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An Integrated Model of Cellular Manufacturing and Supplier Selection Considering Product Quality

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Abstract

Today's business environment has forced manufacturers to produce high-quality products at low cost in the shortest possible delivery time. To cope with this challenge, manufacturing organizations need to optimize the manufacturing and other functions that are in logical association with each other. Therefore, manufacturing system design and supplier selection process are linked together as two major and interrelated decisions involved in viability of production firm. As a matter of fact, production and purchasing functions interact in the form of an organization's overall operation and jointly determine corporate success. In this research, we tried to show the relationship between designing cellular manufacturing system (CMS) and supplier selection process by providing product quality considerations as well as the imprecise nature of some input parameters including parts' demands and defects rates. A unified fuzzy mixed integer linear programming model is developed to make the interrelated cell formation and supplier selection decisions simultaneously and to obtain the advantages of this integrated approach with product quality and reduction of total cost, consequently. Computational results also display the efficiency of the proposed mathematical model for simultaneous consideration of cellular manufacturing design and supplier selection as compared to when these two decisions are separately taken into account.

Keywords: Cellular manufacturing, Supplier selection, Product quality, Integrated model.

1. Introduction

Cellular manufacturing system (CMS) is a plant layout approach which tries to decompose all or part of the manufacturing plant into easy manageable manufacturing cells. A cluster of functionally dissimilar machines is placed in each specific cell to process a group of similar parts in manufacturing and design. Successful implementation of CMS has resulted in quality improvement and production control, increment in productivity, and flexibility through reduction in set-up times, throughput times, lead times, lot sizes, work in process inventories, material handling cost, etc. (Heragu, 1994; Wemmerlov and Hyer, 1989; Wemmerlov and Johnson, 1997). One of the first problems encountered in the implementation of CMS is the cell formation (CF) that includes clustering machines in cells and parts as part groups (i.e., also called part families).

In the past several years, many solution methods have been developed for solving CF problem using a binary machine-part incidence matrix. Mahdavi et al. (2007) proposed a mathematical model for CF problem based on the cell utilization concept. Arkat et al. (2011) presented a bi-objective mathematical model to minimize the number of exceptional elements and the number of voids in the machine-part incidence matrix. They developed an ε-constraint method to solve the model and to generate the efficient solutions. Elbenani and Ferland (2012) introduced a linear binary mathematical programing formulation to generate a solution for the CF problem. They utilized a heuristic approach to solve the problem.

On the other hand, there are a number of research papers dealing with more pragmatic issues including routing flexibilities, operation sequences, reliability of machines, production volumes, set-up and processing times, machine capacities, duplicate machines, and some other production design factors encountered in real factory situation. Caux et al. (2000) addressed the problem of manufacturing CF with alternative process plans and machine capacity constraints. Given the alternative routings for parts processing, capacities of machines, and parts' demands, the problem includes the grouping machines and part process plan selection. The objective was to minimize the intercellular traffic according to machine capacity constraints. Jabal Ameli and Arkat (2008) presented a pure integer linear programming approach for the CF problem considering alternative processing routes, process sequences, machine reliability,

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and production volumes. Wu et al. (2009) proposed a simulated annealing algorithm to solve CF problem considering multiple process routings for parts, so that either the intercellular movements are minimized, or the grouping efficacy is maximized, depending on the definition of the decision objective. Mahdavi et al. (2013) employed sequence data, production volume, and cell size to present an integrated mathematical model considering CF and cell layout simultaneously. Yilmaz and Erol (2014) developed a mathematical programming model to decide when and how such a reconfiguration should be carried out for existing cells. Their study considered reconfiguration in terms of changing part routings, adding new machine type in a cell, removing an existing machine from a cell, duplicate machines and machine transfer to another cell. Deep and Singh (2015) proposed a mixed integer mathematical programming model to design robust machine cells for dynamic part population. Their model incorporates machine cell configuration design problem bridged with the machines allocation problem, the dynamic production problem, and the part routing problem.

Mathematical programming is one of the areas in which fuzzy set theory has been applied extensively to tackle the inherent vagueness, uncertainty, and incompleteness of the data used. In the context of fuzzy mathematical programming, two main classes can be considered: flexible constraints for fuzziness and fuzzy parameters for lack of knowledge (Inuiguchi and Ramic, 2000; Mula et al., 2006). Most CF models assume that the input parameters are deterministic and certain. However, in many practical cases, there are uncertain parameters that sufficient data are not always available for prediction. Hence, fuzzy logic is introduced as a powerful tool for expression of uncertainty through the expert's knowledge. Arikan and Gongur (2009) presented a multi-objective mathematical model for the CMS design with the aim of handling CF and exceptional elements simultaneously in a fuzzy environment. The fuzziness stems from the model parameters which are part demand, machine capacity, and the exceptional elements' elimination costs. The objective functions of their model are minimization of the cost of exceptional element elimination, minimization of the number of outer cell operations, and maximization of the utilized machine capacity. Safaei and Tavakkoli-Moghaddam (2009) proposed an extended fuzzy parametric programming approach to solve a dynamic CF problem considering the uncertain part demand and machine capacity. Kia et al. (2011) developed an integer non-linear programming mathematical model for making the interrelated CF and intracellular layout decisions concurrently in dynamic and fuzzy environments. Their model incorporates several design features including operation sequence, operation time, alternative processing routes, duplicate machines, machine capacity, route selection, production volume of parts and cell reconfiguration.

Most of the production system design models suppose that all of the parts produced are of perfect quality. However, producing defective items is inevitable because of various reasons such as process deterioration, machine breakdown, human mistakes, and some other shortcomings that can occur in the real world of a manufacturing organization. Better designed production system and manufacturing process can improve the quality of products (Inman et al. 2003). CMS leads to achieving just in time (JIT) production system (Sridhar and Rajendran, 1996). JIT is a philosophy of continuous improvement in which non-value adding activities are identified and removed (Brox and Fader, 2002). Reduction of lot sizes supports the JIT philosophy. The JIT advocates that inventory is a blanket that covers problems in production and quality. Reducing inventory uncovers these problems and makes it easier for management to solve (Jaber, 2006). According to a survey on 114 production firms, conducted by Inman (1994), reduction in lot sizes is accompanied by reduction in scraps and reworks. Several researchers (Porteus, 1986; Kim and Hong, 1999; Khouja, 2003; Jaber and Bonney, 2003; Jaber, 2006) also pointed out that rate of generating defective items is reduced with the reduction in lot sizes. Prompt identification of defects allows sources of problems to be detected quickly and reformed. This is the main reason given for justifying the relationship. Urban (1998) presented a simple equation to show the relationship between lot size q and defect rate v. Urban's equation under the JIT philosophy, in which orders break into smaller lot sizes, was expressed as: $v = \lambda + \gamma/q$, where the parameter λ is in $[0, 1)$ and the other parameter γ is negative. As can be seen from the equation, the defect rate v decreases as the lot size q decreases. This simple equation can be used as a critical quality attribute to reach a better designed manufacturing system and to decrease the defect quantities.

Quality-related issues in the CMS literature are limited. Defersha and Chen (2008) proposed a mathematical programming model for integrated and dynamic CMS, considering multi-item and multi-level lot-sizing aspects and the impact of lot size on product quality. Their model minimizes production and quality-related costs and incorporates a number of manufacturing attributes and practical constraints. Rafiee et al. (2011) addressed the integrated CF and inventory lot-sizing problem under the condition of dynamic planning and machine breakdown possibility. Their proposed model seeks to minimize the total cost of machine procurement, cell reconfiguration, preventive and corrective repairs, intracellular and intercellular material handlings, machine operation, part subcontracting, finished and unfinished parts' inventory, and defective parts replacement, while dynamic conditions, alternative routings, machine capacity limitation, operations sequences, cell size constraints, process deterioration, and machine breakdowns are also taken into account. Agarwal (2008) provided a systematic framework for conversion from an existing functional layout to CMS. A total cost model, including set-up cost, work in process inventory cost, quality cost, and set-up time reduction cost, was developed to study the performance and financial aspects of the CMS as an integrated manner. Bootaki et al. (2014) presented a bi-objective cubic CF with two non-homogeneous objective functions in order to minimize the intercellular movements and maximize the part quality index. They suggested a hybrid GA-Augmented ε-constraint method for solving the problem.

For most industries, purchasing function and its associated decisions account for more than 70% of all companies' expenses (Ghodsypour and O'Brien, 2001). Hence, suppliers are directly engaged with corporate success. Raw materials represent a substantial part of the quality of products. Insuring quality at the production input point is one of the crucial determinants for producers that wish to assure right quality products to the customers. Conventionally, designing manufacturing systems and selecting raw material suppliers are two separate decisions. However, production system design can be affected by its interactions with other functions that are logically associated with it. Integrating different aspects of CMS design with supplier selection related issues can lead to a better designed manufacturing system to obtain the advantages of CMS with product quality, and finally reduction of total cost. Although several studies have focused on the quantitative modeling for supplier selection in manufacturing systems, little attention was given in the literature to supplier selection in CMSs. Benhalla et al. (2011) developed a new integrated mathematical model for a multiple plant CMS design on existing factories, taking into consideration the raw material supply process, associated supplier selection, as well as raw material delivery cost to a multi-plant multi-stage CMS design cost. Paydar et al. (2014) proposed a mixed integer linear programming model (MILP) for CMS to integrate CF problem, machine layout, and supplier selection considering the imprecise nature of some critical parameters such as customer demands and machine capacities. They developed a robust optimization method to solve the model with the objective of minimizing total costs including intracellular and intercellular movements costs, machine investment cost, inventory cost, and procurement cost.

The rest of this paper is organized as follows. The problem description and unified mathematical model areis provided in section 2. Solution approach is presented in section 3. Efficiency of the proposed model is validated by means of a numerical illustration in section 4, and finally conclusion is reported in section 5.

2. Problem Description and Mathematical Model

2.1. Description

Consider a two-echelon supply chain consisting of multiple supplier plants and one manufacturer producing multiple products. The integration of making the CF and supplier selection decisions in designing cellular manufacturing and supply chain simultaneously is considered; thus, we face with two implicitly interrelated decisions including:

2.1.1. Supplier Selection Process

According to a survey on 78 related articles appeared in the international journals from 2000 to 2008 conducted by Ho et al. (2010), quality is the most popular criterion (68 papers or 87.18%) in the supplier selection process, and delivery is the second most popular criterion (64 papers or 82.05%), and the third most popular criterion (63 papers or 80.77%) is price/cost. We tried to apply these three main criteria in our presented mathematical model. Due to the variety and technological requirements, there are differences among the inputs or raw materials provided by suppliers with regard to maximum capacity, quality level, lead time, unit price, and not all the suppliers can also produce all kinds of raw materials. The manufacturer, as a seller, has historical performance data on the basis of past records related to quality level and extra time beyond the due date taken to delivery of raw materials by each supplier. The manufacturing organization has to bear extra costs due to quality deficiency and late arrival of raw materials that lead to poor quality level of the finished products and delay in delivery. Moreover, the quality department of the manufacturing organization determines a maximum allowable deficiency level and rejects poor quality raw materials. The suppliers also consider a minimum acceptable utilized capacity for each type of raw material, that is, each supplier only accepts orders for which the utilized capacity would be equal to or greater than economic pre-determined value. The quantity of each type of raw material provided by each supplier plant should be determined.

2.1.2. CF design

In the considered manufacturing plant with cellular layout, required operations of several part types are processed on different machines with limited capacities, which have been placed in the number of pre-determined manufacturing cells. The customers' demands for each part type are uncertain. To cope with this uncertainty, triangular fuzzy number (figure 1) is used on the basis of experts' knowledge. Machines can be replicated to meet capacity constraints and to reduce intercellular movements. Each part type has one or more processing routes along which required operations are performed in a given sequence. In order to better monitor cells, the upper and lower bounds of the number of machines in each cell are specified in advance. The existence of too many machines in one cell creates cluttered flows, reducing monitoring machines. A production lot of parts can be split into processing routes with different defect rates, and the optimal lot splitting should be determined to minimize the number of defective parts. We used Urban's equation in which the number of defective items in a lot size of q is equal to v.q (i.e., v.q = λ.q + γ). Both λ and γ are considered as fuzzy parameters and are expressed in terms of triangular fuzzy numbers. The manufacturing organization has to bear extra cost by producing defective parts. Defective items require additional efforts in the form of redundant activities, reworks, or scraps that add cost or value to the product in contrast to the elimination of waste emphasized by the JIT philosophy. The average extra cost of one defective part of each type is determined using historical data and is applied to account for the total cost of defective items.

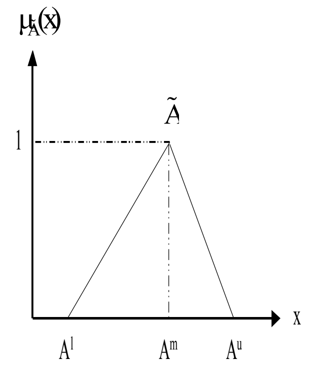

Fig. 1. The triangular possibility distribution of fuzzy parameter $\tilde{A}$

2.2. Mathematical Model

Now, regarding the above descriptions, we present an effective fuzzy mixed integer linear programming (FMILP) model to make CF and supplier selection decisions, concurrently.

2.2.1. Indexing Sets

p	Index of part types, p = 1, 2, …, P
j	Index of operations, j = 1, 2, …, J_{pr}
r	Index of processing routes, r = 1, 2, …, R_p
k	Index of cells, k = 1, 2, …, C
m	Index of machine types, m = 1, 2, …, M
i	Index of raw materials, i = 1, 2, …, I
s	Index of suppliers, s = 1, 2, …, S

2.2.2. Parameters

$\tilde{D}_p$	Demand of part type p.
a_{pjrm}	1, if operation j of part type p along route r can be processed on machine type m; 0, otherwise. [In fact, this parameter shows the machine type required to process operation j of part type p along route r.]
PT_{pjr}	Processing time of operation j of part type p along route r.
SC_{pr}	Set-up cost of part type p along route r.
RC_p	Repair cost for one defective part of type p.
IC_m	Investment cost of machine type m.
OC_m	Operation cost per unit time of machine type m.
CM_m	Capacity of one unit of machine type m.
IMC_p	Unit cost to move part type p between cells.
LB_k	Lower size limit for cell k.
UB_k	Upper size limit for cell k.
$\tilde{\lambda}_{pr}$	The first fuzzy parameter for calculating number of defective items.
$\tilde{\gamma}_{pr}$	The second fuzzy parameter for calculating number of defective items.
L_{is}	Minimum acceptable capacity utilization of supplier s for raw material type i.
CS_{is}	Capacity of supplier s for raw material type i.
UR_{ip}	Usage rate of raw material type i for producing one unit of part type p.
FC_{is}	Fixed cost of selecting raw material type i from supplier s.
IRC_{is}	Per unit cost of raw material type i from supplier s.
MADL	Maximum allowable deficiency level.
QL_{is}	Quality level of raw material type i of supplier s.
UQP_{is}	Unit quality deficiency penalty cost of supplier s for raw material type i.
LTD_{is}	Lead time delay of supplier s for raw material type i.
UDP_{is}	Unit delay penalty cost of supplier s for raw material type i.
LPN	Large positive number.

2.2.3. Decision Variables

N_{mk}	Number of machines type m in cell k.
z_{pr}	1, if route r of part p is set-up; 0, otherwise.
y_{pr}	Quantity of type p parts processed along route r.
x_{pjrk}	Quantity of type p parts processed by operation j along route r in cell k.
dq_{pr}	Defect quantity of part type p along route r.
u_{is}	1, if raw material type i of supplier s is selected; 0, otherwise.
w_{is}	Quantity of raw material type i provided by supplier s.
x^{+}_{pjrk} , x^{-}_{pjrk}	Auxiliary variables used to account for intercellular movements.
t_{pjrk}	Binary auxiliary variable used to formulate logical constraints.
dq^{+}_{pr}	Auxiliary variable used to prevent dq_{pr} to be negative.

2.2.4. Objective Function and Constraints

Minimize Z =

$$\sum_{m=1}^{M}\sum_{k=1}^{C} IC_m.N_{mk} + \sum_{p=1}^{P}\sum_{j=1}^{J_{pr}}\sum_{r=1}^{R_p}\sum_{m=1}^{M}\sum_{k=1}^{C} PT_{pjr}.a_{pjrm}.OC_m.x_{pjrk} + \sum_{p=1}^{P}\sum_{r=1}^{R_p} SC_{pr}.z_{pr} \tag{1}$$

$$+\sum_{p=1}^{P}\sum_{j=1}^{J_{pr}-1}\sum_{r=1}^{R_p}\sum_{k=1}^{C} IMC_p.x^{+}_{pjrk} + \sum_{p=1}^{P}\sum_{r=1}^{R_p} RC_p.dq_{pr} + \sum_{i=1}^{I}\sum_{s=1}^{S} IRC_{is}.w_{is}$$

$$+\sum_{s=1}^{S} FC_{is}.u_{is} + \sum_{i=1}^{I}\sum_{s=1}^{S}(1-QL_{is}).UQP_{is}.w_{is} + \sum_{i=1}^{I}\sum_{s=1}^{S} LTD_{is}.UDP_{is}.w_{is}$$

Subject to:

$$\sum_{p=1}^{P}\sum_{j=1}^{J_{pr}}\sum_{r=1}^{R_p} PT_{pjr}.a_{pjrm}.x_{pjrk} \le CM_m.N_{mk} \qquad \forall m,k \tag{2}$$

$$LB_k \le \sum_{m=1}^{M} N_{mk} \le UB_k \qquad \forall k \tag{3}$$

$$\sum_{k=1}^{C} t_{pjrk} = z_{pr} \qquad \forall p,j,r \tag{4}$$

$$x_{pjrk} \le LPN.t_{pjrk} \qquad \forall p,j,r,k \tag{5}$$

$$x_{p,j+1,r,k} - x_{pjrk} = x^{+}_{pjrk} - x^{-}_{pjrk} \qquad \forall p, j \ne J_{pr}, r, k \tag{6}$$

$$y_{pr} = \sum_{k=1}^{C} x_{pjrk} \qquad \forall p,j,r \tag{7}$$

$$\sum_{r=1}^{R_p} y_{pr} = \tilde{D}_p + \sum_{r=1}^{R_p} dq_{pr} \qquad \forall p \tag{8}$$

$$dq_{pr} - dq^{+}_{pr} = \tilde{\lambda}_{pr}.y_{pr} + \tilde{\gamma}_{pr}.z_{pr} \qquad \forall p,r \tag{9}$$

$$\sum_{s=1}^{S} w_{is} = \sum_{p=1}^{P}\sum_{r=1}^{R_p} UR_{ip}.y_{pr} \qquad \forall i \tag{10}$$

$$L_{is}.u_{is} \le w_{is} \le CS_{is}.u_{is} \qquad \forall i,s \tag{11}$$

$$(1-QL_{is}).u_{is} \le MADL \qquad \forall i,s \tag{12}$$

$$x_{pjrk}, y_{pr}, dq_{pr}, w_{is}, x^{+}_{pjrk}, x^{-}_{pjrk}, dq^{+}_{pr} \ge 0 \qquad \forall p,j,r,k,i,s \tag{13}$$

$$N_{mk} \ge 0 \text{ and integer} \qquad \forall m,k \tag{14}$$

$$z_{pr}, u_{is}, t_{pjrk} \in \{0,1\} \qquad \forall p,j,r,k,i,s \tag{15}$$

The objective function given in Eq. (1) seeks to minimize machine investment cost, operational cost, process routes set-up cost, intercellular movements cost, repair cost, raw material procurement cost, raw material selection fixed cost, quality deficiency penalty cost, and lead time delay penalty cost, respectively. Inequality (2) ensures that available time capacity of machines does not exceed. Cell-size limitation is considered in constraint (3). Eq. (4) allocates each operation of each part type along each specific route to only one cell when the route is set up. Constraint (5) prevents the decision variable x_{pjrk} to take a positive value, unless the auxiliary binary variable t_{pjrk} be equal to 1. Eq. (6) is used to account for the number of intercellular movements. Eq. (7) is related to the quantity of parts processed in each specific route. Constraint (8) corresponds to the production quantity for each part type that is equal to the sum of part demand and quantity of defective items. Eq. (9) considers Urban's equation to account for the quantity of defective items. Constraint (10) is related to the quantity of raw materials that should be procured. Minimum acceptable capacity utilization and maximum capacity of suppliers are considered in constraint (11). Constraint (12) guarantees the rejection of poor quality raw materials. Finally, constraints (13)-(15) define variables type.

3. Solution Methodology

To solve the mathematical model, we need an approach to transform the FMILP model into an equivalent auxiliary crisp MILP. Defuzzification is the procedure of decoding a fuzzy value and computing its corresponding crisp measure. Different fuzzy numbers of ranking methods have been introduced to obtain compromise solutions for dealing with fuzzy mathematical programming models. The defuzzification of triangular fuzzy number can be performed by applying the possibility theory (Chang, 1996; Enea and Piazza, 2004) or centroid methods (Wang and Parkan, 2006). According to Yager (1981), the crisp measure is the abscissa of the center of gravity:

$$A^R = \frac{A^l + A^m + A^u}{3} \tag{16}$$

Now, we present the equivalent crisp constraints using the above equation:

$$\sum_{r=1}^{R_p} y_{pr} = \left(\frac{D^l_p + D^m_p + D^u_p}{3}\right) + \sum_{r=1}^{R_p} dq_{pr} \qquad \forall p \tag{17}$$

$$dq_{pr} - dq^{+}_{pr} = \left(\frac{\lambda^{l}_{pr} + \lambda^{m}_{pr} + \lambda^{u}_{pr}}{3}\right).y_{pr} + \left(\frac{\gamma^{l}_{pr} + \gamma^{m}_{pr} + \gamma^{u}_{pr}}{3}\right) \quad (18)$$

$\forall p, r$

Consequently, we would obtain an auxiliary crisp MILP model as follows:

Minimize Z
Subject to: **(19)**
(2)-(7), (10)-(15), (17) and (18)

4. Numerical Illustration

To verify the capability of the proposed model in an uncertain environment and to illustrate the need for an integrated manner, a comprehensive numerical example is presented. This example includes three cells, five types of machines, seven part types, ten raw material types, and six potential suppliers. The detailed data are in Tables 1-7. Table 1 contains the fuzzy demand value for each part type, unit intercellular movements cost, and unit repair cost for defective items. Data, pertaining to the operational issues, include data of machine types, processing time required by each operation in each route, set-up cost of each route, and also the fuzzy values of λ and γ for calculating the defect quantities are shown in Table 2. Table 3 shows the data related to machine investment cost, machine capacity, and operational cost per unit time of each machine type. Table 4 reports the bill of material that denotes the quantity of raw material type i required to produce one unit of part type p.

Finally, supplier information containing fixed cost and raw material price, expected quality level, average lead time delay, unit quality deficiency penalty cost, unit lead time delay penalty cost, minimum acceptable capacity utilization, and maximum capacity of suppliers are given in Tables 5-7.

Table 1
Data for part types

Part	$\tilde{D}_p$	IMC_p	RC_p
1	(4600, 5100, 5300)	0.12	4
2	(3700, 4000, 4600)	0.13	5
3	(3200, 3600, 4000)	0.13	3
4	(3700, 4000, 4900)	0.15	4
5	(3000, 4100, 4300)	0.13	5
6	(3700, 4200, 4400)	0.14	6
7	(3900 ,4100, 4900)	0.12	4

Table 2
Operational data for part types

Part	**Route**	**Opr1 Opr2 Opr3 (a_{pjrm}, PT_{pjr})***	**SC_{pr}**	$\tilde{\lambda}_{pr}$	$\tilde{\gamma}_{pr}$
1	1	(1, 5)* − (4, 4) − (2, 5)	2000	(0.05, 0.09, 0.10)	(-30, -55, -65)
	2	(5, 3) − (1, 5) − (2, 4)	1950	(0.07, 0.11, 0.12)	(-30, -50, -100)
	3	(3, 3) − (4, 4) − (5, 6)	2020	(0.065, 0.095, 0.11)	(-25, -60, -65)
2	1	(3, 3) − (2, 6)	1900	(0.08, 0.13, 0.15)	(-40, -50, -90)
	2	(2, 4) − (4, 6)	1950	(0.125, 0.145, 0.15)	(-40, -80, -90)
3	1	(5, 6) − (2, 6) − (1, 7)	2050	(0.12, 0.16, 0.17)	(-50, -100, -120)
	2	(4, 4) − (1, 8) − (3, 6)	2020	(0.11, 0.12, 0.16)	(-40, -60, -110)
4	1	(1, 6) − (2, 5) − (3, 9)	1800	(0.07, 0.09, 0.14)	(-40, -50, -60)
	2	(3, 7) − (5, 5) − (4, 8)	1860	(0.07, 0.09, 0.11)	(-30, -55 , -65)
5	1	(2, 5) − (3, 4) − (4, 4)	1950	(0.085, 0.13, 0.145)	(-40, -50, -90)
	2	(1, 6) − (3, 4) − (5, 4)	1950	(0.08, 0.09,0.13)	(-20, -30, -70)
	3	(3, 5) − (2, 4) − (4, 4)	1920	(0.04, 0.11, 0.15)	(-25, -60, -65)
6	1	(3, 5) − (5, 4) − (2, 6)	1870	(0.06, 0.07, 0.08)	(-20, -30, -40)
	2	(5, 5) − (4, 4) − (1, 7)	1920	(0.06, 0.08, 0.13)	(-25, -45, -50)
7	1	(1, 5) − (2, 6)	1780	(0.06, 0.09, 0.15)	(-30, -40, -80)
	2	(4, 5) − (3, 6)	1840	(0.07, 0.09, 0.11)	(-30, -50, -70)

Table 3
Data for machine types

Machine type	Time capacity (minutes)	Investment cost	Operational cost (per minutes)
1	24600	2000	0.12
2	24000	2150	0.13
3	25800	2050	0.15
4	24600	2200	0.14
5	25200	2100	0.12

Table 4
Usage rate matrix

		Raw material types									
		1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
Part types	*1*	*2*					*2*			*1*	*1*
	2		*2*			*2*		*1*			
	3			*1*	*3*			*1*			
	4			*1*			*1*		*3*		
	5					*2*				*2*	*2*
	6	*2*	*1*				*1*			*1*	
	7			*2*				*2*			*1*

Table 5
Fixed cost and raw material price data for suppliers (FC, IRC)

Raw material	Supplier1	Supplier2	Supplier3	Supplier4	Supplier5	Supplier6
1	(600, 3.2)*	−	(730, 2.7)	(900, 2.9)	(750, 3.1)	(850, 2.7)
2	(700, 3.2)	(850, 3)	−	−	(750, 2.7)	(700, 3.1)
3	−	(650, 4)	(800, 5)	(900, 4.5)	−	(850, 4.9)
4	(870, 3.5)	(1050, 3.2)	−	−	(730, 4)	(780, 3)
5	(870, 4.1)	(900, 4.1)	(820, 3.6)	(1020, 4.5)	−	(840, 4)
6	−	(750, 3.6)	(650, 3)	(700, 4)	−	(860, 3.4)
7	(560, 3.5)	−	(750, 3.5)	−	(800, 3.5)	(780, 3.5)
8	(790, 3)	−	−	(850, 3.2)	(910, 3.5)	(860, 3.7)
9	−	(770, 2.9)	(650, 3)	(800, 3)	(720, 2.7)	−
10	(990, 2.9)	(800, 3.5)	(800, 3.7)	(950, 3)	(1000, 2.5)	(940, 2.4)

Table 6
Quality and lead time data (QL, LTD)*.

Raw material	Supplier1	Supplier2	Supplier3	Supplier4	Supplier5	Supplier6	(UQP, UDP)
1	(0.92, 2)*	−	(0.87, 1)	(0.90, 0)	(0.91, 0)	(0.87, 3)	(4.2, 0.9)
2	(0.90, 1)	(0.90, 0)	−	−	(0.92, 1)	(0.93, 4)	(3.8, 0.7)
3	−	(0.89, 3)	(0.91, 2)	(0.90, 0)	−	(0.94, 2)	(3.6, 0.8)
4	(0.90, 3)	(0.83, 1)	−	−	(0.91, 2)	(0.90, 1)	(3.5, 0.7)
5	(0.85, 0)	(0.93, 0)	(0.94, 1)	(0.91, 1)	−	(0.90, 0)	(4.4, 0.5)
6	−	(0.94, 1)	(0.93, 0)	(0.93, 0)	−	(0.89, 3)	(4, 0.65)
7	(0.91, 2)	−	(0.90, 1)	−	(0.88, 3)	(0.91, 0)	(3.9, 1.1)
8	(0.91, 1)	−	−	(0.90, 2)	(0.91, 1)	(0.93, 2)	(3.5, 0.8)
9	−	(0.91, 0)	(0.93, 1)	(0.92, 2)	(0.90, 0)	−	(3, 1)
10	(0.88, 4)	(0.92, 0)	(0.95, 1)	(0.87, 3)	(0.90, 0)	(0.91, 4)	(4, 0.85)

Table 7
Minimum acceptable capacity utilization and maximum capacity of suppliers (L, CS)

Raw material	Supplier1	Supplier2	Supplier3	Supplier4	Supplier5	Supplier6
1	(2300, 8500)*	−	(2600, 8000)	(2700, 9000)	(3000, 7000)	(2800, 6500)
2	(2400, 9000)	(2100, 8500)	−	−	(2000, 8500)	(2500, 7500)
3	−	(2400, 9000)	(2600, 8500)	(2200, 9000)	−	(2500, 7000)
4	(3000, 9500)	(3300, 7500)	−	−	(2700, 8500)	(2800, 6200)
5	(3100, 6500)	(3500, 6000)	(2800, 8000)	(3000, 7500)	−	(3200, 6000)
6	−	(3200, 9000)	(3000, 8000)	(2400, 7500)	−	(2800, 7000)
7	(2200, 9000)	−	(2800, 8500)	−	(2700, 9500)	(3000, 6500)
8	(2400, 7500)	−	−	(2500, 6500)	(2700, 6000)	(2800, 8500)
9	−	(3100, 6000)	(3200, 7500)	(2900, 8000)	(2900, 8200)	−
10	(2600, 7500)	(3100, 8500)	(2200, 6500)	(2900, 5500)	(3200, 7000)	(2800, 6500)

Table 8
Optimal solution for CF design production factors in the integrated approach

Part	Route	Zpr	y_{pr}	dq_{pr}	Visited cells sequence	Intercellular movements
1	1	1	1471	68	Cell3−Cell3−Cell3	0
	2	1	3184	258	Cell2−Cell2−Cell2	0
	3	1	682	11	Cell3−Cell3−Cell1	682
2	1	1	4591	491	Cell1−Cell1	0
	2	0	−	−	−	−
3	1	1	600	0	Cell1−Cell2−Cell2	600
	2	1	3368	368	Cell3−Cell3−Cell 3	0
4	1	1	1446	95	Cell2−Cell2−Cell1	1446
	2	1	3075	227	Cell2−Cell2−Cell2	0
5	1	1	614	14	Cell1−Cell3−Cell3	614
	2	0	−	−	−	−
	3	1	3500	300	Cell1−Cell1−Cell1	0
6	1	1	4376	276	Cell1−Cell1−Cell1	0
	2	0	−	−	−	−
7	1	1	2774	227	Cell3−Cell3	0
	2	1	1871	118	Cell1−Cell1	0

Table 9
Machine-cell formation in the integrated approach

	Cell1	Cell2	Cell3
Machine1	0	1	2
Machine2	3	1	1
Machine3	3	1	1
Machine4	1	1	1
Machine5	1	1	0

Table 10
Raw material procurement in the integrated approach

Raw material	Supplier1	Supplier2	Supplier3	Supplier4	Supplier5	Supplier 6
1	3428	–	0	9000	7000	0
2	0	8500	–	–	5058	0
3	–	0	2600	9000	–	6181
4	0	0	–	–	5703	6200
5	0	6000	8000	0	–	3409
6	–	4073	8000	7500	–	0
7	2850	–	8500	–	0	6500
8	7500	–	–	2500	3564	0
9	–	6000	3741	0	8200	–
10	0	8500	2711	0	7000	0

Table 11
Optimal solution for CF design production factors in conventional two-phase procedure

Part	Route	Z_{pr}	y_{pr}	dq_{pr}	Visited cells sequence	Intercellular movements
1	1	0	–	–	–	–
	2	1	5489	489	Cell2–Cell2–Cell2	0
	3	0	–	–	–	–
2	1	1	4591	491	Cell1–Cell1	0
	2	0	–	–	–	–
3	1	1	4129	529	Cell1–Cell1–Cell1	0
	2	0	–	–	–	–
4	1	1	3553	305	Cell2–Cell1–Cell1	3553
	2	1	992	39	Cell3–Cell3–Cell3	0
5	1	0	–	–	–	–
	2	0	–	–	–	–
	3	1	4167	367	Cell3–Cell3–Cell3	0
6	1	1	4376	276	Cell3–Cell3–Cell3	0
	2	0	–	–	–	–
7	1	1	4722	422	Cell3–Cell3	0
	2	0	–	–	–	–

Table 12
Machine-cell formation in conventional two-phase procedure

	Cell1	Cell2	Cell3
Machine1	0	2	1
Machine2	3	1	3
Machine3	3	0	2
Machine4	0	0	1
Machine5	1	1	1

To demonstrate the efficiency of the proposed integrated approach to make the CF and supplier selection decisions simultaneously, as compared to when these two decisions are separately taken into account, the proposed example is solved by eliminating the supplier selection feature at the first phase, and then at the second phase, raw material procurement decision is made on the basis of the obtained CF design. As can be seen from the results in Tables 11 and 12, the optimal cell configurations and its production design factors have changed. Comparing Tables 8 and 11 reveals that there are more set-up numbers and also few defective items in the integrated approach. Setting up more processing routes reduces lot sizes, and consequently reduces the quantity of defective items according to JIT philosophy. The obtained total cost corresponding to the proposed integrated approach is accompanied by about 10% cost saving as compared with the conventional two-phase procedure. Within small systems of such a size, even a modest percentage improvement in the overall cost by employing the integrated approach can be valuable to the overall competitiveness of a manufacturing system. Moreover, simultaneous consideration of supplier selection and cellular manufacturing enables manufacturers to respond quickly to customer requirements. Therefore, the integrated approach to cellular manufacturing design with supplier selection process yields faster response, lower procurement cost, and lower production cost to companies (Paydar et al. 2014).

5. Conclusion

In traditional manufacturing systems, designing production facilities and selecting raw material suppliers were two separate decisions. In this paper, an integrated approach was adopted to analyze, since production and purchasing are interrelated functions and interact as an organization's overall operation. A unified FMILP model was developed to make production and procurement decisions in generalized CF problem and supplier selection simultaneously, together with product quality considerations. Comparing Table 8 with Table 11 as well as Table 9 with Table 12, we found that there are differences among the proposed integrated mathematical model and the conventional two-phase procedure from the perspective of optimal cell configuration and its production design factors. The computational results also showed that the proposed integrated approach with simultaneous consideration of cellular manufacturing design and supplier selection is more effective as compared to when these two decisions are separately taken into account. The unified fuzzy mathematical model attempted in this paper suffers from a large number of constraints and variables, which make it difficult for application in real cases. Hence, meta-heuristic approaches can be developed to cope with real-sized problems in future research studies.

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and production volumes. Wu et al. (2009) proposed a simulated annealing algorithm to solve CF problem considering multiple process routings for parts, so that either the intercellular movements are minimized, or the grouping efficacy is maximized, depending on the definition of the decision objective. Mahdavi et al. (2013) employed sequence data, production volume, and cell size to present an integrated mathematical model considering CF and cell layout simultaneously. Yilmaz and Erol (2014) developed a mathematical programming model to decide when and how such a reconfiguration should be carried out for existing cells. Their study considered reconfiguration in terms of changing part routings, adding new machine type in a cell, removing an existing machine from a cell, duplicate machines and machine transfer to another cell. Deep and Singh (2015) proposed a mixed integer mathematical programming model to design robust machine cells for dynamic part population. Their model incorporates machine cell configuration design problem bridged with the machines allocation problem, the dynamic production problem, and the part routing problem.

Mathematical programming is one of the areas in which fuzzy set theory has been applied extensively to tackle the inherent vagueness, uncertainty, and incompleteness of the data used. In the context of fuzzy mathematical programming, two main classes can be considered: flexible constraints for fuzziness and fuzzy parameters for lack of knowledge (Inuiguchi and Ramic, 2000; Mula et al., 2006). Most CF models assume that the input parameters are deterministic and certain. However, in many practical cases, there are uncertain parameters that sufficient data are not always available for prediction. Hence, fuzzy logic is introduced as a powerful tool for expression of uncertainty through the expert's knowledge. Arikan and Gongur (2009) presented a multi-objective mathematical model for the CMS design with the aim of handling CF and exceptional elements simultaneously in a fuzzy environment. The fuzziness stems from the model parameters which are part demand, machine capacity, and the exceptional elements' elimination costs. The objective functions of their model are minimization of the cost of exceptional element elimination, minimization of the number of outer cell operations, and maximization of the utilized machine capacity. Safaei and Tavakkoli-Moghaddam (2009) proposed an extended fuzzy parametric programming approach to solve a dynamic CF problem considering the uncertain part demand and machine capacity. Kia et al. (2011) developed an integer non-linear programming mathematical model for making the interrelated CF and intracellular layout decisions concurrently in dynamic and fuzzy environments. Their model incorporates several design features including operation sequence, operation time, alternative processing routes, duplicate machines, machine capacity, route selection, production volume of parts and cell reconfiguration.

Most of the production system design models suppose that all of the parts produced are of perfect quality. However, producing defective items is inevitable because of various reasons such as process deterioration, machine breakdown, human mistakes, and some other shortcomings that can occur in the real world of a manufacturing organization. Better designed production system and manufacturing process can improve the quality of products (Inman et al. 2003). CMS leads to achieving just in time (JIT) production system (Sridhar and Rajendran, 1996). JIT is a philosophy of continuous improvement in which non-value adding activities are identified and removed (Brox and Fader, 2002). Reduction of lot sizes supports the JIT philosophy. The JIT advocates that inventory is a blanket that covers problems in production and quality. Reducing inventory uncovers these problems and makes it easier for management to solve (Jaber, 2006). According to a survey on 114 production firms, conducted by Inman (1994), reduction in lot sizes is accompanied by reduction in scraps and reworks. Several researchers (Porteus, 1986; Kim and Hong, 1999; Khouja, 2003; Jaber and Bonney, 2003; Jaber, 2006) also pointed out that rate of generating defective items is reduced with the reduction in lot sizes. Prompt identification of defects allows sources of problems to be detected quickly and reformed. This is the main reason given for justifying the relationship. Urban (1998) presented a simple equation to show the relationship between lot size q and defect rate v. Urban's equation under the JIT philosophy, in which orders break into smaller lot sizes, was expressed as: $v = \lambda + \gamma/q$, where the parameter λ is in [0, 1) and the other parameter γ is negative. As can be seen from the equation, the defect rate v decreases as the lot size q decreases. This simple equation can be used as a critical quality attribute to reach a better designed manufacturing system and to decrease the defect quantities.

Quality-related issues in the CMS literature are limited. Defersha and Chen (2008) proposed a mathematical programming model for integrated and dynamic CMS, considering multi-item and multi-level lot-sizing aspects and the impact of lot size on product quality. Their model minimizes production and quality-related costs and incorporates a number of manufacturing attributes and practical constraints. Rafiee et al. (2011) addressed the integrated CF and inventory lot-sizing problem under the condition of dynamic planning and machine breakdown possibility. Their proposed model seeks to minimize the total cost of machine procurement, cell reconfiguration, preventive and corrective repairs, intracellular and intercellular material handlings, machine operation, part subcontracting, finished and unfinished parts' inventory, and defective parts replacement, while dynamic conditions, alternative routings, machine capacity limitation, operations sequences, cell size constraints, process deterioration, and machine breakdowns are also taken into account. Agarwal (2008) provided a systematic framework for conversion from an existing functional layout to CMS. A total cost model, including set-up cost, work in process inventory cost, quality cost, and set-up time reduction cost, was developed to study the performance and financial aspects of the CMS as an integrated manner. Bootaki et al. (2014) presented a bi-objective cubic CF with two non-homogeneous objective functions in order to minimize the intercellular movements and maximize the part quality index. They suggested a hybrid GA-Augmented ε-constraint method for solving the problem.

For most industries, purchasing function and its associated decisions account for more than 70% of all companies' expenses (Ghodsypour and O'Brien, 2001). Hence, suppliers are directly engaged with corporate success. Raw materials represent a substantial part of the quality of products. Insuring quality at the production input point is one of the crucial determinants for producers that wish to assure right quality products to the customers. Conventionally, designing manufacturing systems and selecting raw material suppliers are two separate decisions. However, production system design can be affected by its interactions with other functions that are logically associated with it. Integrating different aspects of CMS design with supplier selection related issues can lead to a better designed manufacturing system to obtain the advantages of CMS with product quality, and finally reduction of total cost. Although several studies have focused on the quantitative modeling for supplier selection in manufacturing systems, little attention was given in the literature to supplier selection in CMSs. Benhalla et al. (2011) developed a new integrated mathematical model for a multiple plant CMS design on existing factories, taking into consideration the raw material supply process, associated supplier selection, as well as raw material delivery cost to a multi-plant multi-stage CMS design cost. Paydar et al. (2014) proposed a mixed integer linear programming model (MILP) for CMS to integrate CF problem, machine layout, and supplier selection considering the imprecise nature of some critical parameters such as customer demands and machine capacities. They developed a robust optimization method to solve the model with the objective of minimizing total costs including intracellular and intercellular movements costs, machine investment cost, inventory cost, and procurement cost.

The rest of this paper is organized as follows. The problem description and unified mathematical model areis provided in section 2. Solution approach is presented in section 3. Efficiency of the proposed model is validated by means of a numerical illustration in section 4, and finally conclusion is reported in section 5.

2. Problem Description and Mathematical Model

2.1. Description

Consider a two-echelon supply chain consisting of multiple supplier plants and one manufacturer producing multiple products. The integration of making the CF and supplier selection decisions in designing cellular manufacturing and supply chain simultaneously is considered; thus, we face with two implicitly interrelated decisions including:

2.1.1. Supplier Selection Process

According to a survey on 78 related articles appeared in the international journals from 2000 to 2008 conducted by Ho et al. (2010), quality is the most popular criterion (68 papers or 87.18%) in the supplier selection process, and delivery is the second most popular criterion (64 papers or 82.05%), and the third most popular criterion (63 papers or 80.77%) is price/cost. We tried to apply these three main criteria in our presented mathematical model. Due to the variety and technological requirements, there are differences among the inputs or raw materials provided by suppliers with regard to maximum capacity, quality level, lead time, unit price, and not all the suppliers can also produce all kinds of raw materials. The manufacturer, as a seller, has historical performance data on the basis of past records related to quality level and extra time beyond the due date taken to delivery of raw materials by each supplier. The manufacturing organization has to bear extra costs due to quality deficiency and late arrival of raw materials that lead to poor quality level of the finished products and delay in delivery. Moreover, the quality department of the manufacturing organization determines a maximum allowable deficiency level and rejects poor quality raw materials. The suppliers also consider a minimum acceptable utilized capacity for each type of raw material, that is, each supplier only accepts orders for which the utilized capacity would be equal to or greater than economic pre-determined value. The quantity of each type of raw material provided by each supplier plant should be determined.

2.1.2. CF design

In the considered manufacturing plant with cellular layout, required operations of several part types are processed on different machines with limited capacities, which have been placed in the number of pre-determined manufacturing cells. The customers' demands for each part type are uncertain. To cope with this uncertainty, triangular fuzzy number (figure 1) is used on the basis of experts' knowledge. Machines can be replicated to meet capacity constraints and to reduce intercellular movements. Each part type has one or more processing routes along which required operations are performed in a given sequence. In order to better monitor cells, the upper and lower bounds of the number of machines in each cell are specified in advance. The existence of too many machines in one cell creates cluttered flows, reducing monitoring machines. A production lot of parts can be split into processing routes with different defect rates, and the optimal lot splitting should be determined to minimize the number of defective parts. We used Urban's equation in which the number of defective items in a lot size of q is equal to v.q (i.e., v.q = λ.q + γ). Both λ and γ are considered as fuzzy parameters and are expressed in terms of triangular fuzzy numbers. The manufacturing organization has to bear extra cost by producing defective parts. Defective items require additional efforts in the form of redundant activities, reworks, or scraps that add cost or value to the product in contrast to the elimination of waste emphasized by the JIT philosophy. The average extra cost of one defective part of each type is determined using historical data and is applied to account for the total cost of defective items.

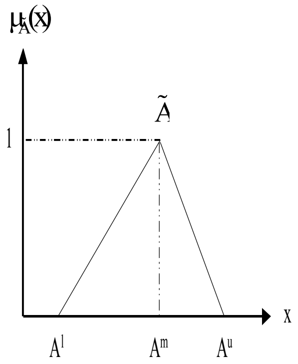

Fig. 1. The triangular possibility distribution of fuzzy parameter $\tilde{A}$

2.2. Mathematical Model

Now, regarding the above descriptions, we present an effective fuzzy mixed integer linear programming (FMILP) model to make CF and supplier selection decisions, concurrently.

2.2.1. Indexing Sets

p	Index of part types, p = 1, 2, …, P
j	Index of operations, j = 1, 2, …, J_{pr}
r	Index of processing routes, r = 1, 2, …, R_p
k	Index of cells, k = 1, 2, …, C
m	Index of machine types, m = 1, 2, …, M
i	Index of raw materials, i = 1, 2, …, I
s	Index of suppliers, s = 1, 2, …, S

2.2.2. Parameters

$\tilde{D}_p$	Demand of part type p.
a_{pjrm}	1, if operation j of part type p along route r can be processed on machine type m; 0, otherwise. [In fact, this parameter shows the machine type required to process operation j of part type p along route r.]
PT_{pjr}	Processing time of operation j of part type p along route r.
SC_{pr}	Set-up cost of part type p along route r.
RC_p	Repair cost for one defective part of type p.
IC_m	Investment cost of machine type m.
OC_m	Operation cost per unit time of machine type m.
CM_m	Capacity of one unit of machine type m.
IMC_p	Unit cost to move part type p between cells.
LB_k	Lower size limit for cell k.
UB_k	Upper size limit for cell k.
$\tilde{\lambda}_{pr}$	The first fuzzy parameter for calculating number of defective items.
$\tilde{\gamma}_{pr}$	The second fuzzy parameter for calculating number of defective items.
L_{is}	Minimum acceptable capacity utilization of supplier s for raw material type i.
CS_{is}	Capacity of supplier s for raw material type i.
UR_{ip}	Usage rate of raw material type i for producing one unit of part type p.
FC_{is}	Fixed cost of selecting raw material type i from supplier s.
IRC_{is}	Per unit cost of raw material type i from supplier s.
MADL	Maximum allowable deficiency level.
QL_{is}	Quality level of raw material type i of supplier s.
UQP_{is}	Unit quality deficiency penalty cost of supplier s for raw material type i.
LTD_{is}	Lead time delay of supplier s for raw material type i.
UDP_{is}	Unit delay penalty cost of supplier s for raw material type i.
LPN	Large positive number.

2.2.3. Decision Variables

N_{mk}	Number of machines type m in cell k.
z_{pr}	1, if route r of part p is set-up; 0, otherwise.
y_{pr}	Quantity of type p parts processed along route r.
x_{pjrk}	Quantity of type p parts processed by operation j along route r in cell k.
dq_{pr}	Defect quantity of part type p along route r.
u_{is}	1, if raw material type i of supplier s is selected; 0, otherwise.
w_{is}	Quantity of raw material type i provided by supplier s.
x^{+}_{pjrk} , x^{-}_{pjrk}	Auxiliary variables used to account for intercellular movements.
t_{pjrk}	Binary auxiliary variable used to formulate logical constraints.
dq^{+}_{pr}	Auxiliary variable used to prevent dq_{pr} to be negative.

2.2.4. Objective Function and Constraints

Minimize Z =

$$\sum_{m=1}^{M}\sum_{k=1}^{C} IC_m.N_{mk} + \sum_{p=1}^{P}\sum_{j=1}^{J_{pr}}\sum_{r=1}^{R_p}\sum_{m=1}^{M}\sum_{k=1}^{C} PT_{pjr}.a_{pjrm}.OC_m.$$

$$\sum_{p=1}^{P}\sum_{r=1}^{R_p} SC_{pr}.z_{pr} \tag{1}$$

$$+\sum_{p=1}^{P}\sum_{j=1}^{J_{pr}-1}\sum_{r=1}^{R_p}\sum_{k=1}^{C} IMC_p.x^{+}_{pjrk} + \sum_{p=1}^{P}\sum_{r=1}^{R_p} RC_p.dq_{pr} +$$

$$\sum_{i=1}^{I}\sum_{s=1}^{S} IRC_{is}.w_{is}$$

$$+\sum_{s=1}^{S} FC_{is}.u_{is} + \sum_{i=1}^{I}\sum_{s=1}^{S}(1-QL_{is}).UQP_{is}.w_{is} +$$

$$\sum_{i=1}^{I}\sum_{s=1}^{S} LTD_{is}.UDP_{is}.w_{is}$$

Subject to:

$$\sum_{p=1}^{P}\sum_{j=1}^{J_{pr}}\sum_{r=1}^{R_p} PT_{pjr}.a_{pjrm}.x_{pjrk} \le CM_m.N_{mk} \qquad \forall m \tag{2}$$

$$LB_k \le \sum_{m=1}^{M} N_{mk} \le UB_k \qquad \forall k \tag{3}$$

$$\sum_{k=1}^{C} t_{pjrk} = z_{pr} \qquad \forall p, j, r \tag{4}$$

$$x_{pjrk} \le LPN.t_{pjrk} \qquad \forall p, j, r, k \tag{5}$$

$$x_{p,j+1,r,k} - x_{pjrk} = x^{+}_{pjrk} - x^{-}_{pjrk} \qquad \forall p, j \ne J_{pr}, r, k \tag{6}$$

$$y_{pr} = \sum_{k=1}^{C} x_{pjrk} \qquad \forall p, j, r \tag{7}$$

$$\sum_{r=1}^{R_p} y_{pr} = \tilde{D}_p + \sum_{r=1}^{R_p} dq_{pr} \qquad \forall p \tag{8}$$

$$dq_{pr} - dq^{+}_{pr} = \tilde{\lambda}_{pr}.y_{pr} + \tilde{\gamma}_{pr}.z_{pr} \qquad \forall p, r \tag{9}$$

$$\sum_{s=1}^{S} w_{is} = \sum_{p=1}^{P}\sum_{r=1}^{R_p} UR_{ip}.y_{pr} \qquad \forall i \tag{10}$$

$$L_{is}.u_{is} \le w_{is} \le CS_{is}.u_{is} \qquad \forall i, s \tag{11}$$

$$(1-QL_{is}).u_{is} \le MADL \qquad \forall i, s \tag{12}$$

$$x_{pjrk}, y_{pr}, dq_{pr}, w_{is}, x^{+}_{pjrk}, x^{-}_{pjrk}, dq^{+}_{pr} \ge 0 \qquad \forall p, j, r, k, i, s \tag{13}$$

$$N_{mk} \ge 0 \text{ and integer} \qquad \forall m, k \tag{14}$$

$$z_{pr}, u_{is}, t_{pjrk} \in \{0,1\} \qquad \forall p, j, r, k, i, s \tag{15}$$

The objective function given in Eq. (1) seeks to minimize machine investment cost, operational cost, process routes set-up cost, intercellular movements cost, repair cost, raw material procurement cost, raw material selection fixed cost, quality deficiency penalty cost, and lead time delay penalty cost, respectively. Inequality (2) ensures that available time capacity of machines does not exceed. Cell-size limitation is considered in constraint (3). Eq. (4) allocates each operation of each part type along each specific route to only one cell when the route is set up. Constraint (5) prevents the decision variable x_{pjrk} to take a positive value, unless the auxiliary binary variable t_{pjrk} be equal to 1. Eq. (6) is used to account for the number of intercellular movements. Eq. (7) is related to the quantity of parts processed in each specific route. Constraint (8) corresponds to the production quantity for each part type that is equal to the sum of part demand and quantity of defective items. Eq. (9) considers Urban's equation to account for the quantity of defective items. Constraint (10) is related to the quantity of raw materials that should be procured. Minimum acceptable capacity utilization and maximum capacity of suppliers are considered in constraint (11). Constraint (12) guarantees the rejection of poor quality raw materials. Finally, constraints (13)-(15) define variables type.

3. Solution Methodology

To solve the mathematical model, we need an approach to transform the FMILP model into an equivalent auxiliary crisp MILP. Defuzzification is the procedure of decoding a fuzzy value and computing its corresponding crisp measure. Different fuzzy numbers of ranking methods have been introduced to obtain compromise solutions for dealing with fuzzy mathematical programming models. The defuzzification of triangular fuzzy number can be performed by applying the possibility theory (Chang, 1996; Enea and Piazza, 2004) or centroid methods (Wang and Parkan, 2006). According to Yager (1981), the crisp measure is the abscissa of the center of gravity:

$$A^R = \frac{A^l + A^m + A^u}{3} \tag{16}$$

Now, we present the equivalent crisp constraints using the above equation:

$$\sum_{r=1}^{R_p} y_{pr} = \left(\frac{D^l_p + D^m_p + D^u_p}{3}\right) + \sum_{r=1}^{R_p} dq_{pr} \qquad \forall p \tag{17}$$

$$dq_{pr}^{-} - dq_{pr}^{+} = \left(\frac{\lambda_{pr}^{l} + \lambda_{pr}^{m} + \lambda_{pr}^{u}}{3}\right).y_{pr} + \left(\frac{\gamma_{pr}^{l} + \gamma_{pr}^{m} + \gamma_{pr}^{u}}{3}\right) \quad (18)$$

$\forall p, r$

Consequently, we would obtain an auxiliary crisp MILP model as follows:

Minimize Z

Subject to: **(19)**

(2)-(7), (10)-(15), (17) and (18)

4. Numerical Illustration

To verify the capability of the proposed model in an uncertain environment and to illustrate the need for an integrated manner, a comprehensive numerical example is presented. This example includes three cells, five types of machines, seven part types, ten raw material types, and six potential suppliers. The detailed data are in Tables 1-7. Table 1 contains the fuzzy demand value for each part type, unit intercellular movements cost, and unit repair cost for defective items. Data, pertaining to the operational issues, include data of machine types, processing time required by each operation in each route, set-up cost of each route, and also the fuzzy values of λ and γ for calculating the defect quantities are shown in Table 2. Table 3 shows the data related to machine investment cost, machine capacity, and operational cost per unit time of each machine type. Table 4 reports the bill of material that denotes the quantity of raw material type i required to produce one unit of part type p.

Finally, supplier information containing fixed cost and raw material price, expected quality level, average lead time delay, unit quality deficiency penalty cost, unit lead time delay penalty cost, minimum acceptable capacity utilization, and maximum capacity of suppliers are given in Tables 5-7.

Table 1
Data for part types

Part	$\tilde{D}_p$	IMC_p	RC_p
1	(4600, 5100, 5300)	0.12	4
2	(3700, 4000, 4600)	0.13	5
3	(3200, 3600, 4000)	0.13	3
4	(3700, 4000, 4900)	0.15	4
5	(3000, 4100, 4300)	0.13	5
6	(3700, 4200, 4400)	0.14	6
7	(3900 ,4100, 4900)	0.12	4

Table 2
Operational data for part types

Part	**Route**	**Opr1 Opr2 Opr3 (a_{pjrm}, PT_{pjr})***	SC_{pr}	$\tilde{\lambda}_{pr}$	$\tilde{\gamma}_{pr}$
1	1	(1, 5)* − (4, 4) − (2, 5)	2000	(0.05, 0.09, 0.10)	(-30, -55, -65)
	2	(5, 3) − (1, 5) − (2, 4)	1950	(0.07, 0.11, 0.12)	(-30, -50, -100)
	3	(3, 3) − (4, 4) − (5, 6)	2020	(0.065, 0.095, 0.11)	(-25, -60, -65)
2	1	(3, 3) − (2, 6)	1900	(0.08, 0.13, 0.15)	(-40, -50, -90)
	2	(2, 4) − (4, 6)	1950	(0.125, 0.145, 0.15)	(-40, -80, -90)
3	1	(5, 6) − (2, 6) − (1, 7)	2050	(0.12, 0.16, 0.17)	(-50, -100, -120)
	2	(4, 4) − (1, 8) − (3, 6)	2020	(0.11, 0.12, 0.16)	(-40, -60, -110)
4	1	(1, 6) − (2, 5) − (3, 9)	1800	(0.07, 0.09, 0.14)	(-40, -50, -60)
	2	(3, 7) − (5, 5) − (4, 8)	1860	(0.07, 0.09, 0.11)	(-30, -55 , -65)
5	1	(2, 5) − (3, 4) − (4, 4)	1950	(0.085, 0.13, 0.145)	(-40, -50, -90)
	2	(1, 6) − (3, 4) − (5, 4)	1950	(0.08, 0.09,0.13)	(-20, -30, -70)
	3	(3, 5) − (2, 4) − (4, 4)	1920	(0.04, 0.11, 0.15)	(-25, -60, -65)
6	1	(3, 5) − (5, 4) − (2, 6)	1870	(0.06, 0.07, 0.08)	(-20, -30, -40)
	2	(5, 5) − (4, 4) − (1, 7)	1920	(0.06, 0.08, 0.13)	(-25, -45, -50)
7	1	(1, 5) − (2, 6)	1780	(0.06, 0.09, 0.15)	(-30, -40, -80)
	2	(4, 5) − (3, 6)	1840	(0.07, 0.09, 0.11)	(-30, -50, -70)

Table 3
Data for machine types

Machine type	**Time capacity (minutes)**	**Investment cost**	**Operational cost (per minutes)**
1	24600	2000	0.12
2	24000	2150	0.13
3	25800	2050	0.15
4	24600	2200	0.14
5	25200	2100	0.12

Table 4
Usage rate matrix

		Raw material types									
		1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
Part types	*1*	*2*					*2*			*1*	*1*
	2		*2*			*2*		*1*			
	3			*1*	*3*			*1*			
	4			*1*			*1*		*3*		
	5					*2*				*2*	*2*
	6	*2*	*1*				*1*			*1*	
	7			*2*				*2*			*1*

Table 5
Fixed cost and raw material price data for suppliers (FC, IRC)

Raw material	Supplier1	Supplier2	Supplier3	Supplier4	Supplier5	Supplier6
1	(600, 3.2)*	−	(730, 2.7)	(900, 2.9)	(750, 3.1)	(850, 2.7)
2	(700, 3.2)	(850, 3)	−	−	(750, 2.7)	(700, 3.1)
3	−	(650, 4)	(800, 5)	(900, 4.5)	−	(850, 4.9)
4	(870, 3.5)	(1050, 3.2)	−	−	(730, 4)	(780, 3)
5	(870, 4.1)	(900, 4.1)	(820, 3.6)	(1020, 4.5)	−	(840, 4)
6	−	(750, 3.6)	(650, 3)	(700, 4)	−	(860, 3.4)
7	(560, 3.5)	−	(750, 3.5)	−	(800, 3.5)	(780, 3.5)
8	(790, 3)	−	−	(850, 3.2)	(910, 3.5)	(860, 3.7)
9	−	(770, 2.9)	(650, 3)	(800, 3)	(720, 2.7)	−
10	(990, 2.9)	(800, 3.5)	(800, 3.7)	(950, 3)	(1000, 2.5)	(940, 2.4)

Table 6
Quality and lead time data (QL, LTD)*.

Raw material	Supplier1	Supplier2	Supplier3	Supplier4	Supplier5	Supplier6	(UQP, UDP)
1	(0.92, 2)*	−	(0.87, 1)	(0.90, 0)	(0.91, 0)	(0.87, 3)	(4.2, 0.9)
2	(0.90, 1)	(0.90, 0)	−	−	(0.92, 1)	(0.93, 4)	(3.8, 0.7)
3	−	(0.89, 3)	(0.91, 2)	(0.90, 0)	−	(0.94, 2)	(3.6, 0.8)
4	(0.90, 3)	(0.83, 1)	−	−	(0.91, 2)	(0.90, 1)	(3.5, 0.7)
5	(0.85, 0)	(0.93, 0)	(0.94, 1)	(0.91, 1)	−	(0.90, 0)	(4.4, 0.5)
6	−	(0.94, 1)	(0.93, 0)	(0.93, 0)	−	(0.89, 3)	(4, 0.65)
7	(0.91, 2)	−	(0.90, 1)	−	(0.88, 3)	(0.91, 0)	(3.9, 1.1)
8	(0.91, 1)	−	−	(0.90, 2)	(0.91, 1)	(0.93, 2)	(3.5, 0.8)
9	−	(0.91, 0)	(0.93, 1)	(0.92, 2)	(0.90, 0)	−	(3, 1)
10	(0.88, 4)	(0.92, 0)	(0.95, 1)	(0.87, 3)	(0.90, 0)	(0.91, 4)	(4, 0.85)

Table 7
Minimum acceptable capacity utilization and maximum capacity of suppliers (L, CS)

Raw material	Supplier1	Supplier2	Supplier3	Supplier4	Supplier5	Supplier6
1	(2300, 8500)*	−	(2600, 8000)	(2700, 9000)	(3000, 7000)	(2800, 6500)
2	(2400, 9000)	(2100, 8500)	−	−	(2000, 8500)	(2500, 7500)
3	−	(2400, 9000)	(2600, 8500)	(2200, 9000)	−	(2500, 7000)
4	(3000, 9500)	(3300, 7500)	−	−	(2700, 8500)	(2800, 6200)
5	(3100, 6500)	(3500, 6000)	(2800, 8000)	(3000, 7500)	−	(3200, 6000)
6	−	(3200, 9000)	(3000, 8000)	(2400, 7500)	−	(2800, 7000)
7	(2200, 9000)	−	(2800, 8500)	−	(2700, 9500)	(3000, 6500)
8	(2400, 7500)	−	−	(2500, 6500)	(2700, 6000)	(2800, 8500)
9	−	(3100, 6000)	(3200, 7500)	(2900, 8000)	(2900, 8200)	−
10	(2600, 7500)	(3100, 8500)	(2200, 6500)	(2900, 5500)	(3200, 7000)	(2800, 6500)

Table 8
Optimal solution for CF design production factors in the integrated approach

Part	Route	Zpr	y_{pr}	dq_{pr}	Visited cells sequence	Intercellular movements
1	1	1	1471	68	Cell3−Cell3−Cell3	0
	2	1	3184	258	Cell2−Cell2−Cell2	0
	3	1	682	11	Cell3−Cell3−Cell1	682
2	1	1	4591	491	Cell1−Cell1	0
	2	0	−	−	−	−
3	1	1	600	0	Cell1−Cell2−Cell2	600
	2	1	3368	368	Cell3−Cell3−Cell 3	0
4	1	1	1446	95	Cell2−Cell2−Cell1	1446
	2	1	3075	227	Cell2−Cell2−Cell2	0
5	1	1	614	14	Cell1−Cell3−Cell3	614
	2	0	−	−	−	−
	3	1	3500	300	Cell1−Cell1−Cell1	0
6	1	1	4376	276	Cell1−Cell1−Cell1	0
	2	0	−	−	−	−
7	1	1	2774	227	Cell3−Cell3	0
	2	1	1871	118	Cell1−Cell1	0

Table 9
Machine-cell formation in the integrated approach

	Cell1	Cell2	Cell3
Machine1	0	1	2
Machine2	3	1	1
Machine3	3	1	1
Machine4	1	1	1
Machine5	1	1	0

Table 10
Raw material procurement in the integrated approach

Raw material	Supplier1	Supplier2	Supplier3	Supplier4	Supplier5	Supplier 6
1	3428	−	0	9000	7000	0
2	0	8500	−	−	5058	0
3	−	0	2600	9000	−	6181
4	0	0	−	−	5703	6200
5	0	6000	8000	0	−	3409
6	−	4073	8000	7500	−	0
7	2850	−	8500	−	0	6500
8	7500	−	−	2500	3564	0
9	−	6000	3741	0	8200	−
10	0	8500	2711	0	7000	0

Table 11
Optimal solution for CF design production factors in conventional two-phase procedure

Part	Route	Z_{pr}	y_{pr}	dq_{pr}	Visited cells sequence	Intercellular movements
1	1	0	−	−	−	−
	2	1	5489	489	Cell2−Cell2−Cell2	0
	3	0	−	−	−	−
2	1	1	4591	491	Cell1−Cell1	0
	2	0	−	−	−	−
3	1	1	4129	529	Cell1−Cell1−Cell1	0
	2	0	−	−	−	−
4	1	1	3553	305	Cell2−Cell1−Cell1	3553
	2	1	992	39	Cell3−Cell3−Cell3	0
5	1	0	−	−	−	−
	2	0	−	−	−	−
	3	1	4167	367	Cell3−Cell3−Cell3	0
6	1	1	4376	276	Cell3−Cell3−Cell3	0
	2	0	−	−	−	−
7	1	1	4722	422	Cell3−Cell3	0
	2	0	−	−	−	−

Table 12
Machine-cell formation in conventional two-phase procedure

	Cell1	Cell2	Cell3
Machine1	0	2	1
Machine2	3	1	3
Machine3	3	0	2
Machine4	0	0	1
Machine5	1	1	1

To demonstrate the efficiency of the proposed integrated approach to make the CF and supplier selection decisions simultaneously, as compared to when these two decisions are separately taken into account, the proposed example is solved by eliminating the supplier selection feature at the first phase, and then at the second phase, raw material procurement decision is made on the basis of the obtained CF design. As can be seen from the results in Tables 11 and 12, the optimal cell configurations and its production design factors have changed. Comparing Tables 8 and 11 reveals that there are more set-up numbers and also few defective items in the integrated approach. Setting up more processing routes reduces lot sizes, and consequently reduces the quantity of defective items according to JIT philosophy. The obtained total cost corresponding to the proposed integrated approach is accompanied by about 10% cost saving as compared with the conventional two-phase procedure. Within small systems of such a size, even a modest percentage improvement in the overall cost by employing the integrated approach can be valuable to the overall competitiveness of a manufacturing system. Moreover, simultaneous consideration of supplier selection and cellular manufacturing enables manufacturers to respond quickly to customer requirements. Therefore, the integrated approach to cellular manufacturing design with supplier selection process yields faster response, lower procurement cost, and lower production cost to companies (Paydar et al. 2014).

5. Conclusion

In traditional manufacturing systems, designing production facilities and selecting raw material suppliers were two separate decisions. In this paper, an integrated approach was adopted to analyze, since production and purchasing are interrelated functions and interact as an organization's overall operation. A unified FMILP model was developed to make production and procurement decisions in generalized CF problem and supplier selection simultaneously, together with product quality considerations. Comparing Table 8 with Table 11 as well as Table 9 with Table 12, we found that there are differences among the proposed integrated mathematical model and the conventional two-phase procedure from the perspective of optimal cell configuration and its production design factors. The computational results also showed that the proposed integrated approach with simultaneous consideration of cellular manufacturing design and supplier selection is more effective as compared to when these two decisions are separately taken into account. The unified fuzzy mathematical model attempted in this paper suffers from a large number of constraints and variables, which make it difficult for application in real cases. Hence, meta-heuristic approaches can be developed to cope with real-sized problems in future research studies.

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