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Application of Fuzzy Mathematical Approach for Cell Formation and Layout Design with Uncertain Condition

Iraj Mahdavi*, Mohammad Mahdi Paydar, Armaghan Heidarzade,
Nezam Mahdavi-Amiri

Abstract— **A fuzzy linear programming approach is taken to solve an extended mathematical linear programming model to handle two important problems in cellular manufacturing systems simultaneously: Cell formation and layout design. We seek to minimize the total cost of inter-cell and intra-cell (forward and backward) movements and the cost of machines. The fuzzy demand and fuzzy machine capacity are also considered in the proposed model. The main advantage of the proposed model is in its consideration of uncertain conditions, batch material handling movements, and sequence operation. To illustrate the applicability of the proposed model, an example with fuzzy extension in data set is selected and computational results are presented.**

Index Terms— **Cell formation, Layout design, Fuzzy linear programming**

I. INTRODUCTION

Over the past three decades, group technology (GT) has emerged as a useful scientific principle in improving the productivity of batch-type manufacturing systems in which many different types of products having relatively low volumes are produced in small lot sizes. Cellular manufacturing is a successful application of group technology concepts. The design of a cellular manufacturing system (CMS) usually begins with two fundamental grouping tasks: Part-family formation and machine-cell formation. Several authors [1]—[6] adopt either a sequential or a simultaneous procedure to group the parts and machines. The sequential procedure used in some of these studies determines the part families first, followed by machine assignments. On the other hand, the simultaneous procedure determines the part families and machine groups concurrently. Some newly developed models are more realistic and appealing to real-world applications [7]—[12] because they take more factors such as demands, processing times, space availabilities, material handling costs, and machine capacities into consideration.

Iraj Mahdavi, Mazandaran University of Science & Technology, Department of Industrial Engineering, Babol, Iran, E.mail: irajarash@rediffmail.com

Mohammad Mahdi Paydar, Mazandaran University of Science & Technology, Department of Industrial Engineering, Babol, Iran, E.mail: mm.paydar@ustmb.ac.ir

Armaghan Heidarzade, Mazandaran, Payam Nour University, Sari, Iran, E.mail: a.heidarzade@ustmb.ac.ir

Nezam Mahdavi-Amiri, Faculty of Mathematical Sciences, Sharif University of Technology, Tehran, Iran, E.mail: nezamm@sharif.edu

Most CMS models assume that the input parameters are deterministic and certain. In practical situations, however, many parameters such as processing time, part demand, and available machine capacity are uncertain and imprecise.

Since sufficient data are not always available for predicting uncertain parameters, fuzzy logic is introduced as a powerful tool for expressing this uncertainty through the expert's knowledge. CMS design problem, as a real life problem, can be investigated in a fuzzy environment due to the fuzzy design parameters [13]—[15].

We propose an effective fuzzy linear programming (FLP) approach for solving practical CMS design problems and handles cell formation and layout design simultaneously. The proposed model considers the fuzziness in part demands and machine capacities.

II. CMS PROBLEM FORMULATION

Here, we formulate the mathematical model based on sequence data in CMS. The problem is considered under the following assumptions.

1- The number of cells is known.

2- The upper bound and lower bound of the cell size is known.

3- Each part type has a number of operations to be processed according to a known sequence. Operations related to each part type must be processed in the order they have been numbered.

4- The processing times for all operations of part types on different machine types are known and deterministic.

5- Parts are moved between and within cells in batches. Inter and intra-cell (forward and backward) batches have different sizes. Inter and intra-cell movement (forward and backward) costs are constant for all moves, but in each cell the distance travel from machines j to j' has been considered.

6- The demand for each part type is given as a piece-wise fuzzy number.

7- The capability of each machine type is known. Also, the capacity of each machine is given as a piece-wise fuzzy number. The fuzzy capacity of machine is determined by the Decision Maker (DM) in terms of "nominal capacity" and "actual capacity". The actual capacity is more realistic and applicable than the nominal capacity. In other words, in moving from the actual capacity towards the nominal capacity values, the risk related to the decision making process increases.

8- The costs of each machine type such as constant cost and variable cost are known.

A. Indexing Sets

i index for parts (i =1, 2,…, P)
j index for machines (j=1,2...,M)
k index for cells (k =1, 2,…, C)
s index for operations (s =1, 2,…,OP)
l index for location of machines (l =1, 2,…, U).

B. Parameters

γ' : Material handling cost between cells.

γ''_f : Forward material handling cost within cells.

γ''_b : Backward material handling cost within cells.

B'_i : Batch size for inter-cell movements of part type i.

B''_{fi} : Batch size for forward intra-cell movements of part type i.

B''_{bi} : Batch size for backward intra-cell movements of part type i.

L_k: Lower bound of the number of machines in cell k.
U_k: Upper bound of the number of machines in cell k.
N_j : Number of machines of type j available for allotment to cells.
t_{isj}: Processing time of operation s of part i with machine j.
$\tilde{D}_i$: Demand quantity of part i; $\tilde{D}_i$ has a piece-wise membership function in a general form $\tilde{D}_i = \left[D_i^L, D_i^U\right)$ as shown in Figure 2. The function defined in the interval of $\left[0, D_i^L\right]$ represents "*risk free*" value-interval (for each part i) and in the interval of $\left[D_i^L, D_i^U\right)$ indicates a tolerance value-interval (for each part i) and decision making under this interval is risky for the DM.
$\tilde{T}_j$: The capacity of machine j; $\tilde{T}_j$ has a piece-wise membership function in a general form $\tilde{T}_j = \left[T_j^L, T_j^U\right)$ as shown in Figure 3. T_j^L represents the "*actual capacity*" of machine type j. Also, T_j^U represents the "*nominal capacity*" of machine j. Likewise, according to Section 2 , decision making under interval $\left[0, T_j^L\right)$ does not have any risk for the DM while decision making by T_j^U has the highest risk for the DM.
C_j: Cost of machine type j.
f_i : Number of operations for part i.
aisj : 1, if operation s of part i is to be processed on machine j; 0, otherwise.

C. Decision Variables

Xisk : 1, if operation s of part i is assigned to cell k; 0, otherwise.
Yjkl : 1, if machine j is assigned to cell k in location l; 0, otherwise.
Zik : 1, if part i is assigned to cell k; 0, otherwise.

$$B_{i,s,s+1,k,l,l',j,j'} = O_{isklj} P_{i,s+1,k,l',j'}$$

$$O_{isklj} = X_{isk} Y_{jkl}$$

$$P_{i,s+1,k,l',j'} = X_{i,s+1,k} Y_{j'kl'}$$

D. Objective function

$$\begin{aligned}
&\text{Min Z} = \\
&\gamma' \times \sum_{i=1}^{P} \left[\left\lceil \frac{\tilde{D}_i}{B'_i} \right\rceil \times \left[\left(f_i - 1 \right) - \left(\sum_{k=1}^{C} \sum_{s=1}^{OP-1} \sum_{j=1}^{M} \sum_{j'=1}^{M} \sum_{l=1}^{U} \sum_{l'=1}^{U} B_{i,s,s+1,k,l,l',j,j'} a_{isj}\, a_{i,s+1,j'} \right) \right] \right] \\
&+ \gamma''_f \times \left(\sum_{i=1}^{P} \sum_{k=1}^{C} \sum_{s=1}^{OP-1} \sum_{j=1}^{M} \sum_{j'=1}^{M} \sum_{l=1}^{U} \sum_{l'=l+1}^{U} \left\lceil \frac{\tilde{D}_i}{B''_{fi}} \right\rceil \left(l' - l \right) B_{i,s,s+1,k,l,l',j,j'} a_{isj}\, a_{i,s+1,j'} \right) \\
&+ \gamma''_b \times \left(\sum_{i=1}^{P} \sum_{k=1}^{C} \sum_{s=1}^{OP-1} \sum_{j=1}^{M} \sum_{j'=1}^{M} \sum_{l'=1}^{U} \sum_{l=l'+1}^{U} \left\lceil \frac{\tilde{D}_i}{B''_{bi}} \right\rceil \left(l - l' \right) B_{i,s,s+1,k,l,l',j,j'}\, a_{isj}\, a_{i,s+1,j'} \right) \\
&+ \sum_{k=1}^{C} \sum_{j=1}^{M} \sum_{l=1}^{U} Y_{jkl} C_j
\end{aligned}$$

E. *Constraints*

$$\sum_{j=1}^{M} \sum_{l=1}^{U} Y_{jkl} \ge L_k \qquad \forall k \qquad (1)$$

$$\sum_{j=1}^{M} \sum_{l=1}^{U} Y_{jkl} \le U_k \qquad \forall k \qquad (2)$$

$$\sum_{k=1}^{C} \sum_{l=1}^{U} Y_{jkl} \le N_j \qquad \forall j \qquad (3)$$

$$\sum_{j=1}^{M} Y_{jkl} \le 1 \qquad \forall k, l \qquad (4)$$

$$\sum_{l=1}^{U} Y_{jkl} \le 1 \qquad \forall k, j \qquad (5)$$

$$\sum_{k=1}^{C} Z_{ik} = 1 \qquad \forall i \qquad (6)$$

$$\sum_{k=1}^{C} X_{isk} = 1 \qquad \forall i, s \qquad (7)$$

$$\sum_{i=1}^{p} \sum_{s=1}^{OP} O_{isklj} t_{isj} \tilde{D}_i \le \tilde{T}_j \qquad \forall j, k, l \qquad (9)$$

$$O_{isklj} - X_{isk} - Y_{jkl} + 1.5 \ge 0 \qquad \forall i, s, k, l, j \qquad (10)$$

$$1.5 O_{isklj} - X_{isk} - Y_{jkl} \le 0 \qquad \forall i, s, k, l, j \qquad (11)$$

$$P_{i,s+1,k,l',j'} - X_{i,s+1,k} - Y_{j'kl'} + 1.5 \geq 0$$
$$\forall i,k,l',j' \text{ and } s = 1,...,OP-1 \quad (12)$$

$$1.5\, P_{i,s+1,k,l',j'} - X_{i,s+1,k} - Y_{j'kl'} \leq 0$$
$$\forall i,k,l',j' \text{ and } s = 1,...,OP-1 \quad (13)$$

$$B_{i,s,s+1,k,l,l',j,j'} - O_{iskl j} - P_{i,s+1,k,l',j'} + 1.5 \geq 0$$
$$\forall i,s,k,l,l',j,j' \quad (14)$$

$$1.5\, B_{i,s,s+1,k,l,l',j,j'} - O_{isklj} - P_{i,s+1,k,l',j'} \leq 0$$
$$\forall i,s,k,l,l',j,j' \quad (15)$$

$$X_{isk}, Z_{ik}, Y_{jkl}, O_{isklj}, P_{i,s+1,k,l',j'}, B_{i,s,s+1,k,l,l',j,j'} \in \{0,1\}$$
$$\forall i,j,s,k,l. \quad (16)$$

The objective function is considered for minimizing the total sum of inter-cell and intra-cell (forward and backward) movement costs and cost of machines. The first term computes the total inter-cell movement costs, where fi-1 indicates the total number of movements of part i. The second term of the objective function computes the total intra-cell forward movement cost respectively. The forward distance travels from machines j to j', which are located in locations l and l', have been shown in the second term by $(l'-l)$. The third term of the objective function computes the total intra-cell backward movement cost. The backward distance travels from machines j to j', which are located in locations l and l' have been shown in the third term by $(l'-l)$. The fourth term represents the cost of all machines required for cells. Inequalities (1) and (2) ensure the lower and upper bound considerations for the number of machines to be allocated to locations of each cell. Inequality (3) ensures that the number of machines available for a given type is not bypassed. Inequality (4) ensures that each machine can be allocated at most to one location of each cell. Inequality (5) ensures that each location of each cell can be allocated to one machine. Equation (6) guarantees that each part must be assigned to one cell. Equation (7) guarantees that each operation of each part must be allocated to one cell. Inequality (8) ensures that each machine workload not exceed its capacity. Constrains (10) – (15) have been applied to linearization of mathematical model. And relation (16) specifies that the decision variables are binary.

III. IMPLEMENTATION OF THE PROPOSED FLP MODEL

Sometimes, all the coefficients of a linear programming problem are imprecise. Such a problem can be formulated as:

$$\min \sum_{j=1}^{n} \tilde{c}_j x_j$$
$$s.t. \quad (17)$$
$$\sum_{j=1}^{n} \tilde{a}_{ij} x_j \leq \tilde{b}_i, \quad 1 \leq i \leq m$$
$$x_j \geq 0.$$

(Denote $A = [\tilde{a}_{ij}]$, $c = (\tilde{c}_j)$, $b = (\tilde{b}_i)$, 1£*i*£*m*, 1£ *j*£*n* .)

We assume that the interval for possible values of a fuzzy parameter is specified by the user as $[a^L, a^U)$. In general, the lower bound, a^L, represents "*risk free*" values in such a way that a solution obtained under these values must be implementable. On the other hand, the upper bound, a^U, represents parameter values which are most certainly unrealistic and ''impossible'', and the solution obtained by use of these values is not implementable and thus decision making based on these values is faced with a high risk level for the decision maker (DM). Moving from ''risk-free'' towards ''impossible'' parameter values, is synonymous to moving from solutions with a high degree to solutions with a low degree of implementability.

Before going into the solution procedure, we need to require that the solution $Z^* = Z^*(c,-A,b)$ of the non-fuzzy version of Equation (1) be an increasing function of the parameters *c*, -*A* and *b*. Also, it is assumed that the user is capable of specifying the intervals $[c^L, c^U), [A^L, A^U)$ and $[b^L, b^U)$ for the possible values of the parameters.

Carlsson and Korhonen [16] proposed a relationship between a solution in problem (17) and its parameters: The solution $Z^* = Z^*(c,-A,b)$ of Equation (17) is an increasing function of the parameter *c*, -*A* and *b*.

Thus, we can reasonably assume that the membership functions are monotonically decreasing functions of the parameters $c, -A$ and b. The monotonically decreasing functions may be linear, piece-wise linear, hyperbolic, exponential, etc..

After a full trade-off between $c, -A$ and b, the solution will always exist at:

$\mu = \mu_c = \mu_A = \mu_b$.

Therefore, we obtain the following equations:

$c = g_c(\mu)$, $A = G_A(\mu)$ and $b = g_b(\mu)$,

where $\mu \in [0,1]$ and g_c, G_A and g_b are inverse functions of μ_c, μ_A and μ_b. Then problem (17) turns to:

$$\min [\mathrm{g_c}(\mu)] x$$
$$s.t. \quad (18)$$
$$[\mathrm{G_A}(\mu)] x \leq \mathrm{g_b}(\mu) \quad \text{and} \quad x \geq 0.$$

Obviously, problem (18) is a nonlinear programming problem. However, it can be solved by any linear programming technique if μ is given. Thus, we can obtain a set of solutions corresponding to a set of μ's and then plot the solution pairs (z^*, μ). By referring to this relationship, the decision maker can choose his/her preferred solution for the implementation.

Using the proposed mathematical model, we find that the fuzzy technological coefficients in constraint (9) appear exactly in the first, second and third terms of the objective function.

The piece-wise linear membership function for fuzzy parameters of part demand, $\tilde{D}_i = \left[D_i^L, D_i^U \right)$ is defined as follows:

$$\mu\left(D_i\right) = \frac{D_i^U - \tilde{D}_i}{D_i^U - D_i^L} \qquad \forall i$$

The inverse functions of $\mu\left(D_i\right)$ is calculated as follows:

$$\tilde{D}_i = D_i^U - \mu\left(D_i\right)\left(D_i^U - D_i^L\right) \qquad \forall i$$

The convex exponential membership function for fuzzy parameters of available capacity for each machine $\tilde{T}_j = \left[T_j^L, T_j^U \right)$ is defined as follows:

$$\mu\left(T_j\right) = \frac{1 - \exp\left[b_c\left(\tilde{T}_j - T_j^U\right) \Big/ T_j{}^L - T_j{}^U \right]}{1 - \exp\left(b_c\right)} \quad \forall j ,$$

where $b_c > 0$ is specified by the DM.

The inverse functions of $\mu\left(T_j\right)$ is calculated as follows:

$$\tilde{T}_j = \frac{1}{b_c}\left(\ln\left[1 - \mu\left(T_j\right)\left(1 - \exp\left(b_c\right)\right)\right]\right)\left(T_j{}^L - T_j{}^U\right) + T_j^U \;\; \forall j .$$

Then, we input the investment functions of part demand and machine capacity in the proposed mathematical model.

IV. NUMERICAL EXAMPLE

To verify the behavior of the proposed model, a comprehensive numerical example is presented to illustrate the applicability of the proposed model in an uncertain environment. This example is solved by a branch and bound (B&B) method with the LINGO 8.0 software.

The example is generated according to the information given in Table 1. It consists of eight part types (P_1, P_2,…, P_8), six machine types (M_1, M_2,…, M_6), where each part type is assumed to have a number of operations (OP_1,OP_2,…,OP_4) that must be processed respectively as numbered in the order and the processing time as shown in the parentheses. For simplicity, the capacity range of all the machines in all the problems is the same (i.e., the range $\left[1500 \,..\, 1600\right]$).

In Table 1, the last three rows include inter and intra-cell (forward and backward) batch size for each part type. The next last row presents the fuzzy interval value of demand in each part type. In this table, the last three columns indicate the number of machines of type *j* available, the cost of machine and fuzzy interval value of machine capacity, respectively. For simplicity, the capacity of all the machines in all the problems is the same. Table 2 shows the other input parameters for solving the above problem.

Table 1. *The typical data set for FLP.*

M \ P	1	2	3	4	5	6	7	8	N_j	C_j
1	0	2 (0.44)	0	3 (0.72)	0	0	3 (0,57)	0	2	600
2	1 (0.31)	1 (0.33)	2 (0.63)	0	2 (0.62)	1 (0.22)	4 (0.5)	2 (0.3)	2	900
3	0	0	1 (0.52)	0	0	2 (0.52)	0	3 (0.47)	2	750
4	0	0	0	1 (0.37)	0	0	1 (0.25)	0	2	700
5	2 (0.51)	0	3 (0.4)	0	1 (0.61)	3 (0.35)	0	1 (0.47)	2	600
6	0	0	0	2 (0.53)	0	0	2 (0.28)	0	2	800
$\tilde{D}_i$	[500, 700]	[400, 550]	[150, 350]	[550, 700]	[250, 500]	[600, 800]	[450, 700]	[200, 500]		
B'_i	20	18	15	23	15	25	18	15		
B''_{fi}	8	6	5	7	5	8	6	5		
B''_{bi}	13	10	9	13	9	14	10	9		

Table 2. *Parameter setting model.*

Parameter	Cell I	Cell II
L_k	2	2
U_k	4	4
Forward intra-cell movement unit cost	4	
Backward intra-cell movement unit cost	10	
Inter-cell movement cost	30	

Obviously, the above problem cannot be solved by any standard linear programming method, because it is nonlinear. However, it can be solved if μ is pre-determined. That is, for each specified value of μ , one can get an optimal solution for the original solution. Therefore, one may choose *n* number of experiments (*n* different μ values) in order to obtain *n* optimal solutions and then present these optimal solutions to the DM.

Here, in solving the proposed model, we assumed μ =0, took *n*=10, and set $\delta = 0.1$. Moreover, the constant $\left(b_c\right)$ in the membership function of machine capacity determined by DM was set to $b_c = 0.7$. Table 3 shows the relationship

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between the optimal profits and the corresponding membership grade. According to this relationship, the DM can then get his optimal solution under a pre-determined allowable imprecision.

Table 3. *The optimal solution for each* μ .

μ	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Inter-cell movement cost	0	0	0	0	0	0	1710	1650	1560	1530	1440
Intra-cell forward movement cost	3916	3792	3664	3548	3408	3284	2780	2664	2552	2444	2324
Intra-cell backward movement cost	2810	2685	2550	2440	2330	2180	1600	1510	1380	1276	1170
Machine cost	5250	5250	5250	5250	5250	5250	4350	4350	4350	4350	4350
Z^*	11976	11727	11464	11238	10988	10714	10240	9974	9642	9400	9084

V. DISCUSSION

For the first six levels $(\mu = 0, 0.1, ..., 0.5)$, the cell configuration for parts and machines are the same as shown in Table 4. This table indicates that the value of EE is zero, the number of voids is 5 and machine 2 is duplicated in cell I and cell II.

For the next five levels of μ $(\mu = 0.6, 0.7, ..., 1)$, the cell arrangement of parts and machines are the same as shown in Table 5. The objective function prefers to eliminate machine number 2 from cell II, because of inter-cell movement cost for parts 2 and 7 is less than the cost of machine 2. Moreover, the value of EE is two and the number of voids is 4. We obtain a set of solutions corresponding to a set of μ's and plot the solution pairs (z^*, μ). By referring to this relationship, the decision maker can choose his/her preferred solution for implementation. For instance, when the DM considers 0.3 degree imprecision as acceptable, the corresponding optimal solution is $Z^* = 9974$.

VI. CONCLUSIONS

This paper proposes a mathematical programming model for an extended cell formation problem and layout design simultaneously with uncertain conditions. The fuzzy demand and fuzzy machine capacity are also considered in this proposed model. The proposed model determines the optimal cell configuration by minimizing inter-cell movement, intra-cell movement (forward and backward) and machine costs. The main advantage of the proposed model is to consider uncertain conditions, batch material handling movements and sequence operation. The model has been constructed by use of the trade-off membership functions of fuzzy parameters. The solutions of the FLP at various levels of μ provide the DM with alternative decision plans at different risk levels.

Table 4. The cell configuration of $\mu = 0, 0.1, ..., 0.5$ **.**

		MACHINES						
		3	2	5	4	6	1	2
PARTS	1	0	1	2	0	0	0	0
	3	1	2	3	0	0	0	0
	5	0	2	1	0	0	0	0
	6	2	1	3	0	0	0	0
	8	3	2	1	0	0	0	0
	2	0	0	0	0	0	2	1
	4	0	0	0	1	2	3	0
	7	0	0	0	1	2	3	4

Table 5. The cell configuration of $\mu = 0.6, 0.7, ..., 1$ **.**

		MACHINES					
		3	2	5	4	6	1
PARTS	1	0	1	2	0	0	0
	3	1	2	3	0	0	0
	5	0	2	1	0	0	0
	6	2	1	3	0	0	0
	8	3	2	1	0	0	0
	2	0	1	0	0	0	2
	4	0	0	0	1	2	3
	7	0	4	0	1	2	3

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