Computers & Industrial Engineering 98 (2016) 323–332

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Multi-objective dynamic cell formation problem: A stochastic programming approach

A.M. Zohrevand [a,*], H. Rafiei [b], A.H. Zohrevand [c]

[a] School of Industrial & Systems Engineering, College of Engineering, University of Tehran, Tehran, P.O. Box 11155-4563, Iran
[b] Department of Industrial Engineering, Faculty of Engineering, College of Farabi, University of Tehran, Iran
[c] Graduate School of Management and Econimics, Sharif University of Technology, Tehran, Iran

ARTICLE INFO

Article history:
Received 21 January 2012
Received in revised form 26 March 2016
Accepted 29 March 2016
Available online 6 April 2016

Keywords:
Dynamic cell formation
Fuzzy sets theory
Human-related issues
Multi-objective optimization
Stochastic programming

ABSTRACT

This paper addresses dynamic cell formation problem (DCFP) which has been explored vastly for several years. Although a considerable body of literature in this filed, two remarkable aspects have been significantly ignored so far, as uncertainty and human-related issues. In order to compensate such a shortage, this paper develops a bi-objective stochastic model. The first objective function of the developed model seeks to minimize total cost of machine procurement, machine relocation, inter-cell moves, overtime utilization, worker hiring/laying-off, and worker moves between cells; while the second objective function maximizes labor utilization of the cellular manufacturing system. In the developed model, labor utilization, worker overtime cost, worker hiring/laying off, and worker cell assignment are considered to tackle some of the most notable human-related issues in DCFP. Considering the complexity of the proposed model, a hybrid Tabu Search–Genetic Algorithm (TS–GA) is proposed whose strength is validated to obtain optimal and near optimal solutions through conducted experimental results.

1. Introduction

Cellular Manufacturing System (CMS) is an important application of Group Technology (GT). GT is a general philosophy that in the manufacturing context, attempts to group parts into part families, and allocate machines into machine cells based upon their similarities both in process and geometrical characteristics. Application of GT yields numerous advantages, not only reduce setup time, lot size, work-in-process (WIP), finished goods inventory, and throughput time, but also improve flexibility in manufacturing systems (Collet & Spicer, 1995; Fry, Breen, & Wilson, 1987; Levasseur, Helms, & Zink, 1995; Singh & Rajamaani, 1996; Süer & Sáiz, 1993). Designing a CMS consists of four major steps including (a) Cell Formation (CF): grouping parts with similar geometric or processing features into part families and grouping required machines into machine cells; (b) group layout: laying out machines within cells; (c) group scheduling: scheduling part families; and (d) resource allocation: assigning manufacturing resources, such as tools, manpower, and materials (Ghotboddini, Rabbani, & Rahimian, 2011).

Many researchers have developed different approaches and models yet to face with the Cell Formation Problem (CFP). Regarding this, Dynamic CFP (DCFP) has recently captivated academic societies, since it is inevitable to adapt system capabilities with market requirements in a static form. To do so, cell configurations are updated during different planning periods to respond dynamic product mix and demand volumes. Though a number of CFP models are found in the literature, two issues are mostly neglected in the presented models. One of the issues corresponds to human-related aspects of CFP, which are challenged in some papers, such as those of Süer (1996), Suresh and Slomp (2001), and Süer et al. (2013). The main attribute of these papers is that human-related issues have been considered in a separate manner with other requirements of CFP through a multi-step framework. In this regard, developing the second objective function of the proposed model, herein seeks to maximize worker utilization. Moreover, worker overtime cost, worker hiring/laying off cost, and worker assignment cost are taken into account within the developed model. On the other hand, indeterministic models have been rarely studied in comparison with the deterministic instances, among which readers are referred to product-mix uncertainty in Seifoddini (1990), fuzzy clustering methods in Lozano, Dobado, Larraneta, and Onieva (2002), fuzzy demands and machine capacities in Safaei, Saeidi-Mehrabad, Tavakkoli-Moghaddam, et al. (2008) and random demands in Süer, Huang, and Maddisetty (2010). In this paper, the proposed model along with the above features, adopts fuzzy stochastic programming to cope with the vagueness involved in part demands, machine capacities in regular time and overtime, and machine selling prices.

The remainder of the paper is structured as follows. Section 2 reviews literature body of DCFP briefly, while the developed model

* Corresponding author.

http://dx.doi.org/10.1016/j.cie.2016.03.026
0360-8352/

is discussed in Section 3. Since the proposed model is nonlinear, two transformations are utilized to linearize the model, which are explained in Section 3 as well. Section 4 presents the solution methodology to deal effectively with flexibility involved in the proposed model. Section 5 explores some numerical experiments in order to validate applicability of the proposed model. Finally, concluding remarks and future research directions are provided in Section 6.

2. Literature review

There are lots of methods for CFP in the literature but here we classify them into two major categories as design-oriented approaches, which group parts into families based on similar design features (Askin & Vakharia, 1991) and production-oriented approaches, which seek aggregation of parts requiring similar processes (Joines, Culbrethe, & King, 1996; Song & Hitomi, 1996). Regarding this, a number of review papers is found, among which the readers are referred to Balakrishnan and Cheng (2007) since the most comprehensive image of CFP has been delineated. In this following, research work with the assumptions close to those of this paper is reviewed.

Song and Hitomi (1996) proposed a mixed-integer model for designing a flexible CMS. Their model contained two integer programs. The first model defines production quantity for each product and, the second model lays out the cells in a finite planning horizon with dynamic demand. Later, Chen (1998) developed a mathematical programming model with the objective function of minimum inter-cell material moves, machine cost and reconfiguration cost in a DCMS. Regarding dynamic nature of production environment, Wicks (1995) proposed a multi-period part family and machine cell formation problem. The objective functions were, minimizing inter-cell material handling cost, minimizing investment in additional machines and minimizing cost of system reconfiguration over the planning horizon. Mungwatanna (2000) mentioned routing flexibility in DCFP. He proposed a non-linear mixed-integer model. Then the model was linearized and solved by Simulated Annealing (SA). Tavakkoli-Moghaddam, Aryanezhad, Safaei, and Azaron (2005) modified the Mungwatanna's model and compared performance of three meta-heuristics, Genetic Algorithm (GA), SA and Tabu Search (TS).

Safaei, Saeidi-Mehrabad, Tavakkoli-Moghaddam, et al. (2008) issued batch inter/intra-cell material handling, while the operation sequence of the production was also determined. They solved the resulted model by a hybrid SA. Safaei, Saidi-Mehrabad, Jabal-Ameli (2008) reformulated the Mungwatanna's model considering fuzzy sets theory. In Aryanezhad, Deljoo, and Mirzapour Al-e-hashem (2009), the authors considered both dynamic cell formation and worker assignment problem developing a non-linear integer program for DCFP based on Mungwatanna's model (2000). They also linearized the developed model in order to reduce its complexity. Saxena and Jain (2011) proposed a multi-objective mixed-integer non-linear programming model to design a DCMS. They integrated many attributes in the developed model, such as breakdown effect, process batch size, transfer batch size for intra-cell moves, and transfer batch size for inter-cell moves. Balakrishnan and Cheng (2005) proposed a two-stage procedure based on the generalized machine assignment problem and dynamic programming. Their model was a flexible framework for modeling cellular manufacturing when product demand changed during the planning horizon. Kioon, Bulgak, and Bektas (2009) developed a mixed-integer non-linear model for DCMS which integrated production planning, dynamic system reconfiguration, and multiple routing. Since their non-linear problem was intractable, some linearization techniques were also proposed. Recent research works have usually considered cell formation as a single objective problem but today's business environment makes multi-objective optimization necessary. Multi-objective optimization offers new opportunity to determine problems with more accurate features and it makes the model become adaptable to the real world expectations. Wang, Tang, and Yung (2009) addressed the DCFP with multiple conflicting objective functions. In their developed solution approach, weights were considered for the developed three conflicting objective functions in order to form a single weighted sum of objective functions. The objective functions were minimizing machine relocation cost in the process of cell reconfiguration, maximizing utilization of machine capacity, and minimizing total number of intra-cell moves over the entire planning horizon. In order to solve the proposed model, a scatter search algorithm was developed and results were compared with the results of solver CPLEX. Safaei and Tavakkoli-Moghadam (2009) proposed an integrated mathematical model of the multi-period cell formation and production planning in a DCMS. Minimizing costs of machine, inter/intra-cell movement, reconfiguration, partial subcontracting, and inventory carrying was the objective function of their proposed model. Recently Ghotboddini et al. (2011) proposed a multi-objective mixed-integer model for DCMS. The model considered some real world critical conditions in lean production that had been neglected in the literature so far. Their model solved part-machine grouping simultaneously with labor assignment in order to minimize costs of reassignment of human resources, overtime cost of equipment and labor, and maximize utilization rate of human resource.

Although numerous research papers are found in the literature body of CFP, there are some aspects of this problem, which have been mostly neglected. Among them, worker assignment and system uncertainty are notable. Regarding worker-related issues of CFP, some research papers have been published so far (Cesani & Steudel, 2005; Slomp, Bokhorst, et al., 2005; Slomp, Chowdary, et al., 2005; Slomp & Suresh, 2005; Suresh & Slomp, 2001; Süer, 1996; Süer, Kamat, Mese, & Huang, 2013). Süer (1996) presented a two-phase hierarchical methodology for operator assignment and cell loading in labor-intensive manufacturing cells. Also, Slomp, Bokhorst, et al. (2005) addressed cell load balancing in trade-off with worker training costs using a developed integer program. Additionally, the labor load balancing was considered by Slomp and Suresh (2005) using a two-stage goal programming approach and by Slomp, Bokhorst, et al. (2005) and Slomp, Chowdary, et al. (2005) in designing virtual cells using a two-phase mathematical approach. The main common attribute of the worker-related papers is that the worker-related decisions are made in a different stage with the decisions of operations and production. As an instance, Suresh and Slomp (2001) addressed a multi-objective cellular design problem including labor group decisions using pattern recognition after part-machine grouping had been conducted. Their developed model partitioned workers into functionally specialized labor pools. Also, Süer et al. (2013) developed a two-stage methodology to optimize number of cells, crew size, cell loading, and cell scheduling. Some other samples considering worker assignment in DCMS include those of Egilmez, Erenay, and Süer (2014), Süer, Arikan, et al. (2009), Süer, Cosner, et al. (2009), and Süer, Vazquezb, and Cortes (2005). As mentioned earlier, all published research papers coped with the worker-related problem in a sequential manner, while this paper tackles the problem integrated with other aspects of DCFP.

Another aspect of CFP that has been mostly neglected is taking system uncertainty into account using probabilistic models. In this regard, two categories of stochastic and fuzzy models have been developed so far. Seifoddini (1990) minimized the expected inter-cell handling cost in the case of product-mix uncertainty, whereas Saidi-Mehrabad and Ghezavati (2009) adopted queuing theory approach to cope with the uncertainty of a CMS. Egilmez, Süer, and Huang (2012) developed a stochastic optimization approach to minimize numbers of cells and machines in a certain risk level, while operation times and customer demands were assumed normal variables. They conducted numerical simulation to compare different risk levels with respect to four performance measures cell utilization, WIP, total waiting time, and total number of waiting units. On the other hand, Lozano et al. (2002), Park and Suresh (2003), and Torkul, Cedimoglou, and Geyik (2006) adopted a fuzzy clustering method to form part-machine assignment to cells. Moreover, Safaei, Saeidi-Mehrabad, Tavakkoli-Moghaddam, et al. (2008) extended their previous deterministic model by assuming part demands and machine capacity parameters as fuzzy triangular numbers. They solved three small-size problems by LINGO package. In Arikan and Gungor (2009) model, the part demands, machine capacities, machine purchasing costs and exceptional elements elimination costs were assumed as fuzzy numbers. In this regard, part demands, machine capacities in regular time and overtime, and machine selling costs were modeled using fuzzy triangular parameters. Moreover, labor utilization in the considered DCFP was maximized as the second objective function.

3. Proposed model

In this section and considering the research gap, a new mathematical formulation is developed in order to consider human-related issues as well as common criteria of DCFP. Using required indices, parameters and variables defined as below, the mathematical formulation is developed in (1)-(16).

Indices

c	index for manufacturing cells ($c = 1, \ldots, C$)
m	index for machine types ($m = 1, \ldots, M$)
p	index for part types ($p = 1, \ldots, P$)
t	index for time periods ($t = 1, \ldots, T$)
j	index for operations belonging to part type p ($j = 1, \ldots, J_p$)

Parameters

C	maximum number of allowed cells
M	number of machine types
P	number of part types
T	number of periods
J_p	number of operations required for part type p
D_{pt}	demand for part type p in period t
φ_p	inter-cell movement cost per unit of part type p batch
B_p	batch size of product type p
π_m	selling cost of machine type m
μ_m	purchasing cost of machine type m
γ_m^+	installing cost of machine type m
γ_m^-	removing cost of machine type m
T_m	time capacity of machine type m in regular time
T'_m	time capacity of machine type m in overtime
m_t	hiring cost in period t
n_t	laying off cost in period t
UB	maximum cell size
LB	minimum cell size
OC_t	worker cost per unit of overtime
δ_c	cost of moving worker to cell c
α_{jpm}	required time of machine type m per unit of part type p on operation j
β_{jp}	required time of worker per unit of part type p on operation j
WT	available time per worker

Variables

Y_{mct}	1, if machine type m is allocated to cell c in period t; 0, otherwise
X_{jpmct}	1, if operation j of part type p is performed on machine m in cell c in period t; 0, otherwise
N_{mct}	number of machine type m allocated to cell c in period t
N^+_{mct}	number of machine type m added to cell c in period t
N^-_{mct}	number of machine type m removed from cell c in period t
K^+_{mt}	number of machine type m purchased at the beginning of period t
K^-_{mt}	number of machine type m sold at the beginning of period t
W^+_t	number of workers hired in period t
W^-_t	number of workers laid off in period t
W^+_{ct}	number of workers added to cell c in period t
W^-_{ct}	number of workers removed from cell c in period t
W_{ct}	number of workers assigned to cell c in period t
MHU_{ct}	minimum worker utilization of cell c in period t
τ_{mt}	overtime utilization on machine m in period t

$$\begin{aligned} Min\ Z_1 = &\sum_{t=1}^{T}\sum_{m=1}^{M}(\mu_m K^+_{mt} - \tilde{\pi}_m K^-_{mt}) + \sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M}(\gamma^+_m \cdot N^+_{mct} + \gamma^-_m \cdot N^-_{mct}) \\ &+ \frac{1}{2}\sum_{t=1}^{T}\sum_{p=1}^{P}\phi_p\left\lceil\frac{\widetilde{D}_{pt}}{B_p}\right\rceil \cdot \sum_{c=1}^{C}\sum_{j=1}^{J_p}\left|\sum_{m=1}^{M}X_{(j+1)pmct} - \sum_{m=1}^{M}X_{jpmct}\right| \\ &+ \sum_{t=1}^{T}OC_t \cdot \sum_{m=1}^{M}\tau_{mt} + \sum_{t=1}^{T}(W^+_t m_t + W^-_t n_t) + \sum_{c=1}^{C}\delta_c \cdot \sum_{t=1}^{T}W^+_{ct} \end{aligned} \quad (1)$$

$$Max\ Z_2 = \sum_{c=1}^{C}\sum_{t=1}^{T}MHU_{ct} \quad (2)$$

$$\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{j=1}^{J_p}X_{jpmct}\alpha_{jpm}\widetilde{D}_{pt} \leqslant \widetilde{T}_m\sum_{c=1}^{C}N_{mct} + \tau_{mt} \quad \forall m,t \quad (3)$$

$$\sum_{c=1}^{C}N_{mct} - \sum_{c=1}^{C}N_{mc(t-1)} = \sum_{c=1}^{C}N^+_{mct} - \sum_{c=1}^{C}N^-_{mct} \quad \forall m,t \quad (4)$$

$$\sum_{c=1}^{C}N^+_{mct} - \sum_{c=1}^{C}N^-_{mct} = K^+_{mt} - K^-_{mt} \quad \forall m,t \quad (5)$$

$$\tau_{mt} \leqslant \widetilde{T}'_m \quad \forall m,t \quad (6)$$

$$LB \leqslant \sum_{m=1}^{M}N_{mct} \leqslant UB \quad \forall c,t \quad (7)$$

$$N_{mct} \leqslant M \cdot Y_{mct} \quad \forall m,c,t \quad (8)$$

$$\frac{\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{j=1}^{J_p}X_{jpmct}\beta_{jp}\widetilde{D}_{pt}}{W_{ct}\cdot\widetilde{WT}} \geqslant MHU_{ct} \quad \forall c,t \quad (9)$$

$$\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{j=1}^{J_p}X_{jpmct} \leqslant M \cdot \widetilde{D}_{pt} \quad \forall p,t \quad (10)$$

$$Y_{mct} \leqslant M \cdot \sum_{p=1}^{P}\sum_{j=1}^{J_p} X_{jpmct} \quad \forall m,c,t \tag{11}$$

$$\sum_{c=1}^{C} W_{ct} - \sum_{c=1}^{C} W_{c(t-1)} = \sum_{c=1}^{C} W_{ct}^{+} - \sum_{c=1}^{C} W_{ct}^{-} \quad \forall t \tag{12}$$

$$\sum_{c=1}^{C} W_{ct}^{+} - \sum_{c=1}^{C} W_{ct}^{-} = W_t^{+} - W_t^{-} \quad \forall t \tag{13}$$

$$X_{jpmct}, \quad Y_{mct} \in \{0,1\}, \quad \forall j,p,m,c,t \tag{14}$$

$$K_{mt}^{+}, \quad K_{mt}^{+}, \quad N_{mct}, \quad N_{mct}^{+}, \quad N_{mct}^{-}, \quad W_{ct}, \quad W_{ct}^{+}, \quad W_{ct}^{-}, \quad W^{+}, \quad W^{-} \geqslant 0, \quad \text{int} \quad \forall m,c,t \tag{15}$$

$$MHU_{ct}, \quad \tau_{mt} \geqslant 0, \quad \forall p,m,c,t \tag{16}$$

Objective function (1) seeks to minimize the costs of machine procurement, machine relocation, inter-cell moves, overtime utilization, and human-related issues. With respect to the workers, worker overtime cost, worker hiring/laying off cost, and worker assignment cost are taken into account within the developed objective function. It is noted that the different relocation costs are considered in order to install or remove machines to/or from a cell based upon the consideration mentioned by Deljoo, Mirzapour Al-e-hashem, Deljoo, and Aryanezhad (2010). Objective function (2) maximizes the minimum labor ratio of system worker utilization. In other words, the worker utilization is maximized by this objective function. Constraints (3) consider time capacities of machines, while their quantities are controlled in Constraints (4) and (5). Limitations of overtime and cell sizes are modeled in (6) and (7), respectively. Relations between N_{mct} and Y_{mct} are taken into account in (8). Constraints (9) calculate minimum worker utilization in the planning periods. Xs and Ys get their values in Constraints (10) and (11). Constraints (12) and (13) consider numbers of assigned workers to cells and numbers of workers in the periods, respectively. In order to consider the dynamic nature of DCFP, some parameters are changing during different planning periods, including the part demands, worker hiring/laying off costs, and worker overtime costs. Moreover, variables Y_{mct}, N_{mct}, N_{mct}^{+}, N_{mct}^{-}, W_{ct}, W_{ct}^{+} and W_{ct}^{-} address required reconfiguration of cells in planning periods. Similarly, this is conducted using $K_{mt}^{+}, K_{mt}^{-}, W_t^{+}$ and W_t^{-} for total system reconfiguration as is done using X_{jpmct} for part re-assignment. In addition to the defined parameters and variables, Constraints (3)–(5) and (7)–(13) ensure dynamic reconfiguration of part assignment, cells, and the total CMS.As above-described model, objective function (1) and Constraints (9) are non-linear and are linearized using the following procedures. First, two auxiliary variables ϑ_{jpct}^{+} and ϑ_{jpct}^{-} are defined in order to linearize the absolute term of objective function (1). This linearization is performed using (17) and adding (18) to the constraints of the model.

$$\left| \sum_{m=1}^{M} X_{(j+1)pmct} - \sum_{m=1}^{M} X_{jpmct} \right| = \vartheta_{jpct}^{+} - \vartheta_{jpct}^{-} \tag{17}$$

$$\vartheta_{jpct}^{+} - \vartheta_{jpct}^{-} = \sum_{m=1}^{M} X_{(j+1)pmct} - \sum_{m=1}^{M} X_{jpmct} \quad \forall j,p,m,c,t \tag{18}$$

Next, the following procedure is used to linearize Constraints (9). To do so, auxiliary variables maximum worker idleness of cell c in period t, MHI_{ct}, are defined and utilized as:

$$MHI_{ct} = 1/MHU_{ct} \quad \forall c,t$$

$$\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{j=1}^{J_p} X_{jpmct}\beta_{jp}\widetilde{D}_{pt} \geqslant 0 \rightarrow MHI_{ct} \cdot \sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{j=1}^{J_p} X_{jpmct}\beta_{jp}\widetilde{D}_{pt} \leqslant W_{ct} \cdot \widetilde{WT} \quad \forall c,t$$

$$\zeta_{jpmct} = X_{jpmct} MHI_{ct} \rightarrow MHI_{ct} \cdot \sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{j=1}^{J_p} X_{jpmct}\beta_{jp}\widetilde{D}_{pt} = \sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{j=1}^{J_p} X_{jpmct}\beta_{jp}\zeta_{jpmct} \quad \forall c,t$$

In order to control values of ζ_{jpmct}, Constraints (19)–(22) are added to the constraints of the model, while objective function (2) is substituted by (23).

$$\zeta_{jpmct} \leqslant MHI_{ct} \quad \forall j,p,m,c,t \tag{19}$$

$$\zeta_{jpmct} \leqslant M \cdot X_{jpmct} \quad \forall j,p,m,c,t \tag{20}$$

$$\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{j=1}^{J_p} \zeta_{jpmct}\beta_{jp}\widetilde{D}_{pt} \leqslant W_{ct} \cdot \widetilde{WT} \quad \forall j,p,m,c,t \tag{21}$$

$$MHI_{ct}, \quad \zeta_{jpmct} \geqslant 0 \quad \forall j,p,m,c,t \tag{22}$$

$$Min\ Z_2 = \sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{j=1}^{J_p} \zeta_{jpmct} \tag{23}$$

4. Solution methodology

In this section, three major components of the developed solution methodology are explained. Hence, adopted solution approach, the proposed hybrid meta-heuristic algorithm and the relevant pseudo-code of the proposed algorithm are presented. In this regard, Section 4.1 comprises two main components with respect to the fuzzy parameters of the proposed mathematical model and its multi-objective structure. First, the adopted approach from Lai and Hwang (1992) is described to express how the fuzzy parameters of the proposed model are tackled. Next, a weighted sum approach is utilized to convert the multi-objective structure into a single-objective one.

4.1. Adopted approach toward proposed stochastic program

Since the model proposed in this paper bears indeterministic parameters, it is categorized as a stochastic programming model with ambiguous data in the objective function and the left-hand side of the constraints. Without loss of generality, the considered problem is as follows:

$$P:$$
$$Min \quad \widetilde{Z} = \widetilde{C}X$$
$$\widetilde{A}X \geqslant B$$

To convert the above stochastic model to a crisp one, two different approaches are applied with respect to the fuzzy objective function and the fuzzy constraints, separately (Lai & Hwang, 1992). First, the coefficient $\tilde{a} = (a^p, a^m, a^o)$ with three respective parameters as the pessimistic, the most possible and the optimistic values of $\tilde{a}$ is converted to $a' = (w_1a^p + w_2a^m + w_3a^o)$.

Second, since $\tilde{c} = (c^p, c^m, c^o)$, the distribution of the objective function $\widetilde{Z}$ is $\widetilde{Z} = [(C^pX, 0), (C^mX, 1), (C^oX, 0)]$. Moreover, minimization nature of the objective function results in the three objective functions to push the distribution into left:

Table 1
Parameter data of the numerical example.

Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value
T	2	WT	550	μ_m	U(100,200)	B_p	U(10,50)
M	4	β_{jp}	U(0,1)	π_m	$\mu_m/3$	φ_p	50
J_p	2	δ_c	$6 \times OC_t$	T_m	500	D_{pt}	U(100,500)
C	3	OC_t	U(10,50)	T'_m	150	α_{jpm}	U(0,1)
UB	4	m_t	$10 \times OC_t$	γ_m^+	$\mu_m/10$		
LB	1	n_t	$11 \times OC_t$	γ_m^-	$\mu_m/13$		

$$\begin{aligned} &Min \quad C^m X \\ &Max \quad (C^m X - C^p X) \\ &Min \quad (C^o X - C^m X) \end{aligned}$$

Therefore, the stochastic model P is converted to model P' by applying the two above-mentioned procedures.

$$\begin{aligned} &P': \\ &Min \quad \mathbf{Z}_1 = C^m X \\ &Max \quad \mathbf{Z}_2 = (C^m X - C^p X) \\ &Min \quad \mathbf{Z}_3 = (C^o X - C^m X) \\ &(w_1 A^p + w_2 A^m + w_3 A^o) X \geqslant B \end{aligned}$$

Next, the three resulted objective functions are aggregated into a single objective function using formula (24).

$$Min\ Z = \sum_i \alpha_i \cdot \frac{Z_i}{Z_i^*} \tag{24}$$

in which α_i indicates relative importance of the ith objective function, pursuing condition $-1 \leqslant \alpha_i \leqslant 1, \sum_i |\alpha_i| = 1$. Furthermore, Z_i^* are the ideal solutions of the objective functions which are optimized individually subject to the constraints of the problem. Using the above-mentioned procedure to handle the fuzzy parameters of the proposed mathematical model and its multi-objective structure, objective functions (1) and (23) are converted into single objective function (25).

$$Min\ Z = \alpha_1 \cdot \frac{Z_1^m}{Z_1^{m*}} - \alpha_2 \cdot \frac{(Z_1^m - Z_1^p)}{(Z_1^m - Z_1^p)^*} + \alpha_3 \cdot \frac{(Z_1^o - Z_1^m)}{(Z_1^o - Z_1^m)^*} + \alpha_4 \cdot \frac{Z_2}{Z_2^*} \tag{25}$$

As an instance in (25), Z_1^p corresponds to the pessimistic value of objective function (1).

In order to clarify how the adopted approach is applied, a numerical example is randomly generated. In this example, parameter data are generated using uniform distribution upon the values in Table 1. In order to fuzzify parameters D_{pt}, WT, T_m, T'_m and π_m, it is assumed that their nominal values are generated upon values in Table 1 and their spreads are considered between (0.75 × *nominal value*) and (1.25 × *nominal value*).

```
s ← s0
  sBest ← s
  aspirationLevel←fitness(sBest)
  tabuList ← null
  while (not stoppingCondition())
  Generate(Neghborhod)  ← GA Crossover Operator
    candidateList ← null
    for(sCandidate in sNeighborhood)
        if(not containsTabuElements(sCandidate, tabuList))
            candidateList ← sCandidate
        end
        If(containsTabuElements(sCandidate, tabuList))
            If(fitness(sCandidate)>aspirationLevel)
               candidateList← sCandidate
               aspirationLevel← fitness(sCandidate)
           end
       end
    end
    sCandidate ← LocateBestCandidate(candidateList)
    if(fitness(sCandidate) > fitness(sBest))
        sBest ← sCandidate
        tabuList ← featureDifferences(sCandidate, sBest)
        while(size(tabuList) > maxTabuListSize)
            ExpireFreatures(tabuList)
        end
    end
end
return(sBest)
```

Fig. 2. Pseudo-code of the proposed TS–GA.

After defining the parameters of the example, four objective functions Z_1, Z_2, Z_3, and Z_4 in (25) are optimized individually, whose obtained values have been 32,249, 1290, 3872, and 1, respectively.

Period 1		P4	P6	P3	P5	P1	P2
C1	M2	1		1	2		
	M1			2	1		
	M3		2				
	M4	2	1				
C2	M2					1	
	M4					2	1

Period 2		P1	P2	P4	P6	P3	P5
C1	M2	1		1			
	M4	1	1	2	1		
	M3				2		
C2	M2					1	2
	M1					2	1

Fig. 1. Optimal cell configurations of two planning periods of the example.

Period 1		P2	P6	P3	P5	P1	P4
C1	M2			1	2		
	M1			2	1		
	M3		2				
	M4	1	1				
C2	M2					1	1
	M4					2	2

Period 2		P2	P6	P3	P5	P1	P4
C2	M3		2				
	M4	1	1				
	M1			2			
	M2			1			
C3	M1				1		2
	M4					2	
	M3						
	M2				2	1	1

Fig. 3. Best-found cells configurations of two planning periods of the example using TS–GA.

Table 2
Generated test problems.

Problem no.	$C \times M \times P \times T \times J_P$	$LB \times UB$	T_m	γ_m^+	γ_m^-	μ_m	π_m
1	$3 \times 6 \times 6 \times 3 \times 1$	2×4	(5000,6000)	(400,700)	(400,700)	(4000,8000)	(2000,6000)
2	$3 \times 6 \times 7 \times 3 \times 2$	3×4	(7000,8000)	(300,600)	(300,600)	(5000,7000)	(3000,5000)
3	$3 \times 6 \times 8 \times 2 \times 2$	3×4	(5000,6000)	(400,700)	(400,700)	(3000,6000)	(1000,4000)
4	$3 \times 7 \times 8 \times 3 \times 2$	3×6	(8000,9000)	(300,600)	(300,600)	(5000,8000)	(3000,6000)
5	$3 \times 8 \times 9 \times 2 \times 3$	3×5	(4000,5000)	(400,700)	(400,700)	(4000,8000)	(2000,6000)
6	$3 \times 10 \times 10 \times 2 \times 3$	3×6	(5000,6000)	(300,600)	(300,600)	(3000,8000)	(1000,6000)
7	$3 \times 10 \times 12 \times 2 \times 3$	3×6	(6000,7000)	(300,600)	(300,600)	(5000,8000)	(3000,6000)
8	$4 \times 15 \times 20 \times 3 \times 3$	3×5	(5000,6000)	(300,600)	(300,600)	(4000,7000)	(2000,5000)
9	$4 \times 20 \times 30 \times 2 \times 3$	3×5	(7000,8000)	(400,700)	(400,700)	(5000,9000)	(3000,7000)
10	$12 \times 25 \times 78 \times 4 \times 3$	3×5	(16,000,18,000)	(300,600)	(300,600)	(5000,8000)	(3000,6000)
11	$12 \times 30 \times 89 \times 5 \times 3$	3×5	(18,000,21,000)	(300,600)	(300,600)	(4000,8000)	(2000,5000)
12	$15 \times 40 \times 107 \times 6 \times 3$	3×5	(23,000,25,000)	(400,700)	(400,700)	(3000,8000)	(1000,6000)

Interval values demonstrate the values in which corresponding data are generated upon uniform distribution

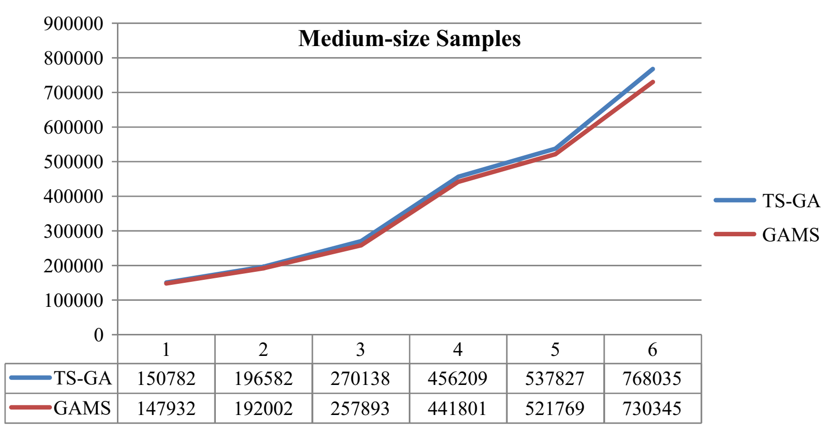

Fig. 4. Comparison of best-found solution values between GAMS and the proposed TS–GA solutions (Problem no. 1–6).

Later, the mathematical model of the numerical example is optimized with respect to aggregated objective function (25). The optimized results are 139,748, 75,464, 13,262, and 1.28 for objective functions Z_1, Z_2, Z_3, and Z_4, respectively. Hence, the fuzzy value of the first objective function is shown using asymmetric fuzzy triangular number (124,726, 139,488, 142,952) for which a defuzzification procedure is adopted. Next, a single objective function value is obtained upon which decision maker chooses the most suitable decision. Some defuzzification procedures include mean of maximum, center of area, and bi-sector of area methods among which the center of area method is adopted as it is suitable for asymmetric fuzzy triangular numbers (Torabi & Rafiei, 2012). Having the center of area method applied, the optimal values of 138,294 and 1.28 are attained for the first and the second objective functions, respectively. Fig. 1 shows optimal cell configurations in two planning periods of the numerical example. Numbers in Fig. 1 show production sequence of every part; in other words, it is demonstrated on which machine every part is processed first and then it is loaded on the next machine.

Upon the demonstrated results in Fig. 1, it is shown that machine M1 is moved from Cell 1 in Period 1 to Cell 2 in Period 2. Moreover, machine M4 is removed from Cell 2 in Period 2;

therefore, total number of machines in the system reduces in Period 2 in comparison with Period 1.

4.2. Hybrid Tabu Search–Genetic Algorithm (TS–GA)

The two metaheuristics, which have been successfully implemented in the field of DCFP, are GA and TS (as shown in Tavakkoli-Moghaddam et al. (2005)). In this study, hybrid TS–GA is developed, which is mainly structured upon TS whose Tabu list mechanism improve both algorithm exploitation and algorithm exploration. Also, GA crossover operator is utilized due to its flexible nature that facilitates its implementation in a wide range of applications with acceptable performance. TS is a "higher level" heuristic procedure for solving optimization problems. This method was originally proposed by Fred Glover in 1986. In combinatorial problems, solutions generated by this method, are usually very close to the global optimum and are among the most effective ones. Because of this fact, TS is extremely popular in the field of metaheuristic algorithms. This algorithm was designed to guide other algorithms, such as local search methods, to escape from the trap of local optimality. TS uses a local or neighborhood search procedure to iteratively move from one potential solution x to an improved solution x' in the neighborhood of x, until some stopping criteria have been satisfied. Local search procedures often become trapped in low-quality solution areas. In order to avoid these pitfalls and explore regions of the search space that would be left unexplored by other local search procedures, TS carefully explores the neighborhood of each solution as the search progresses. The solutions admitted to the new neighborhood, $N(x)$, are determined through the use of memory structures. Using these memory structures, the search progresses by iteratively moving from the current solution x to an improved solution x' in $N(x)$. These memory structures form what is known as the Tabu list, a set of rules and banned solutions, used to filter the solutions that will be admitted to be explored by the search in the neighborhood $N(x)$. In its simplest form, a Tabu list is a short-term set of the solutions that have been visited in the recent past. The memory structures used in TS can be divided into three categories (Glover, 1990):

- *Short-term*: The list of solutions which are recently met; if a potential solution appears on this list, it cannot be revisited until it reaches an expiration point.
- *Intermediate-term*: A list of rules intended to bias the search toward the promising areas of the search space.
- *Long-term*: Rules that promote diversity in the search process

Glover (1990) presented a list of applications of TS. Choosing search space and neighborhood structure are by far the most critical steps in the design of any TS meta-heuristics. There are several methods to provide the neighborhood, but regarding the difficulty of the so-called methods, we propose to use the GA crossover operator to generate the neighborhood.

4.3. Pseudo-code of the proposed algorithm

To clarify the proposed algorithm in the previous section, the relevant pseudo-code is presented. By means of the pseudo-code, the details of the proposed algorithm are demonstrated. Also, it is declared how it is coded using computer programming packages. In this regard, Fig. 2 presents pseudo-code of the proposed TS–GA algorithm.

The explained numerical example in Section 4.1 is solved using the developed hybrid TS–GA. The values of the obtained individually optimized objective functions Z_1, Z_2, Z_3, and Z_4 are 32,396, 1276, 3893 and 1, respectively. Next, the aggregated objective function value has been optimized with the values (124,902,

Table 3
Cell configurations of the large-size test problems using the proposed TS-GA.

Problem no.	CPU time (s)	$T=1$				$T=2$				$T=3$			
		$C=1$	$C=2$	$C=3$	$C=4$	$C=1$	$C=2$	$C=3$	$C=4$	$C=1$	$C=2$	$C=3$	$C=4$
7	12	1, 2, 3, 7, 10	3, 4, 5, 9	2, 6, 8, 10		1, 2, 5, 10	2, 3, 4, 8, 9	6, 7, 8, 10		1, 5, 8, 9, 10	2, 3, 4, 7, 10	3, 6, 8, 10	
8	12	1, 2, 3, 5, 9, 10	1, 3, 6, 7	2, 4, 5, 10		1, 2, 5, 8, 9	2, 3, 4, 7	2, 6, 7, 10		1, 5, 8, 10	2, 3, 4, 7, 10	3, 6, 8, 9	
9	22	1, 2, 6, 9, 11, 14	3, 6, 9, 11, 12, 14, 15	2, 5, 7, 10, 12, 13, 15	4, 8, 10, 12, 13, 15	1, 2, 6, 8, 10, 14, 15	3, 5, 9, 11, 12, 13	2, 4, 7, 9, 12, 13	4, 8, 11, 12, 15	1, 3, 6, 8, 11, 13, 15	3, 5, 9, 10, 12, 14	2, 4, 7, 10, 12, 14, 15	4, 8, 11, 12, 13, 15
10	36	2, 5, 7, 8, 12, 13, 16, 17, 19, 20	1, 4, 10, 14, 15, 17, 18	2, 3, 6, 8, 11, 16, 19, 20	1, 6, 7, 10, 14, 18, 19, 20	2, 5, 7, 8, 9, 13, 16, 18, 19, 20	1, 4, 13, 14, 15, 17, 18	1, 3, 6, 8, 9, 11, 16, 17, 20	1,4, 6, 7, 9, 14, 16, 19, 20	2, 5, 7, 8, 9, 13, 16, 18, 19, 20	1, 4, 13, 14, 15, 17, 18	1, 3, 6, 8, 9, 11, 16, 17, 20	1,4, 6, 7, 9, 14, 16, 19, 20

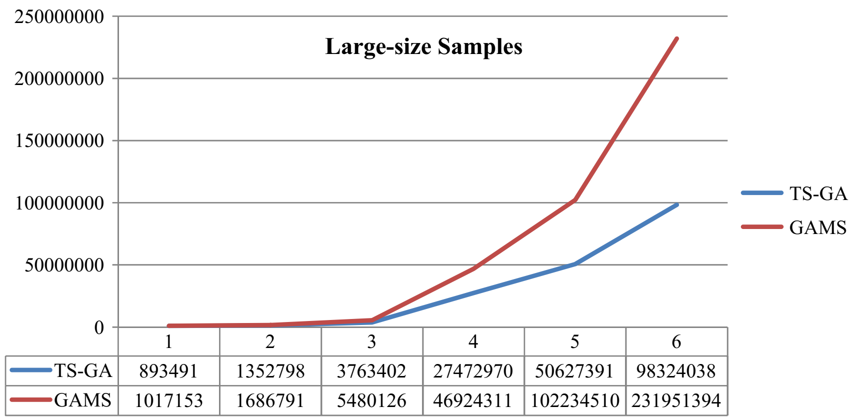

Fig. 5. Comparison of best-found solution values between GAMS and the proposed TS–GA solutions (Problem no. 7–12).

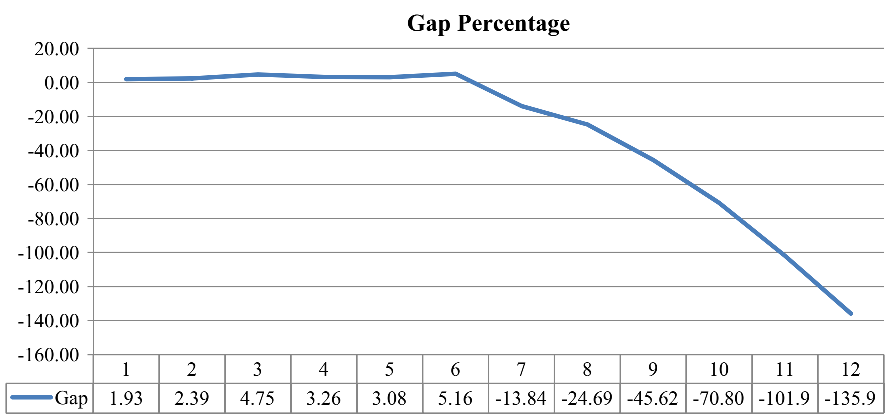

Fig. 6. Gap between best-found solution values between GAMS and the proposed TS–GA solutions.

139,525, 143,346), and 1.31 for the first and the second objective functions, respectively. Using the defuzzification method, the best found value of the first objective function is calculated as 141,325 whose gap is nearly 2% of the obtained value using GAMS.

As seen in Fig. 3, the best found solution of the TS–GA for the numerical example substituted Parts 2 and 4 in comparison with the solution in Fig. 1.

5. Numerical experiments

In order to validate the developed TS–GA algorithm, twelve test problems are randomly generated, whose parameters are presented in Table 2. Among the generated problems, the first six problems are utilized so as to validate the proposed algorithm strength in obtaining optimal solutions by comparing the results of TS–GA with the results of GAMS. The next six test problems are solely solved using the TS–GA. In Table 2, the problem sizes and the intervals upon which parameters are generated uniformly are presented.

Moreover, inter-cell move cost is assumed 75 per batch and available working time per worker is 420 min. In this regard, the regular time cost is considered 8 per time unit; henceforth, overtime cost is 1.4 times the regular time and cost of moving workers between cells is 3 times the regular time cost. Also, the regular time cost is multiplied by a random number drawn from intervals [30,45] and [40,60] as for hiring and firing costs, respectively. In addition to the above-mentioned data, the inter-cell batch size is 25 and the demands are generated uniformly in [0,100]. Finally, the overtime capacity is assumed 15% of the regular time. It is noted that parameters π_m, D_{pt}, WT, T_m and T'_m are fuzzy numbers whose centers are generated as described above and the lower and upper values are generated by multiplying the centers by 0.75 and 1.25, respectively.

To validate performance of the proposed TS–GA, the first six problems are solved using software package GAMS to reach global optimal solutions and the resulted objective function values are compared with the ones by the proposed TS–GA. In this regard, the proposed algorithm is coded in C++ programming language using a personal computer with Intel® 2.53 GHz processor with 4 MB RAM. Results of the comparisons are drawn in Figs. 4 and 5. Moreover, Fig. 6 demonstrates the gap percentage between the best-found solution values between GAMS and the developed TS–GA upon formula $\frac{TSGA\,value - GAMS\,value}{TSGA\,value} \times 100$. It is noted that the obtained results of GAMS are reported with the time limit of 5400 s (90 min), while the obtained results of the developed TS–GA are presented upon the defined stopping criteria (number of population generation and number of generations without improvement). As seen in Fig. 6, the obtained results of the sample problems show that the gap values between GAMS and TS–GA do not exceed approximately 5% in the cases for which the optimal solutions are found by GAMS. Also, it is noted that the remainder of the test problems indicate superiority of the developed TS–GA for large-size problem instances. Hence, the optimality strength of the developed TS–GA is acceptable and the algorithm performs reliably.

Among the results shown in Fig. 5, the developed TS–GA is applied to solve the test problems 7–12. Table 3 presents the best-found solutions of the large-size test problems during the first three planning periods. In this table, the numbers in each cell correspond to the machines which are assigned to the cell. It is noted that the results of instances 11–12 are not shown due to their large sizes.

6. Conclusions and future research directions

Cellular manufacturing system is one of the most appealing aspects of the well-known GT philosophy, which has been considerably explored by academicians and practitioners during recent years. One of the emerging issues in CMS is the dynamic nature of the system due to varying product mix and product demand volumes, which resulted in the introduction of DCFP. Although a huge body of literature has been published in this area, two major aspects have been still neglected. The first one is human-related issues, as explicitly expressed by several authors, which mentioned in the literature. On the other hand, stochastic nature of DCFP is another issue. Some research papers are found in the literature that have considered uncertainty by applying fuzzy sets theory. In this regard, a very limited number of papers have coped with the involved uncertainty using fuzzy mathematical approach, the stochastic programming. In this paper, the two mentioned neglected issues were modeled and analyzed in DCFP using a bi-objective mathematical model. Additionally, a hybrid TS–GA algorithm was proposed to tackle the computational complexity of the developed model. Finally, numerical experiments were performed to validate the strength of the proposed algorithm. In order to validate the developed TS–GA, GAMS global optimal solutions and TS–GA near optimal solutions were compared for six problem instances. Upon the obtained results, the optimality gaps produced by TS–GA are not larger than five percent those obtained by means of GAMS. With respect to the six generated large-size problem instances, TS–GA outperformed GAMS significantly in terms of objective function values.

To continue the outlined research direction of this paper, two main suggestions are made. First, developing more sophisticated human-related concepts is worthwhile to explore. For instance, studying learning effects on DCFP might make the developed models more effective and practical. Also, it might be interesting to develop a DCFP model with variable inter-cell move batch sizes. In the developed model, the batch size will be minimized, because it reduces work-in-process inventories.

References

Arikan, F., & Gungor, Z. (2009). Modeling of a manufacturing cell design problem with fuzzy multi-objective parametric programming. *Mathematical and Computer Modelling, 50*, 407–420.

Aryanezhad, M. B., Deljoo, V., & Mirzapour Al-e-hashem, S. M. J. (2009). Dynamic cell formation and the worker assignment problem: A new model. *International Journal of Advanced Manufacturing Technology, 41*, 329–342.

Askin, R. G., & Vakharia, A. J. (1991). Group technology – Cell formation and operation. In D. I. Cleland & B. Bidanda (Eds.), *The automated factory handbook: Technology and management* (pp. 317–336). New York: TAB Books.

Balakrishnan, J., & Cheng, C. H. (2005). Dynamic cellular manufacturing under multi period planning horizons. *Journal of Manufacturing Technology Management, 16*(5), 516–530.

Balakrishnan, J., & Cheng, C. H. (2007). Multi-period planning and uncertainty issues in cellular manufacturing: A review and future directions. *European Journal of Operational Research, 177*, 281–309.

Cesanı, V. I., & Steudel, H. J. (2005). A study of labor assignment flexibility in cellular manufacturing systems. *Computers & Industrial Engineering, 48*, 571–591.

Chen, M. (1998). A mathematical programming model for systems reconfiguration in a dynamic cell formation condition. *Annals of Operations Research, 77*(1), 109–128.

Collet, S., & Spicer, R. (1995). Improving productivity through cellular manufacturing. *Production and Inventory Management Journal, 36*(1), 71–75.

Deljoo, V., Mirzapour Al-e-hashem, S. M. J., Deljoo, F., & Aryanezhad, M. B. (2010). Using genetic algorithm to solve dynamic cell formation problem. *Applied Mathematical Modelling, 34*, 1078–1092.

Egilmez, G., Erenay, B., & Süer, G. A. (2014). Stochastic skill-based manpower allocation in a cellular manufacturing system. *Journal of Manufacturing Systems, 33*(4), 578–588.

Egilmez, G., Süer, G. A., & Huang, J. (2012). Stochastic cellular manufacturing system design subject to maximum acceptable risk level. *Computers & Industrial Engineering, 63*, 842–854.

Fry, T., Breen, M., & Wilson, M. (1987). A successful implementation of group technology and cell manufacturing. *Production and Inventory Management Journal, 28*(3), 4–6.

Ghotboddini, M. M., Rabbani, M., & Rahimian, H. (2011). A comprehensive dynamic cell formation design: Benders' decomposition approach. *Expert Systems with Applications, 38*(3), 2478–2488.

Glover, F. (1990). Tabu search: A tutorial. *Interfaces*.

Joines, J., Culbrethe, C., & King, R. (1996). Manufacturing cell design: An integer programming model employing genetic algorithms. *IIE Transactions, 28*, 69–85.

Kioon, S. A., Bulgak, A. A., & Bektas, T. (2009). Integrated cellular manufacturing systems design with production planning and dynamic system reconfiguration. *European Journal of Operational Research, 192*, 414–428.

Lai, Y. J., & Hwang, C. L. (1992). *Fuzzy mathematical programming, methods and applications*. Springer-Verlag.

Levasseur, G., Helms, M., & Zink, A. (1995). Conversion from a functional to the cellular manufacturing layout at Steward Inc. *Production and Inventory Management Journal, 36*(3), 37–42.

Lozano, S., Dobado, D., Larraneta, J., & Onieva, L. (2002). Modified fuzzy C-means algorithm for cellular manufacturing. *Fuzzy Sets and Systems, 126*, 23–32.

Mungwatanna, A. (2000). *Design of cellular manufacturing systems for dynamic and uncertain production requirement with presence of routing flexibility* (PhD thesis). VA: Blacksburg State University Virginia.

Park, S., & Suresh, N. C. (2003). Performance of fuzzy ART neural network and hierarchical clustering for part-machine grouping based on operation sequences. *International Journal of Production Research, 41*(14), 3185–3216.

Safaei, N., Saeidi-Mehrabad, M., Tavakkoli-Moghaddam, R., & Sassani, F. (2008). A fuzzy programming approach for a cell formation problem with dynamic and uncertain conditions. *Fuzzy Sets and Systems, 159*, 215–236.

Safaei, N., Saidi-Mehrabad, M., & Jabal-Ameli, M. S. (2008). A hybrid simulated annealing for solving an extended model of dynamic cellular manufacturing system. *European Journal of Operational Research, 185*, 563–592.

Safaei, N., & Tavakkoli-Moghadam, R. (2009). Integrated multi-period cell formation and subcontracting production planning in dynamic cellular manufacturing systems. *International Journal of Production Economics, 120*, 301–314.

Saidi-Mehrabad, M., & Ghezavati, V. R. (2009). Designing cellular manufacturing systems under uncertainty. *Journal of Uncertain Systems, 3*(4), 315–320.

Saxena, L. K., & Jain, P. K. (2011). Dynamic cellular manufacturing systems design – A comprehensive model. *International Journal of Advanced Manufacturing Technology, 53*, 11–34.

Seifoddini, H. (1990). A probabilistic model for machine cell formation. *Journal of Manufacturing Systems, 9*(1), 69–75.

Singh, N., & Rajamaani, D. (1996). *Cellular manufacturing systems: Planning and control*.New York: Chapman and Hall.

Slomp, J., Bokhorst, J. A. C., & Molleman, E. (2005). Cross-training in a cellular manufacturing environment. *Computers & Industrial Engineering, 48*, 609–624.

Slomp, J., Chowdary, B. V., & Suresh, N. C. (2005). Design of virtual manufacturing cells: A mathematical programming approach. *Robotics and Computer-Integrated Manufacturing, 21*, 273–288.

Slomp, J., & Suresh, N. C. (2005). The shift team formation problem in multi-shift manufacturing operations. *European Journal of Operational Research, 165*, 708–728.

Song, S., & Hitomi, K. (1996). Integrating the production planning and cellular, layout for flexible cell formation. *Production Planning & Control, 7*(6), 585–593.

Süer, G. A. (1996). Optimal operator assignment and cell loading in labor-intensive manufacturing cells. *Computers & Industrial Engineering, 26*(4), 155–159.

Süer, G. A., Arikan, F., & Babayiğit, C. (2009). Effects of different fuzzy operators on fuzzy bi-objective cell loading problem in labor-intensive manufacturing cells. *Computers & Industrial Engineering, 56*(2), 476–488.

Süer, G. A., Cosner, J., & Patten, A. (2009). Models for cell loading and product sequencing in labor-intensive cells. *Computers & Industrial Engineering, 56*(1), 97–105.

Süer, G. A., Huang, J., & Maddisetty, S. (2010). Design of dedicated, shared and remainder cells in a probabilistic demand environment. *International Journal of Production Research, 48*(19), 5613–5646.

Süer, G. A., Kamat, K., Mese, E., & Huang, J. (2013). Minimizing total tardiness subject to manpower restriction in labor-intensive manufacturing cells. *Mathematical and Computer Modelling, 57*, 741–753.

Süer, G. A., & Sáiz, M. (1993). Cell loading in cellular manufacturing systems. *Computers & Industrial Engineering, 25*(1–4), 247–250.

Süer, G. A., Vazquezb, R., & Cortes, M. (2005). A hybrid approach of genetic algorithms and local optimizers in cell loading. *Computers & Industrial Engineering, 48*(3), 625–641.

Suresh, N. C., & Slomp, J. (2001). Labor assignment and grouping in cellular manufacturing––A multi-objective methodology. *International Journal of Production Research, 39*(18), 4103–4131.

Tavakkoli-Moghaddam, R., Aryanezhad, M., Safaei, N., & Azaron, A. (2005). Solving a dynamic cell formation problem using metaheuristics. *Applied Mathematics and Computation, 170*, 761–780.

Torabi, S. A., & Rafiei, H. (2012). An optimization framework towards prioritization in fuzzy comparison matrices. *Expert Systems with Applications, 39*, 638–646.
Torkul, O., Cedimoglou, I. H., & Geyik, A. K. (2006). An application of fuzzy clustering to manufacturing cell design. *Journal of Intelligent and Fuzzy Systems, 17*, 173–181.
Wang, X., Tang, J., & Yung, K. (2009). Optimization of the multi-objective dynamic cell formation problem using a scatter search approach. *International Journal of Advanced Manufacturing Technology, 44*, 318–329.
Wicks, E. (1995). *Designing cellular manufacturing systems with time varying product mixed and resource availability* (PhD thesis).Blacksburg, VA: Virginia Polytechnic Institute and State University.