the classification of parts into *part families* and grouping machines into *machine cells* in CMS as shown in Figure 1. In part family design, parts can be formed based on similar geometries, functions, materials or processes. Meanwhile, in

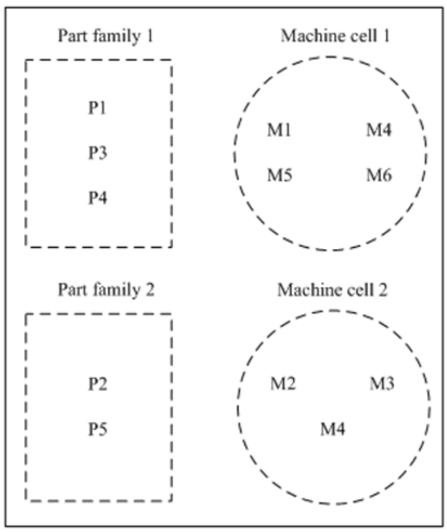

Figure 1. Cellular manufacturing system with two part families and two machine cells.

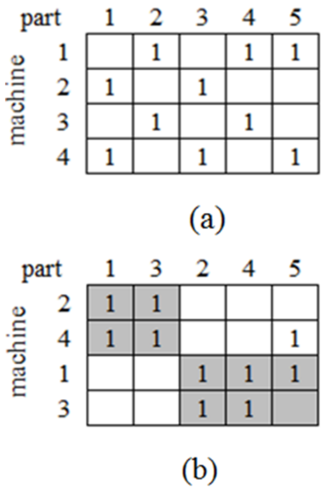

Figure 2. Part-machine incidence matrix of five parts and four machines.

machine cell design, dissimilar machines are brought together and then dedicated to the involved part family (Offodile, 1992; Wang, 1998; Wang, 2003; Papaioannou and Wilson, 2010; Nouri and Hong, 2013). Consequently, the manufacturing cell formation is seemly to decompose a manufacturing system into sub-systems (Kusiak, 1987).

To show the relationship between parts and machines, the part-machine incidence matrix, $\{ a_{ij} \}$ is defined. The part-machine incidence matrix is a set in which columns and rows represent parts and machines, respectively. The zero-one matrix is considered that the (i,j)th element of $\{ a_{ij} \}$ is 1 if the j-th part needs to operate on the i-th machine; otherwise it is 0. The result of the manufacturing cell formation is obtained as a diagonal block (Boctor, 1991; Kusiak and Cho, 1992). As shown in Figure 2(a), the part-machine incidence matrix of five parts and four machines is created. For example, part 1 has to operate on machine number 2 and 4. After rearranging the columns and rows, the result of part-machine cell formation is shown in Figure 2(b).

Practically, not all parts within the part family can constantly be processed only within a single machine cell. So, interaction between two machine cells is always unavoidable. For example, the element a_{45} in Figure 2(b) is an inter-cell movement as mentioned above. One solution to eliminate this element is that machine 4 should be duplicated and assigned to both cells for increasing production performance because part 5 does not have to be processed outside the belonging cell anymore. Such assignment of the duplicated machine can eliminate transferred parts between cells as shown in Figure 3. However, setup cost of the duplicated machine is needed.

In a machine duplication process of existing methods, the DM has to assign the duplicated machines by him/herself. For example, from the method introduced by Seifoddini and Wolfe (1986), it is suggested that the DM starts the duplication process to the machine that creates the largest number of exceptional elements or the interaction between cells and continues the duplication process to the remaining bottleneck machines. By this method, the DM has to decide how many duplicated machines should be added, which is complicated. At the same time, setup cost of machines has to be considered after the duplication process. So, the DM should seriously pay attention when he or she follows this approach.

3. Fuzzy Multi–objective Optimization Model based on Perfect Grouping Concept

In this section, we propose a fuzzy multi–objective optimization model for manufacturing cell formation in CMS. The following notations are used in the proposed model.

Index sets:

i index of machine, for all $i = 1, 2, \ldots, m$.

j index of part, for all $j = 1, 2, \ldots, p$.

k index of cell, for all $k = 1, 2, \ldots, n$.

g index of objective or goal, for all $g = 1, 2, \ldots, q$.

Decision variables:

x_{ik} is 1 if machine i is assigned to cell k; otherwise x_{ik} is 0.

y_{jk} is 1 if part j is assigned to family k; otherwise y_{jk} is 0.

Parameters:

a_{ij} is 1 if the j-th part needs to operate on the i-th machine; otherwise a_{ij} is 0.

U is the total number of 1s contained in the incidence matrix, $\{ a_{ij} \}$ calculated as $U = \sum_{i=1}^{m} \sum_{j=1}^{p} a_{ij}$.

m_k^u is the maximum number of allowed machines in each cell k.

m_d^l and m_d^u are the minimum and maximum limits for the number of duplicated machines.

T_s^u is the maximum acceptable value for the total setup cost.

s_i is the setup cost of duplicated machine i.

3.1 The concept of perfect grouping

In the concept of perfect grouping, all 1s occupy in the diagonal sub-matrices, and all 0s are arranged in the off-diagonal sub-matrices (Chandrasekharan and Rajagopalan, 1986a; Chandrasekharan and Rajagopalan, 1986b; Chandrasekharan and Rajagopalan, 1987; Nunkaew and Phruksaphanrat, 2013b) as shown in Figure 4. This kind of matrix is

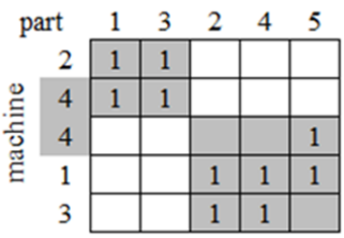

Figure 3. Machine duplication.

$$\begin{bmatrix}
1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1
\end{bmatrix}$$

Figure 4. Ideal-diagonal matrix.

called an *ideal-diagonal matrix*. However, the solution of the cell formation depends on the primary input data. Such an ideal-diagonal matrix may not always be obtained for a given data set or in practical real-world manufacturing cell formation problems.

There are many existing methods to solve a manufacturing cell formation. Some of those methods emphasize the mutuality in a group of parts or machines (Kusiak, 1987; Singh, 1993; Wang and Roze, 1997; Wang, 2003). Some methods attempt to create the block diagonalization of matrices (King, 1980; Chandrasekharan and Rajagopalan, 1987; Boctor, 1991). Moreover, mathematical and metaheuristic methods have also been proposed (Goncalves and Resende, 2004; Mahdavi *et al.*, 2007; Mahdavi *et al.*, 2009; Safaei *et al.*, 2008; Wu *et al.*, 2008; Paydar and Sahebjamnia, 2009; Mahdavi *et al.*, 2010b; Arkat *et al.*, 2011; Fallahalipour *et al.*, 2011, Dalfard, 2013). Nevertheless, obtaining solutions from existing methods are still inefficient when there are many parts and machines to be considered.

In this paper, two aspects of the perfect grouping concept are concerned. Firstly, the optimal solutions of manufacturing cell formation should not have any *exceptional elements*. Secondly, *void elements* are also not preferred. These two types of elements are the important performance measures of the perfect grouping (Wang, 2003; Nunkaew and Phruksaphanrat, 2013b). Exceptional and void elements are described in detail in the following subsections.

3.1.1 Exceptional elements

The e*xceptional elements* (EEs) are often contained in the manufacturing cell formation (Boctor, 1991; Wang and Roze, 1997). They indicate discrepancies in the sub-matrices. When an EE occurs, it means that the considered part operates on any machines outside the cell. So, the degree of interaction between cells can be evaluated by the number of EEs. As shown in Figure 2(b), the EE is represented by the element a_{45} (the element of part 5 that needs to operate on machine 4). This element does not belong to the same machine cell of the part 5's family. This kind of interaction between cells makes disadvantages in CMS. The DM has to pay more attention to operations between cells. So, the number of EEs must be minimized. The number of EEs can be quantitatively calculated by Equation 1.

$$EE = U - \sum_{k=1}^{n} \sum_{i=1}^{m} \sum_{j=1}^{p} x_{ik} y_{jk} a_{ij} \,. \tag{1}$$

Generally, conventional methods try to reduce the number of exceptional elements. However, void elements are ignored.

3.1.2 Void elements

The *void elements* (VEs) are used to evaluate the compactness of a part-machine cell design within block sub-matrices (Nunkaew and Phruksaphanrat, 2011b). The VE can be observed if part j does not require machine i, which is the machine in the machine cell of the part j's family. This phenomenon indicates that the ineffective solutions occur in the sub-matrices because there is a part that does not use all machines within the machine cell as shown in Figure 2(b). The element a_{35} (the element of part 5 and machine 3) is the VE because part 5 does not require machine 3 that is one of the machines within the machine cell for part 5's family. We can clearly see that part-machine cell will be better utilized if part 5 requires machine 3, and it is assigned to that cell because that sub-matrix would be considered to be a perfect grouping. The number of VEs can be calculated by

$$VE = \sum_{k=1}^{n} \sum_{i=1}^{m} \sum_{j=1}^{p} (1 - a_{ij}) x_{ik} y_{jk} \,. \tag{2}$$

3.2 Objective functions

This paper proposes the new method for solving the manufacturing cell formation based on the perfect grouping concept. Two elements of the perfect grouping, EEs and VEs, are considered in the proposed model. These elements should not exist in the resulting matrix. So, two objective functions can be explained in detail below.

Minimizing the number of EEs (first priority objective function)

$$\min\ f_1(x_{ik}, y_{jk}) = U - \sum_{k=1}^{n} \sum_{i=1}^{m} \sum_{j=1}^{p} x_{ik} y_{jk} a_{ij} \,. \tag{3}$$

The aim of this objective function in the proposed model is to find the solutions of manufacturing cell formation that has as few EEs as possible. By the idea of a perfect grouping, most of the elements should be assigned to sub-matrices which means that fewer EEs would occur.

Minimizing the number of VEs (second priority objective function)

$$\min\ f_2(x_{ik}, y_{jk}) = \sum_{k=1}^{n} \sum_{i=1}^{m} \sum_{j=1}^{p} (1 - a_{ij}) x_{ik} y_{jk} \,. \tag{4}$$

Although manufacturing cells in the CMS have several advantages, lower machine and labor utilization are common disadvantages (Singh, 1993). So, reducing the number of VEs should also be considered in the manufacturing cell formation to increase utilization of cells. The second objective function is considered to find the solutions of manufacturing cell formation that has as few VEs as possible. Most of 0s are not assigned to the sub-matrices, which mean that fewer VEs occur.

3.3 Linearization of the objective functions

Obviously, the term $x_{ik} y_{jk}$ (product of two binary variables) in Equations 3 and 4 are quadratic functions. So the objective functions are nonlinear functions that may cause a problem in solving efficiency especially in a large scale cell formation problem. To transform this nonlinear term into a linear binary programming, new additional variables w_{ijk} are used to replace a product of $x_{ik} y_{jk}$. Let $w_{ijk} = x_{ik} y_{jk}$ and w_{ijk} = 0 or 1. The following two linear constraints are added to the model (Chen *et al*., 2010);

$$x_{ik} + y_{jk} \leq w_{ijk} + 1, \forall i, \forall j, \forall k, \quad (5)$$

$$x_{ik} + y_{jk} \geq 2w_{ijk}, \forall i, \forall j, \forall k. \quad (6)$$

The new objective functions become

$$\min f_1(w_{ijk}) = U - \sum_{k=1}^{n} \sum_{i=1}^{m} \sum_{j=1}^{p} w_{ijk} a_{ij}, \quad (7)$$

and

$$\min f_2(w_{ijk}) = \sum_{k=1}^{n} \sum_{i=1}^{m} \sum_{j=1}^{p} (1 - a_{ij}) w_{ijk}. \quad (8)$$

3.4 Lexicographic fuzzy goal programming

Generally, in multi-objective problem, several conflicting objectives are considered. Such kind of the problem is called multiple objective decision making (MODM) problem. Methods to solve this problem are fuzzy linear programming (Li and Lai, 2000; El-Wahed, 2001), compromise programming (Zeleny, 1982; Romero, 1990), interactive approaches (Zeleny, 1982), etc. Furthermore, one of the most popular methods to solve MODM problems is goal programming (GP) (Charnes and Cooper, 1965; Zeleny, 1982; Romero, 1990).

However, in many MODM problems, certain goals are much more important than others. This means that the DM cannot simultaneously consider the attainment of all goals. Differentiating goals into different levels of importance, in which a higher level goal must first be satisfied before lower level goals are considered, called pre-emptive or lexicographic ordering. Fuzzy goal programming with a priority structure for ordering goals is called lexicographic fuzzy goal programming (LFGP) (Hannan, 1981; Li and Hwang, 1994). The LFGP model is defined as follows:

$$\text{lex max} = [p_1 f_1(\lambda), p_2 f_2(\lambda), ..., p_T f_T(\lambda)], \quad (9)$$

subject to

$$\lambda_g \leq \mu(f_g), \forall g, \quad (10)$$

$$\lambda_g \geq \lambda_g^*, \forall g, \quad (11)$$

$$\lambda_g \in [0,1], \forall g. \quad (12)$$

where λ_g is a satisfactory level for goal *g*, λ_g^* is an acceptable satisfactory level for goal *g*, and $\mu(f_g)$ is the membership function for goal *g*.

In LFGP, there are *T* priority levels (where each priority may include K_t goals for *t* = 1, 2,…, *T*) with pre-emptive weights $p_t >>> p_{t+1}$, and $f_t(\lambda)$ is the satisfactory function of priority *t*. The problem is then partitioned into *T* sub-problems or *T* fuzzy goal programming. For simplicity, the goals are ranked according to the following rule: if $r < s$, then goal set $G_r(x)$ has higher priority than goal set $G_s(x)$ (Li and Hwang, 1994; Nunkaew and Phruksaphanrat, 2010; 2011b).

3.5 Membership function

A fuzzy set (Zadeh, 1965; Zimmermann, 1978; 1991) is dedicated to each goal of the objective functions in the proposed model. Defining the specific target (τ_g) and acceptable deviation (Δ_g) of each goal *g* in setting the membership function is based on the positive-ideal solution (PIS) and negative-ideal solution (NIS) (Yoon and Hwang, 1995; Chen, 2000; Abo-Sinna *et al*., 2008). The PIS is the best possible solution (A^*) in which each objective function is optimized, whereas the NIS is the worst feasible value (A^-) for each objective function (Yoon and Hwang, 1995). By the PIS and NIS, all possible solutions can be covered in the membership function.

In the proposed model, the first goal is to reduce the number of EEs to the most preferred value. Similarly, the second goal is to reduce the number of VEs to the most preferred value. From the DM's viewpoint, the PIS is used to set the most preferred value with a satisfactory degree of 1. In the same way, a satisfactory degree of 0 is assigned to the NIS. Acceptable deviation from the goal can be calculated as the difference between the PIS and NIS ($\Delta_g = |\text{PIS - NIS}|$). Assume that a linear membership function under the *at most* fuzzy relation is used for each goal *g* (Phruksaphanrat and Ohsato, 2003; Phruksaphanrat and Ohsato, 2004). Then, the membership function of the *g*-th goal based on the DM's preference is shown in Figure 5. Mathematical representation of the membership function is given in Equation 13.

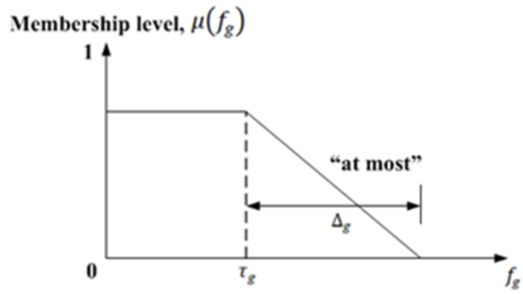

Figure 5. Linear membership function under the *at most* condition.

$$\mu(f_g)=\begin{cases}1, & \text{if } f_g \le \tau_g,\\ 1-\left(\dfrac{f_g-\tau_g}{\Delta_g}\right), & \text{if } \tau_g \le f_g \le \tau_g+\Delta_g,\\ 0, & \text{if } f_g \ge \tau_g+\Delta_g.\end{cases} \quad (13)$$

3.6 Proposed efficient fuzzy multi–objective model

In the proposed method, the LFGP model is constructed. The two fuzzy goals about EEs and VEs are considered. The satisfaction level (λ_g) of each goal g (g = 1, 2) needs to be satisfied consecutively. For applying the proposed model to solve the part-machine cell formation problem, the membership function ($\mu(f_g)$), the aspiration level (τ_g), the acceptable satisfactory level (λ_g^*) and the acceptable deviation (Δ_g) for each goal have to be set. To enhance the performance of the manufacturing cell, duplicated machines are usually assigned to the cell. This is the way to reduce interaction between cells. However, budget of machine setup cost should be in concern. This issue takes into account during the cell formation process. In this paper, the financial constraint about machine setup cost is added in the proposed formulation model to control the setup cost of machine duplication. Then, the proposed linearized LFMO model for the manufacturing cell formation problem with the assignment of duplicated machine and the consideration of machine setup cost is derived as follows,

$$\text{lex max}=[\lambda_1,\lambda_2], \quad (14)$$

subject to constraints (5) and (6),

$$\lambda_g \le 1-\left(\frac{f_g-\tau_g}{\Delta_g}\right), \ \forall g, \quad (15)$$

$$\lambda_g \ge \lambda_g^*, \ \forall g, \quad (16)$$

$$m_d^l \le \sum_{k=1}^{n} x_{ik} \le m_d^u, \ \forall i, \quad (17)$$

$$\sum_{i=1}^{m}(s_i \sum_{k=1}^{n} x_{ik}) \le T_s^u, \quad (18)$$

$$\sum_{k=1}^{n} y_{jk} = 1, \ \forall j, \quad (19)$$

$$\sum_{i=1}^{m} x_{ik} \le m_k^u, \ \forall k, \quad (20)$$

$$\sum_{i=1}^{m} x_{ik} \ge 1, \ \forall k, \quad (21)$$

$$\sum_{j=1}^{p} y_{jk} \ge 1, \ \forall k, \quad (22)$$

$$x_{ik}, y_{jk}, w_{ijk} = 0 \text{ or } 1, \ \forall i, \forall j, \forall k, \quad (23)$$

$$0 \le \lambda_g^* \le 1, \ \forall g. \quad (24)$$

Equation 14 is the objective function of the proposed model for lexicographically maximizing the satisfaction level of each fuzzy goal. Equations 15 and 16 are the satisfaction level of each fuzzy goal according to Equations 7 and 8. The limit for the number of duplicated machines is shown in Equation 17. The total setup cost of machine duplication is limited to T_s^u as shown in Equation 18. Equation 19 is added to ensure that each part will be assigned to only one cell. Equation 20 controls the number of machines in each cell k which is limited to m_k^u. Equations 21 and 22 are non-empty cell constraints. The binary decision variables are expressed in Equation 23. The acceptable satisfaction level of each goal is limited to values between 0 and 1 as shown in Equation 24. The effectiveness of the proposed linearized LFMO model for the manufacturing cell formation problem with the assignment of duplicated machine and the consideration of machine setup cost is illustrated in the following section. The number of variables and constraints in the proposed linearized model are presented in Table 1 and 2, respectively.

Table 1. Number of variables in the proposed linearized model.

Variable	Count
x_{ik}	$m \times n$
y_{jk}	$p \times n$
w_{ijk}	$m \times p \times n$
Sum = $(m \times n) + (p \times n) + (m \times p \times n)$	

Table 2. Number of constraints in the proposed linearized model.

Constraint	Count	Constraint	Count	Constraint	Count
(5)	$m \times p \times n$	(17)	m	(21)	n
(6)	$m \times p \times n$	(18)	1	(22)	n
(15)	q	(19)	p	(23)	$(m \times n) + (p \times n) + (m \times p \times n)$
(16)	q	(20)	n	(24)	q
Sum = $3(m \times p \times n) + (m \times n) + (p \times n) + 3(n+q) + m+1$					

Machines	Parts 1	2	3	4	5	6	7	8	9	10	11	12
A ($1,500)			1	1		1				1		
B ($2,000)	1	1		1	1				1	1	1	1
C ($3,500)		1	1	1	1	1			1		1	
D ($4,000)			1	1	1	1				1		
E ($3,000)							1					1
F ($2,150)				1		1	1			1		
G ($1,750)							1					1
H ($3,505)	1	1						1	1		1	

Figure 6. Incidence matrix and setup cost of machine i (s_i).

4. Numerical Example and Discussions

The 37-operations manufacturing cell formation problem, involving 12 parts and 8 machines has been selected as an example to demonstrate the efficiency of the proposed model. The incidence matrix and machine setup costs are shown in Figure 6. The part-machine cells can be formed using the p-median model, which is a similarity based methods or other traditional cell formation methods (Kusiak, 1987; Boctor, 1991; Wang and Roze, 1997). Nevertheless, the result obtained from these conventional methods solves only part families and machine cell problems but the assignment of duplicated machines (to eliminate the exceptional elements or interaction between cells) and also the total setup cost of selected machines are not considered.

Conversely, the proposed linearized LFMO model can solve both forming and duplicating processes at the same time. Moreover, the machine setup cost is also controlled. For this example, three cases of different minimum and maximum number of duplicated machine for each type of machine (m_d^l , m_d^u) are set. In applying the proposed model for this example, the DM firstly needs to find the PIS and NIS of each objective function for setting the aspiration level or goal and defining its membership function. Let P_1 , N_1 and P_2 , N_2 represents the PIS and NIS of objective 1 and objective 2 accordingly. These parameters of three cases are shown in Table 3.

Moreover, suppose the DM prefers the acceptable satisfaction levels of the first goal and the second goal (the λ_1^* and λ_2^*) of each case as shown in Table 4 under the following constraints. The number of manufacturing cells is three ($n = 3$). There are not more than six machines in each cell ($m_k^u = 6$) and not more than $32,000 is allowed for total machine setup cost ($T_s^u = 32{,}000$). So, the proposed linearized LFMO model for this example can be expressed as follows,

$$\text{lex max} = [\lambda_1, \lambda_2],$$

subject to

$$x_{ik} + y_{jk} \le w_{ijk} + 1,\ i = 1, 2, \ldots, 8, j = 1, 2, \ldots, 12, k = 1, 2, 3,$$

$$x_{ik} + y_{jk} \ge 2w_{ijk},\ i = 1, 2, \ldots, 8, j = 1, 2, \ldots, 12, k = 1, 2, 3,$$

$$\lambda_1 \le 1 - \left(\frac{[37 - \sum_{k=1}^{3} \sum_{i=1}^{8} \sum_{j=1}^{12} w_{ijk} a_{ij}] - \tau_1}{\Delta_1} \right),$$

$$\lambda_2 \le 1 - \left(\frac{[\sum_{k=1}^{3} \sum_{i=1}^{8} \sum_{j=1}^{12} (1 - a_{ij}) w_{ijk}] - \tau_2}{\Delta_2} \right),$$

$$\lambda_1 \ge \lambda_1^*,$$

$$\lambda_2 \ge \lambda_2^*,$$

$$m_d^l \le \sum_{k=1}^{3} x_{ik} \le m_d^u,\ i = 1, 2, \ldots, 8,$$

$$\sum_{i=1}^{8} (s_i \sum_{k=1}^{3} x_{ik}) \le 32{,}000,$$

$$\sum_{k=1}^{3} y_{jk} = 1, j = 1, 2, \ldots, 12,$$

$$\sum_{i=1}^{8} x_{ik} \le 6, k = 1, 2, 3,$$

$$\sum_{i=1}^{8} x_{ik} \ge 1, k = 1, 2, 3,$$

$$\sum_{j=1}^{12} y_{jk} \ge 1, k = 1, 2, 3,$$

$$x_{ik}, y_{jk}, w_{ijk} = 0 \text{ or } 1, i = 1, 2, \ldots, 8, j = 1, 2, \ldots, 12, k = 1, 2, 3,$$

$$0 \le \lambda_g^* \le 1, g = 1, 2.$$

Advantages of the proposed linearized LFMO model are not only the easiness in cell formation with the consideration of machine setup cost, but also the flexibility to find a satisfying solution. In the proposed model, there are three related important elements, which are a number of EEs, VEs and selected machines. Change in each element always affects the others. Illustratively, when the number of EEs is minimized, the number of VEs is increased in order to assign

Table 3. Parameters of three cases.

Case No.	m_d^l , m_d^u	P_1 , N_1	P_2 , N_2	τ_1 , τ_2
I	1 , 1	0 , 37	3 , 46	0 , 3
II	1 , 2	0 , 37	2 , 52	0 , 2
III	1 , 3	0 , 37	2 , 52	0 , 2

the EEs to the appropriate cell. Moreover, the duplicated machines are also added to support this activity. So, the setup cost of the machines also increased. Conversely, when EEs are acceptable and VEs is minimized, the number of selected machines can be reduced and only the necessary machines are assigned to the cell to maintain the important operations. Then, the setup cost of the machine can be decreased. By these phenomena, there are many alternative solutions in formulating the problem. Using the proposed model to solve this example, the DM can adjust the satisfactory values of the λ_1^* and λ_2^* to find the satisfied alternative solutions as detailed shown in Table 4. In case I, both of the minimum and maximum numbers of machine duplication for each type of machine are set to 1 ($m_d^l = 1$, $m_d^u = 1$). It means that only single unit of each type of machine can be used. So, this scenario refers to the normal cell formation model, which an assignment of duplicated machine is not done. Then, a large number of EEs occur in this kind of solution.

To enhance the performance of manufacturing cells in case II, the m_d^l and m_d^u are set to 1 and 2, respectively. m_d^u equals to 2 means that duplicated machines are allowed. So, the number of EEs can be reduced when the satisfactory values of the λ_1^* is set between 0.8 and 0.9. However, when the satisfactory values of the is set lower than 0.7 (which means a large number of EEs are accepted), the obtained solution of cell formation is the same as the one which achieved from case I. Moreover, the total setup cost is also low because the assignment of duplicated machines is unnecessary.

Table 4. Different level of the λ_1^* and λ_2^*, satisfied alternative solutions of three cases.

Case No.	λ_1^*, λ_2^*	λ_1, λ_2	EEs , VEs	Number of selected machines, [duplicated machine]	Total machine setup cost ($)	{Part family}/ (Machine cell)
I	1.0 , 0.7	! , !	! , !	! , !	!	!
	0.9 , 0.7	0.91 , 0.77	7 , 12	8 , [0]	21,405	{3,4,5,6,9,10,11}/(A,B,C,D,F) {1,2,8,}/(H) {7,12}/(E,G)
	0.8 , 0.7	0.85 , 0.95	9 , 4	8 , [0]	21,405	{3,4,6,10}/(A,C,D,F) {1,2,5,8,9,11}/(B,H) {7,12}/(E,G)
	0.7 , 0.7	0.85 , 0.95	9 , 4	8 , [0]	21,405	{3,4,6,10}/(A,C,D,F) {1,2,5,8,9,11}/(B,H) {7,12}/(E,G)
II	1.0 , 0.7	! , !	! , !	! , !	!	!
	0.9 , 0.7	0.92 , 0.88	3 , 8	11 , [3]	29,055	{3,4,6,10}/(A,C,D,F) {1,2,5,8,9,11}/(B,C,H) {7,12}/(B,E,F,G)
	0.8 , 0.7	0.81 , 0.92	7 , 6	9 , [1]	23,405	{3,4,6,10}/(A,D,F) {1,2,5,8,9,11}/(B,C,H) {7,12}/(B,E,G)
	0.7 , 0.7	0.76 , 0.96	9 , 4	8 , [0]	21,405	{3,4,6,10}/(A,C,D,F) {1,2,5,8,9,11}/(B,H) {7,12}/(E,G)
III	1.0 , 0.7	1.0 , 0.82	0 , 11	12 , [4]	31,055	{3,4,5,6,10}/(A,B,C,D,F) {1,2,8,9,11}/(B,C,H) {7,12}/(B,E,F,G)
	0.9 , 0.7	0.92 , 0.88	3 , 8	11 , [3]	29,055	{3,4,6,10}/(A,C,D,F) {1,2,5,8,9,11}/(B,C,H) {7,12}/(B,E,F,G)
	0.8 , 0.7	0.84 , 0.92	6 , 6	9 , [1]	24,905	{3,4,6,10}/(A,C,D,F) {1,2,5,9,11}/(B,C,H) {7,8,12}/(E,G)
	0.7 , 0.7	0.76 , 0.96	9 , 4	8, [0]	21,405	{3,4,6,10}/(A,C,D,F) {1,2,5,8,9,11}/(B,H) {7,12}/(E,G)

! There is no feasible solution under the DM requirements

In case III, the m_d^l and m_d^u are respectively set to 1 and 3. All of EEs can be eliminated when the λ_1^* is set at 1. The necessary machines are duplicated and assigned to the cells meanwhile the total setup cost is still not over the budget. This solution is the one which the interaction between cells does not occur.

All 3 cases are solved using Premium Solver Platform V10.5.0.0 on a PC with Intel® Core™ 2 Duo CPU and 4.00 GB RAM. The proposed linearized model can solve these problems within the maximum computational time of 66 seconds. Whereas using non-linearized model (Equation 14 with constraints 15-24 according to Equation 3 and 4), the maximum computational time is 221 seconds. These results clearly show that the proposed linearized model is more capable to find the efficient solutions for the large-scale problems within a reasonable computational time.

5. Conclusions

This paper proposes a new lexicographic fuzzy multi–objective optimization model for a manufacturing cell formation problem with the consideration of machine duplication and machine setup cost. Conventionally, matrix rearrangement methods, mathematical programming methods and heuristic methods have been proposed to solve the manufacturing cell formation problem. However, the DM has to reconsider the duplicated machines for enhancing a cell performance and reducing an interaction between cells by him/herself. This way is complicated especially for huge incidence matrix. So, the efficient solution cannot be guaranteed. Besides, the setup cost of machinery is not considered. Based on the perfect grouping concept, two crucial performance measures, EEs and VEs, are applied to the proposed lexicographic fuzzy optimization model. The proposed model is also enhanced by converting the original quadratic objective functions to the linear objective functions. So the proposed linearized model is now capable to solve large-scale cell formation problems. Moreover, financial constraint is also integrated into the proposed model to control the setup cost of machines. So, not only assignment of part families and machine cells can be done but also the decision of the appropriate machine duplication and the consideration of machine setup cost are integrated simultaneously. Moreover, this method can generate preferred alternative solutions for the DM by adjustment of an acceptable satisfactory level. These benefits make the proposed model outperforms the existing methods. It can be effectively applied to the real-world manufacturing cell formation problem in many industries such as electronic manufacturing service (EMS), original equipment manufacturer (OEM), food manufacturing, etc.

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