



A novel robust possibilistic cellular manufacturing model considering worker skill and product quality

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Abstract. Design of an appropriate Cellular Manufacturing System (CMS) leads to system flexibility and production efficiency by using the similarities in the manufacturing process of products. One of the main issues in these systems is to consider product quality level and worker's skill level in the production process. This study proposes a comprehensive bi-objective possibilistic nonlinear mixed-integer programming model under uncertain environment to design a suitable CMS with the aim of minimizing the total costs and total inaction of workers and machines, simultaneously. In this respect, the demand for each product with a specific quality level and linguistic parameters such as product quality level, worker's skill level, and job hardness level on machines are considered under fuzzy environment. To this end, the robust possibilistic programming approach is tailored to cope with fuzzy impute parameters. Finally, a real case study is provided to show the efficiency and applicability of the proposed model. In this respect, the proposed approach could reduce the total costs by 23.6% and the total inaction of workers and machines by 11.7% in comparison with real practice. In addition, the performance of the presented model is demonstrated by comparing the results obtained from the proposed model and actual practice.

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1. Introduction

The implementation of cellular manufacturing systems has some benefits including setup time reduction, material handling cost saving, quality management, work-in-process inventory reduction, and machine utilizing improvement. Thus, some steps that should be taken to design an appropriate Cellular Manufacturing System (CMS) include:

1. Cell formation, which means that a group of prod-

ucts with similar jobs are assigned to part families and related machines in machine cells;

2. Group layout, which is established in both intra-cell (i.e., machines assigned within each cell) and inter-cell (i.e., cells related to one another) layouts;
3. Group scheduling;
4. Resource allocation, that is, to assign humans, tools, and material resources [1-3].

In this paper, the first, second, and forth stages of cellular manufacturing design are studied under the dynamic environment, which is called the Dynamic Cellular Manufacturing System (DCMS) [4]. Hence, the cell formation, group layout, and resource allocation are performed by considering the final quality of the

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product based on the quality level of demand, hardness level of jobs on machines, and skill level of workers.

Rosenblatt [5] first introduced a dynamic programming approach for designing a layout problem. In this respect, Mahdavi et al. [6] proposed an integer mathematical programming model for the design of CMS by considering the features of dynamic system reconfiguration, multi-period production planning, machine capacity, duplicate machines, worker assignment, and available time for workers with the aim of minimizing the backorder and holding costs; machine and reconfiguration costs; hiring, firing, and salary costs; and inter-cell material handling cost. Saxena and Jain [7] presented an integrated dynamic model, which combined some features of existing models including machine breakdown, reliability, production planning, production cost, intra-cell movement, etc., in a single model with the aim of minimizing the total cost. Paydar et al. [8] developed a comprehensive integer linear programming model based on some features such as sequence of operations, multi-period production planning, intra-cell layout, alternative process routing, dynamic system reconfiguration, lot splitting, machine capacity, duplicate machines, and material flow between machines. Kia et al. [9] presented a dynamic mixed integer non-linear programming model to design a group layout of CMS based on the production planning decisions.

In classical cell formation methods, cells are designed and then, workers are assigned to the cells, while relationships between jobs to skills and skills to workers are ignored. In addition, skill level of workers can be related to hardness of jobs on machines. Therefore, considering skill level of workers regarding the hardness of jobs may be a main factor in worker/machine assignment. In this respect, a few researchers have focused on humans'/workers' skill level for solving cellular manufacturing problems.

Norman et al. [10] proposed a mixed integer programming model for assigning the workers to manufacturing cells based on the their skills to maximize the efficiency of the organization. Suksawat et al. [11] proposed a novel approach by considering the skilled workers-based scheduling technique to solve their manufacturing cell problem. Duan et al. [12] proposed an assembly system based on cellular manufacturing features and considered the workers' skill, collaboration between worker and machine, assembly information guidance, and safe design for collaboration. Egilmez et al. [13] presented an optimization approach with skill-based worker allocation, in which the performance of each worker was considered for more accurate worker allocation to the manufacturing cells with the aim of maximizing the rate of production. The survey of the studies on the worker skills in CMS problems shows that poor attention has been paid to this area.

Thus, this paper considers the worker skill level for allocation of the worker to the machine with specific job hardness level. Lim et al. [14] presented multi-objective hybrid algorithms for layout optimization in multi-robot assembly for solving the cellular manufacturing problems. Rezazadeh and Khiali-Miab [15] developed a novel mathematical model for designing the reliable cellular manufacturing systems, which led to decrease in manufacturing costs, improved total reliability of the manufacturing system, and improved product quality. In addition, a two-layer genetic algorithm was presented to address the complexity of cell formation problems to obtain near optimal solutions. Aalaei and Davoudpour [16] proposed a novel mathematical programming model for a CMS along with supply chain design regarding labor assignment with the aim of minimizing the total cost of holding, inter-cell material handling, external transportation, fixed cost for producing each part in each plant, and machine and labor salaries. Forghani and Mohammadi [17] presented an integrated approach to solving the layout problems and cell formation, simultaneously.

Considering the real-world complexity of cellular manufacturing problems, some important parameters (e.g., product demand, processing time, product mix, available machine capacity, and inter-arrival time) are difficult to determine precisely. To address this issue, these parameters should be defined as inputs to the model under uncertainty to cope with imprecise conditions in cellular manufacturing. Different approaches have been developed to deal with the uncertainty, including fuzzy programming, stochastic programming, and robust optimization approach [18,19].

In fuzzy environment, Safaei and Tavakkoli-moghaddam [20] developed a mixed-integer programming model to solve the manufacturing problems under uncertainty and dynamic situations. In their study, product demand and machine capacity were considered as fuzzy parameters. Kia et al. [21] proposed a new integer non-linear programming model under fuzzy environment to solve the layout design of dynamic CMS. Behret and Satoglu [22] surveyed the fuzzy methods, especially fuzzy programming and fuzzy clustering, and employed them in the design of CMS. In their study, product demand, inter-cell flow cost, and machine purchasing were considered under uncertain situation. Paydar and Saidi-Mehrabad [23] extended a novel bi-objective possibilistic mathematical model for integrating production, procurement, and distribution planning by considering the uncertain nature of some significant parameters such as machine capacity and customers' demands.

Hence, Tavakkoli-Moghaddam et al. [24] developed a novel mathematical model to solve the facility layout problem in CMS with stochastic demands with the aim of minimizing the total costs of in-

tra and inter-cell movements. Ghezavati and Saidi-Mehrabad [25] implemented a scenario-based stochastic programming method to solve the integrated cell formation and group scheduling decision. Ghezavati and Saidi-Mehrabad [26] presented a cellular manufacturing model in which arrival and processing times of products were stochastic. They solved the imprecise problem by applying a queuing-based analysis. Egilmez et al. [27] proposed a stochastic non-linear programming model to solve a cell formation problem in which processing times and product demand were uncertain. Salarian et al. [28] considered the processing time, product demand, and inter-arrival time for product as stochastic parameters in solving the CMS problems. Bagheri et al. [29] proposed a novel dynamic mathematical model for CMS regarding production factors such as machine reliability and alternative process routing with stochastic service and arrival times. Rabbani et al. [30] focused on manpower allocation and cell loading problems with the aim of manpower allocation to cellular manufacturing with consideration of training and learning policies when demand was stochastic.

In addition, employing the robust optimization, Ghezavati et al. [31] presented a novel mathematical robust optimization model for a CMS integrated with tactical aspects regarding supply chain network features in the presence of imprecise processing time and demand parameters. Forghani et al. [32] provided a novel robust optimization approach to address data uncertainty. In their study, an interval approach unlike the scenario-based approaches was regarded to handle demand imprecision in the process of layout design and cell formation. Tavakkoli-Moghaddam et al. [33] developed a robust mathematical programming model to solve a CMS integrated with production planning under dynamic and uncertainty environments. Sakhaei et al. [34] presented a robust optimization approach for a novel integrated dynamic mixed-integer programming model under imprecise nature parameters to solve the CMS with production planning and unreliable machines problems, simultaneously. Review of the literature that has employed the robust optimization in CMS problems shows that considering the robust optimization approach to deal with uncertainty is more interested.

In this paper, a nonlinear mixed-integer programming model is developed under uncertainty and dynamic environments. In addition, the quality of products is managed during the operation process based on worker's skill and job hardness levels on machines. Table 1 summarizes the cellular manufacturing models and methods developed based on some features such as cell formation, worker/machine assignment, job hardness level on machines, and worker's skill level. As presented in Table 1, the features of job hardness and product quality levels have not been considered by

authors in the recent literature. Also, other features such as worker's skill level as well as worker flexibility and uncertainty have received less attention in the related literature. In this regard, only two studies have developed the mathematical models by considering workers' skill level among others. In addition, most of the earlier studies have considered the cell formation, machine allocation, route flexibility, machine capacity, and multi-period features to solve their CMS problems. By proposing a nonlinear mixed-integer programming model, this research attempts to fill in this gap in the CMS literature.

The rest of this paper is outlined as follows: Section 2 presents the proposed model based on the problem description and assumptions. In Section 3, the proposed approach to solving the developed model is provided. Then, a case study is considered to show the validity of the proposed approach in Section 4. Furthermore, sensitivity analysis is provided in Section 5 to present the robustness and sensitiveness of results. Finally, some concluding remarks and future directions are presented in Section 6.

2. Proposed model

In this section, a novel mixed-integer nonlinear programming model is presented under the dynamic environment to solve cell manufacturing problems. First, the problem description is presented in detail and then, assumptions considered for modeling the proposed approach are presented.

2.1. Problem description

The cellular manufacturing problem, which is considered in this paper, is shown in Figure 1. To address the issue, a number of cells (k) and machines (m), which operate some specific jobs (j) for different products (p) by workers (w), are provided. Each worker has a specific skill (s) regarding hardness of jobs on machines (h), which leads to a specific product quality level (q). Also, each machine has a certain capacity (ML_m) and each product is produced under uncertain processing

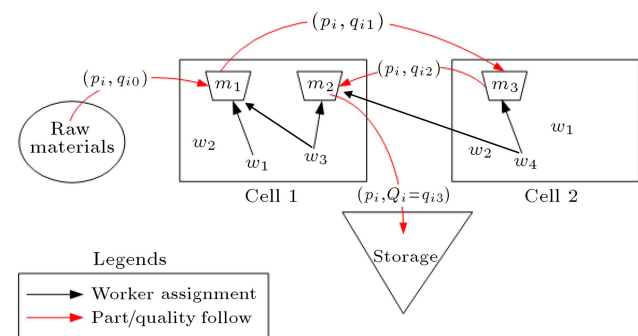


Figure 1. The structure of the cellular manufacturing problem regarding the product quality level.

Table 1. Cellular manufacturing models and their characteristics.

Author	Year	Cell formation	Model characteristic										Objective(s)	Solution method
			Allocation		Job hardness level	Flexibility		Operation sequence	Product quality level	Capacity		Worker skill level		
Worker	Machine	Worker	Route	Worker		Worker	Machine			Machine				
Norman et al. [10]	(2002)	✓						✓		✓			Single	Scenario based and using CPLEX
Fantahun et al. [38]	(2006)	✓		✓					✓		✓		Single	Using LINGO software
Mahdavi et al. [39]	(2009)	✓	✓			✓				✓		✓	Single	Using LINGO software
Solimanpur et al. [40]	(2010)	✓						✓					Single	Ant colony optimization
Mahdavi et al. [41]	(2011)	✓	✓			✓				✓		✓	Single	Fuzzy goal programming -based approach
Kia et al. [42]	(2012)	✓				✓		✓			✓		Single	Simulated annealing
Torabi and Amiri [43]	(2012)		✓		✓			✓			✓		Single	Interactive possibilistic programming
Chang et al. [44]	(2013)	✓			✓			✓					Multi	Tabu search
Kia et al. [45]	(2013)	✓	✓		✓			✓		✓		✓	Single	Using GAMS 22.0 software (CPLEX solver)
Egilmez et al. [13]	(2014)	✓				✓				✓			Single	Statistical analysis and Monte-Carlo simulation
Shirazi et al. [46]	(2014)	✓	✓		✓			✓			✓		Single	Simulated annealing
Deep and Singh [47]	(2015)	✓	✓		✓						✓		Single	Genetic algorithm
Sakhaii et al. [34]	(2016)	✓	✓		✓			✓			✓	✓	Single	Robust optimization approach
This study		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Multi	RPP and branch and cut algorithms

time (PT_{jwm}). In addition, the number of cells (NC) must be specified and the minimum (NL) and maximum (NU) numbers of machines in each cell are determined by a decision maker or user of the model. Hence, each worker has an available time to work (WL_w), which must satisfy the minimum work time (LWL_w) and maximum work time ($LM L_m$). In addition, the demand of each customer by a specific quality level (d_{pq}^t) is achieved at the start of each period (t). In this respect, the output quality level of the produced products ($\lambda_{O_{jpm}}^w$) is affected by job hardness on machines (H_{jm}) and workers' skills (S_{wm}^s), and the final quality level of products is determined based on the minimum quality level of processes of produced products. In a certain situation, the linguistic variables of product quality, job hardness level on machines, and worker's skills are defined in three levels. In this respect, Table 2 clearly expresses the interaction between the linguistic variables. However, products require some different operations (O_{jpm}) in available routing (R_p), which should be processed in an appropriate route (θ_{rp}^t) with regard to assigning products to a cell (Y_{jpm}^k) and to a machine (ξ_{jpm}^h). Hence, each product has a material flow conservation and concatenated production sequence ($V_{jpkk'}^{mm'}$). In addition, if one cell is established (CF_k), machines could be allocated to cells (X_{mk}) and workers could be assigned to machines (Z_{wjm}^t) regarding their skill level (ϖ_{wjm}^s). However, the proposed model is formulated with the aim of minimizing total costs, including cost of worker employment (CW_w^s), processing cost of machines (CM_m^h), fixed cost of establishing each cell (CC_k), intra-cell movement cost of cells (CI_k), and inter-cell movement cost between cells ($CO_{kk'}$), and the total inaction of workers and machines.

Table 2 demonstrates that a worker with a specific skill level on each machine, which has a specific job hardness level, produces a product with a certain quality level (i.e., best quality = q_1 , moderate quality = q_2 , and worst quality = q_3). For example, as indicated in Table 2, a beginner worker cannot work on machines with high hardness level, and they will produce a product with moderate quality (q_2) if they work on machines with low hardness level. Hence, qualities of

output products manufactured by other workers are evaluated based on the aforementioned procedure.

In real cases, defining the above linguistic variables (i.e., machine hardness level, worker's skill level, and product quality level) is difficult and often vague. Thus, considering the linguistic variables under uncertainty is more suitable and makes the proposed model more applicable in the real world.

2.2. Assumptions

The proposed dynamic non-linear mixed integer programming model with the aim of minimizing the total costs and inaction of workers and machines is formulated under the following assumptions:

1. Each product must be assigned to only one cell;
2. Each machine must be assigned to only one cell;
3. Each product has a number of process routings, which could be selected among the available routs;
4. A lower bound for workers load and machines load must be satisfied;
5. The working capacity is considered for each machine and worker;
6. The hardness of job is not related to each product;
7. The quality of the product is defined based on the linguistic variables;
8. The hardness of jobs on the machine is determined based on linguistic terms;
9. The skill level of each worker is specified based on linguistic variables;
10. Each product has a number of jobs that must be processed based on its jobs sequence;
11. The processing time of all jobs for a product on each machine is known;
12. The operation cost of each machine and the working cost of each worker per minutes are known;
13. The processing time of each product can be different in various machines (routing flexibility);
14. Minimum and maximum numbers for each machine, which could be assigned to a cell, are known;
15. There is an only one type of each machine;
16. Inventory is not allowable.

2.3. Notations

The notations including sets, parameters, and decision variables are defined as follows:

Sets

- p Index of products, $p = 1, 2, \dots, P$;
 m, m' Index of machines, $m = 1, 2, \dots, M$,
 $m' = 1, 2, \dots, M'$;

Table 2. The output quality level of products regarding job hardness and worker skills.

Hardness level of jobs	Skill level of workers		
	Beginner	Semi-skilled	Expert
Low	q_2	q_1	q_1
Moderate	q_3	q_2	q_1
High	—	q_3	q_1

w	Index of workers, $w = 1, 2, \dots, W$;
t	Index of periods, $t = 1, 2, \dots, T$;
j	Index of jobs, $j = 1, 2, \dots, J$;
s	Index of skills, $s = 1, 2, \dots, S$;
h	Index of hardness, $h = 1, 2, \dots, H$;
q	Index of quality, $q = 1, 2, \dots, Q$;
k, k'	Index of cells, $k = 1, 2, \dots, K$, $k' = 1, 2, \dots, K'$;
r	Index of routes, $r = 1, 2, \dots, R$.

Parameters

R_p	Number of available routings for product p ;
S_{wm}^s	The skill level s of worker w on machine m ;
H_{jm}^h	The hardness level h of job j on machine m ;
O_{jpm}	The required job j for product p that needs to be processed by machine m ;
$\lambda_{O_{jpm}}^w$	The output quality q of required job j for product p by worker w on machine m ;
d_{pq}^t	The demand of product p with quality q at period t ;
db_{pq}^t	$db_{pq}^t = \begin{cases} 1 & d_{pq}^t > 0 \\ 0 & d_{pq}^t = 0 \end{cases} \quad \forall p, q, t$
CW_w^s	The cost of employing worker w with the skill level of s ;
CM_{mj}^h	The processing cost of machine m with hardness level h for job j ;
CC_k	Fixed cost of establishing each cell;
CI_k	The intra-cell movement cost of cell k ;
$CO_{kk'}$	The inter-cell movement cost of cell k to cell k' ;
WL_w^t	The load of worker w with regards to the available time;
ML_m^t	The load of machine m with regards to the available time;
PT_{jwm}	Processing time of job j done by worker w on machine m ;
NL	Minimum number of machines in each cell;
NU	Maximum number of machines in each cell;
NC	Number of cells that should be formed;
LWL_w^t	The lower bound of worker load for worker k ;
$LM L_m^t$	The lower bound of machine load for machine m .

Decision variables

X_{mk}	1 if machine m is assigned to cell k , 0 otherwise;
Y_{jpm}^{kq}	1 if product p with quality level q is processed by job j on machine m in cell k , 0 otherwise;
ξ_{jpm}^{hq}	1 if product p with quality level q is processed by job j on machine m with hardness h , 0 otherwise;
Z_{wjm}	1 if worker w is assigned to machine m for job j , 0 otherwise;
ϖ_{wjm}^s	1 if worker w for performing the job j on machine m has skill level s , 0 otherwise;
$V_{jpkk'}^{mm'q}$	1 if job $j + 1$ of product p with quality level q is processed by machine m' in cell k' after performing job j on machine m in cell k , 0 otherwise;
θ_{rp}^t	1 if route r for product p is selected as the process plan in period t , 0 otherwise;
Pr_{pq}^t	Amount of product p produced with quality level q in period t ;
CF_k	1 if cell k is formed, 0 otherwise;
PQ_{pq}	The quality level q of product p ; its value is related to the quality level of produced product is as follows:

$$PQ_{pq} = \begin{cases} q_1 & \\ q_2 & \text{If } Pr_{pq}^t > 0 \\ q_3 & \\ 0 & \text{If } Pr_{pq}^t = 0 \end{cases} \quad \forall p, q$$

2.4. Proposed model

$$\begin{aligned} \min \quad Z_{TC} = & \left(\sum_{j=1}^J \sum_{p=1}^P \sum_{q=1}^Q \sum_{m=1}^M \sum_{k=1}^K CI_k Y_{jpm}^{kq} \right. \\ & + \sum_{j=1}^J \sum_{p=1}^P \sum_{q=1}^Q \sum_{m=1}^M \sum_{m'=1}^{M'} \sum_{k=1}^K \sum_{k'=1}^{K'} CO_{kk'} V_{jpkk'}^{mm'q} \Big) \\ & + \left(\sum_{s=1}^S \sum_{w=1}^W \sum_{j=1}^J \sum_{m=1}^M \varpi_{wjm}^s CW_w^s \right) \\ & + \left(\sum_{j=1}^J \sum_{p=1}^P \sum_{q=1}^Q \sum_{m=1}^M \sum_{h=1}^H \xi_{jpm}^{hq} CM_{mj}^h \right) \\ & + \left(\sum_{k=1}^K CC_k CF_k \right), \end{aligned} \quad (1)$$

$$\begin{aligned} \min \quad Z_{IA} = & \left(\sum_{t=1}^T \sum_{w=1}^W W L_w^t \right. \\ & \left. - \sum_{w=1}^W \sum_{j=1}^J \sum_{m=1}^M P T_{jwm} Z_{wjm} \right) \\ & + \left(\sum_{t=1}^T \sum_{m=1}^M M L_m^t \right. \\ & \left. - \sum_{k=1}^K \sum_{w=1}^W \sum_{p=1}^P \sum_{q=1}^Q \sum_{m=1}^M \sum_{j=1}^J P T_{jwm} Y_{jpm}^{kq} \right), \quad (2) \end{aligned}$$

$$\sum_{k=1}^K X_{mk} C F_k = 1, \quad \forall m, \quad (3)$$

$$N L \leq \sum_{k=1}^K \sum_{m=1}^M X_{mk} C F_k \leq N U, \quad \forall m, k, \quad (4)$$

$$\sum_{k=1}^K C F_k \leq N C, \quad \forall k, \quad (5)$$

$$\begin{aligned} L M L_m^t & \leq \sum_{k=1}^K \sum_{p=1}^P \sum_{q=1}^Q \sum_{j=1}^J \sum_{w=1}^W \sum_{r=1}^R P T_{jwm} Y_{jpm}^{kq} \theta_{rp}^t \\ & \leq M L_m^t, \quad \forall m, t, \quad (6) \end{aligned}$$

$$L W L_w^t \leq \sum_{j=1}^J \sum_{m=1}^M P T_{jwm} Z_{wjm} \leq W L_w^t, \quad \forall w, t, \quad (7)$$

$$\sum_{t=1}^T \sum_{q=1}^Q d_{pq}^t = \sum_{t=1}^T \sum_{q=1}^Q P r_{pq}^t, \quad \forall p, \quad (8)$$

$$P r_{pq}^1 \leq d_{pq}^1, \quad \forall p, q, \quad (9)$$

$$P r_{pq}^t \leq d_{pq}^t + \sum_{t=2}^{T-1} (d_{pq}^{t-1} - P r_{pq}^{t-1}), \quad \forall p, q, t \geq 2, \quad (10)$$

$$\sum_{k=1}^K \sum_{m=1}^M Y_{jpm}^{kq} O_{jpm} = d_{pq}^t, \quad \forall j, p, q, t, \quad (11)$$

$$\sum_{h=1}^H \xi_{jpm}^{hq} \geq Y_{jpm}^{kq}, \quad \forall j, p, q, m, k, \quad (12)$$

$$\begin{aligned} \sum_{j=1}^J \sum_{p=1}^P \sum_{q=1}^Q \sum_{m=1}^M H_{jm}^h \xi_{jpm}^{hq} & \geq \sum_{w=1}^W \sum_{m=1}^M \lambda_{O_{jpm}}^w, \\ \forall j, p, h, \quad (13) \end{aligned}$$

$$\sum_{s=1}^S \varpi_{wjm}^s \geq Z_{wjm}, \quad \forall w, j, m, \quad (14)$$

$$\begin{aligned} \sum_{w=1}^W \sum_{j=1}^J \sum_{m=1}^M S_{wm}^s \varpi_{wjm}^s & \geq \sum_{w=1}^W \sum_{m=1}^M \lambda_{O_{jpm}}^w, \\ \forall j, p, s, \quad (15) \end{aligned}$$

$$\begin{aligned} \sum_{w=1}^W \sum_{m=1}^M \sum_{j=1}^J \lambda_{O_{jpm}}^w \varpi_{wjm}^s \xi_{jpm}^{hq} & \geq P Q_{pq}, \\ \forall p, q, s, h, \quad (16) \end{aligned}$$

$$\begin{aligned} Y_{jpm}^{kq} + Y_{(j+1)pm'}^{k'q} - 2V_{jpkk'}^{mm'q} & \geq 0, \\ \forall j, p, q, m, m', k, k', \quad (17) \end{aligned}$$

$$\begin{aligned} Y_{jpm}^{kq} + Y_{(j+1)pm'}^{k'q} - V_{jpkk'}^{mm'q} & \leq 1, \\ \forall j, p, q, m, m', k, k', \quad (18) \end{aligned}$$

$$\sum_{r=1}^{R_p} \theta_{rp}^t = d b_{pq}^t, \quad \forall p, q, t, \quad (19)$$

$$P Q_{pq}, P r_{pq}^t \geq 0, \quad (20)$$

$$\begin{aligned} X_{mk}, Y_{jpm}^{kq}, \xi_{jpm}^{hq}, Z_{wjm}, \varpi_{wjm}^s, V_{jpkk'}^{mm'q}, C F_k, \theta_{rp}^t \\ \in \{0, 1\}. \quad (21) \end{aligned}$$

The objective function (1) is to minimize the total costs, in which the first term is the intra- and inter-cell movements costs, the second term is the cost of employing workers regarding their skill levels, the third term is the processing cost of machines regarding their hardness, and the fourth term is related to the fixed cost of constructing cells. The objective function (2) minimizes the total inaction of workers and machines, simultaneously.

Constraints (3) and (4) determine that each machine could be assigned to only one cell and identify the minimum and maximum numbers of machines which should be located in each cell, respectively. Constraint (5) ensures the maximum number of cells that could be formed. Constraints (6) and (7) ensure that the minimum and maximum machine loads and worker loads must be satisfied, respectively. Constraint (8) ensures that the demand for each product must be satisfied within the periods. Constraints (9) and (10) denote that excess production is not allowed. Constraint (11) guarantees that each production job is assigned to one machine and one cell. Constraint (12) determines the reactions to the job assignments regarding machine

hardness. Constraint (13) expresses that the machine with lower hardness should be selected. Constraint (14) assures that the worker is assigned to the machine for the specific job when they have the minimum skill level for that specific job. Constraint (15) denotes that the appropriate worker with suitable skill level is selected to produce the product with the best quality level. Constraint (16) establishes the relationship between the product quality level, which should be produced, and the skill level of workers and the hardness of machines. Constraints (17) and (18) ensure the material flow conservation and guarantee that all consecutive jobs of a product involve a concatenated production sequence, resulting in complete processing of the products. Constraint (19) shows that only one process routing must be selected. Relations (20) and (21) indicate the integer and binary variables, respectively.

3. Proposed solution approach

In this section, the proposed solution approach is presented to solve the proposed model as well as to deal with uncertain parameters. In this respect, the compact model, which enhances the presentation of the solution approach, is the following:

$$f_1(x) : C_1 Y, \quad (22)$$

$$f_2(x) : C_2 Y, \quad (23)$$

$$A_1 Y Z = B_1, \quad (24)$$

$$A_2 Y Z \leq B_2, \quad (25)$$

$$A_3 Y Z \geq B_3, \quad (26)$$

$$P_1 Y \leq B_4, \quad (27)$$

$$P_2 Y \geq B_5, \quad (28)$$

$$R_1 X = B_6, \quad (29)$$

$$R_2 X \leq B_7, \quad (30)$$

$$P_3 Y = B_8, \quad (31)$$

$$A_4 Y Z - R_3 X \geq B_9, \quad (32)$$

$$P_4 Y - P_5 Z \geq B_{10}, \quad (33)$$

$$X \geq 0, \quad Y, Z \in \{0, 1\}. \quad (34)$$

Relations (22) and (23) represent the objective functions of the propose model. Constraint (24) is related to Constraint (3), and Constraints (25) and (26)

correspond to Constraints (4) and (6). In addition, Constraint (27) is related to Constraints (5), (7), and (18) and Constraint (28) corresponds to Constraints (7), (13), (15), and (17). In this respect, Constraint (29) is related to Constraint (8), Constraint (30) corresponds to Constraints (9) and (10), and Constraint (31) corresponds to Constraints (11) and (19). Also, Constraint (32) relates to Constraint (16). In addition, Constraint (33) corresponds to Constraints (12) and (14). Finally, Constraint (34) determines that the X vector is positive variable and the Y and Z vectors are binary variables.

To solve the proposed bi-objective mixed-integer non-linear mathematical model, three phases should be tailored:

- I) The well-known linearization approach represented by Paydar and Saidi-Mehrabad [35] is utilized to obtain a linear model;
- II) The possibilistic programming approach first introduced by Pishvae et al. [36] is applied to deal with uncertainty;
- III) An efficient simple augmented e-constraint technique introduced by Zhang and Reimann [37] is implemented to convert the proposed bi-objective model to a single-objective one.

3.1. Linearization

As represented in the compact model, Eqs. (24)-(26) and (32) are non-linear. In this regard, some auxiliary variables should be defined and some constraints should be added to the basic model for linearization of the proposed model [35]. In this respect, let X and Y be binary variables; then, define $F = X \times Y$, the following variables and constraints are provided to convert the non-linear compact model to a linear one.

$$F = X \times Y, \quad (35)$$

$$F - X - Y + \varepsilon \geq 0, \quad (36)$$

$$\varepsilon \times F - X - Y \leq 0, \quad (37)$$

$$X, Y \in \{0, 1\} \quad \text{and} \quad 1 < \varepsilon < 2, \quad (38)$$

where ε is constant, and $\varepsilon \in \mathbb{R}$.

In addition, when a positive variable such as S is multiplied by a binary variable such as D , the following auxiliary variable and constrains must be regarded for linearization:

$$Z = S \times D, \quad (39)$$

$$Z \geq S - M(1 - D), \quad (40)$$

$$Z \leq S + M(1 - D), \quad (41)$$

$$Z \leq MD, \quad (42)$$

$$S \geq 0, \quad D \in \{0, 1\}. \quad (43)$$

where M is a large positive number.

3.2. Robust possibilistic programming

In complex real world, lack of experimental data leads to the uncertainty of the input parameters, which should be considered for solving the imprecise problems. Fuzzy set theory is one of the powerful and convenient tools among scholars to deal with uncertainty.

In the proposed cellular manufacturing model, the nature of some important parameters is imprecise. Thus, considering these uncertain parameters in the procedure of the solution approach could help us to deal with the problem close to real world. Hence, the product demand with a specific quality level is recognized in each period and may change during the planning horizon. Therefore, identifying the customer demand and determining an exact value for it are impossible in real cases. Also, as expressed in the introduction, the processing time of each machine is known as an important parameter in cellular manufacturing problems, which should be considered under uncertainty. In addition, some parameters are defined based on linguistic variables, which should be considered as uncertain parameters, because specifying the values of linguistic parameters is performed vaguely and hesitantly. In this respect, some parameters such as the skill level of workers on each machine, the hardness of each job for each machine, and the output quality of processing procedures are more interesting to consider under imprecision. Consequently, the uncertainty of the proposed cellular manufacturing model is higher than the that of the other developed models with respect to the defined assumption for the presented model. To address the issue, the Robust Possibilistic Programming (RPP) approach is tailored to solve the proposed possibilistic model. In this regard, the trapezoidal possibility distributions are provided to model the uncertain parameters. Considering the aforementioned illustrations, Basic Possibilistic Chance Constraint Programming (BPCCP) can be represented as follows:

$$f_1(x) : C_1 Y, \quad (44)$$

$$E(f_2(x)) : E(\tilde{C}_2) Y, \quad (45)$$

$$Nec(\tilde{A}_2 F \leq B_2) \geq \alpha_1, \quad (46)$$

$$Nec(\tilde{A}_3 F \geq B_3) \geq \alpha_2, \quad (47)$$

$$Nec(\tilde{P}_1 Y \leq \tilde{B}_4) \geq \alpha_3, \quad (48)$$

$$Nec(\tilde{P}_2 Y \geq \tilde{B}_5) \geq \alpha_4, \quad (49)$$

$$Nec(R_1 X = \tilde{B}_6) \geq \beta_1, \quad (50)$$

$$Nec(R_2 X \leq \tilde{B}_7) \geq \alpha_5, \quad (51)$$

$$Nec(\tilde{A}_4 F - R_3 X \geq B_9) \geq \alpha_6, \quad (52)$$

$$X \geq 0, \quad F, Y \in \{0, 1\}, \quad \text{and}$$

$$0.5 < \alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6, \alpha_7, \beta_1 \leq 1. \quad (53)$$

To meet the requirements of the aforementioned constraints, Eqs. (46)-(52), (54) and (55) drawn from Figure 2, and Eqs. (56) and (57) obtained from Figure 3 should be considered.

$$Nec(\tilde{A}x \leq B) = 1 - \sup_{t > k}(\mu_A(t)), \quad (54)$$

$$Nec(\tilde{A}x \leq B) = \begin{cases} 0 & t < A_3 \\ \frac{t-A_3}{A_4-A_3} & A_3 \leq t < A_4 \\ 1 & t > A_4 \end{cases} \quad (55)$$

$$Nec(Ax \leq \tilde{B}) = 1 - \sup_{t < k}(\mu_B(t)), \quad (56)$$

$$Nec(Ax \leq \tilde{B}) = \begin{cases} 0 & t \geq B_2 \\ \frac{B_2-t}{B_2-B_1} & B_1 \leq t < B_2 \\ 1 & t < B_1 \end{cases} \quad (57)$$

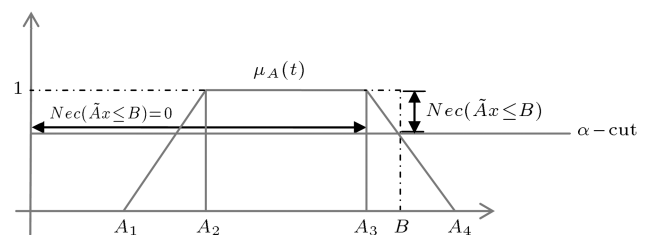


Figure 2. Necessity measure for $t > k$.

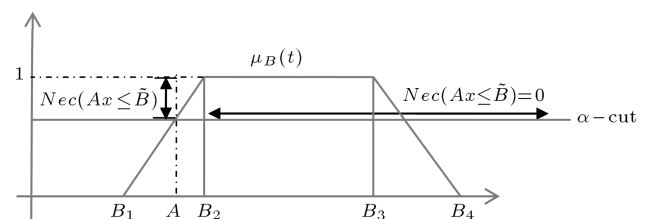


Figure 3. Necessity measure for $t < k$.

Therefore, the BCCP model could be reformulated as follows:

$$f_1(x) : C_1 Y, \quad (58)$$

$$E(f_2(x)) : E \left(\frac{c_{2(1)} + c_{2(2)} + c_{2(3)} + c_{2(4)}}{4} \right) Y, \quad (59)$$

$$(\alpha_1 A_{2(4)} + (1 - \alpha_1) A_{2(3)}) F \leq B_2, \quad (60)$$

$$(\alpha_2 A_{3(1)} + (1 - \alpha_2) A_{3(2)}) F \geq B_3, \quad (61)$$

$$(\alpha_3 P_{1(4)} + (1 - \alpha_3) P_{1(3)}) Y \leq \alpha_3 B_{4(1)} + (1 - \alpha_3) B_{4(2)}, \quad (62)$$

$$(\alpha_4 P_{2(1)} + (1 - \alpha_4) P_{2(2)}) Y \geq \alpha_4 B_{5(4)} + (1 - \alpha_4) B_{5(3)}, \quad (63)$$

$$R_1 X \leq \frac{\beta_1}{2} B_{6(3)} + \left(1 - \frac{\beta_1}{2}\right) B_{6(4)}, \quad (64)$$

$$R_1 X \geq \frac{\beta_1}{2} B_{6(2)} + \left(1 - \frac{\beta_1}{2}\right) B_{6(1)}, \quad (65)$$

$$R_2 X \leq \alpha_5 B_{7(1)} + (1 - \alpha_5) B_{7(2)}, \quad (66)$$

$$(\alpha_6 A_{4(1)} + (1 - \alpha_6) A_{4(2)}) F - R_3 X \geq B_9, \quad (67)$$

$$X \geq 0, \quad F, Y \in \{0, 1\}, \quad \text{and}$$

$$0.5 < \alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6, \beta_1 \leq 1. \quad (68)$$

Consequently, the robust possibilistic programming model is obtained as follows:

$$f_1(x) : C_1 Y, \quad (69)$$

$$\begin{aligned} & E(f_2(x)) + \delta(f_{2\max}(x) - f_{2\min}(x)) \\ & + \psi_1 [A_{2(4)} - \alpha_1 A_{2(4)} - (1 - \alpha_1) A_{2(3)}] \\ & + \psi_2 [\alpha_2 A_{3(1)} + (1 - \alpha_2) A_{3(2)} - A_{3(1)}] \\ & + \psi_3 [P_{1(4)} - \alpha_3 P_{1(4)} - (1 - \alpha_3) P_{1(3)}] \\ & + \psi_4 [\alpha_3 B_{4(1)} + (1 - \alpha_3) B_{4(2)} - B_{4(1)}] \\ & + \psi_5 [\alpha_4 P_{2(1)} + (1 - \alpha_4) P_{2(2)} - P_{2(1)}] \\ & + \psi_6 [B_{5(4)} - \alpha_4 B_{5(4)} - (1 - \alpha_4) B_{5(3)}] \\ & + \psi_7 [\alpha_5 B_{7(1)} + (1 - \alpha_5) B_{7(2)} - B_{7(1)}] \\ & + \psi_8 [\alpha_6 A_{4(1)} + (1 - \alpha_6) A_{4(2)} - A_{4(1)}] \end{aligned}$$

$$\begin{aligned} & + \ell_1 \left[\frac{\beta_1}{2} B_{6(3)} + \left(1 - \frac{\beta_1}{2}\right) B_{6(4)} - B_{6(3)} \right] \\ & + \ell_1 \left[B_{6(2)} - \frac{\beta_1}{2} B_{6(2)} - \left(1 - \frac{\beta_1}{2}\right) B_{6(1)} \right], \quad (70) \end{aligned}$$

$$(\alpha_1 A_{2(4)} + (1 - \alpha_1) A_{2(3)}) F \leq B_2, \quad (71)$$

$$(\alpha_2 A_{3(1)} + (1 - \alpha_2) A_{3(2)}) F \geq B_3, \quad (72)$$

$$(\alpha_3 P_{1(4)} + (1 - \alpha_3) P_{1(3)}) Y \leq \alpha_3 B_{4(1)} + (1 - \alpha_3) B_{4(2)}, \quad (73)$$

$$(\alpha_4 P_{2(1)} + (1 - \alpha_4) P_{2(2)}) Y \geq \alpha_4 B_{5(4)} + (1 - \alpha_4) B_{5(3)}, \quad (74)$$

$$R_1 X \leq \frac{\beta_1}{2} B_{6(3)} + \left(1 - \frac{\beta_1}{2}\right) B_{6(4)}, \quad (75)$$

$$R_1 X \geq \frac{\beta_1}{2} B_{6(2)} + \left(1 - \frac{\beta_1}{2}\right) B_{6(1)}, \quad (76)$$

$$R_2 X \leq \alpha_5 B_{7(1)} + (1 - \alpha_5) B_{7(2)}, \quad (77)$$

$$(\alpha_6 A_{4(1)} + (1 - \alpha_6) A_{4(2)}) F - R_3 X \geq B_9, \quad (78)$$

$$X \geq 0, \quad F, Y \in \{0, 1\}, \quad \text{and}$$

$$0.5 < \alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6, \beta_1 \leq 1, \quad (79)$$

where $f_{2\min}(x)$ and $f_{2\max}(x)$ are denoted by $c_{2(1)}$ and $c_{2(4)}$, respectively. As indicated in the aforementioned model, the non-linear RPP model could be linearized.

3.3. Multi-objective programming

The proposed bi-objective model is converted to a single-objective one based on efficient simple augmented e-constraint (SAUGMECON) method, which was presented by Zhang and Reimann [37], as follows:

$$\min \left(f_1(x) + \delta \left(\frac{f_2(x)}{r_2} + \frac{f_3(x)}{r_3} + \dots + \frac{f_p(x)}{r_p} \right) \right), \quad (80)$$

$$\text{s.t.} \quad f_2(x) \leq \varepsilon_2,$$

$$f_3(x) \leq \varepsilon_3,$$

$$\vdots$$

$$f_p(x) \leq \varepsilon_p, \quad (81)$$

$$x \in S, \quad (82)$$

where δ is a small number commonly determined between $[10^{-3}, 10^{-6}]$ and r_p , $p \in [1, P]$ is the range of the p th objective. Hence, the SAUGMECON

method is established by considering the features of both traditional e-constraint and AUGMECON. In this regard, the traditional e-constraint is considered to add some inequalities to the objectives in constraint space and the sum of weighted constraint objectives is combined into an objective function.

3.4. Exact solution procedure

In this section, the proposed mixed integer linear programming model is solved utilizing GAMS 22.1 software regarding CPLEX solver. However, the exact solution process considered is the traditional simplex based on branch and cut algorithm, which includes exact algorithms consisting of an approach integrating cutting plane method and branch and bound algorithm. These methods work by solving a sequence of linear programming relaxations for the integer programming problem. In addition, the cutting plane methods can approximate the integer programming problem in the best way by enhancing the relaxation of the problem. Moreover, the branch and bound algorithm is implemented by sophisticated divide and conquer approach to solve the problems. A branch and cut algorithm procedure is outlined as shown in Algorithm 1.

Meanwhile, a user supplied routine can be called after a node is applied by the solver in the branch

and bound tree. The available information from this node, such as the current incumbency, the branch and bound tree, and the LP solution, is considered in the original namespace of the GAMS database. Then, the solver can call for finding both violated cuts and a better incumbency. The obtained information from the aforementioned GAMS programs must import the found cuts/an integer solution from the solver and export results to another GAMS database, which are imported by the solver after the violated cuts or a better incumbent GAMS program terminate. Thereby, the solver can add the found violated cuts to its cut pool to resolve the linear programming at the node and then, recall the user supplied cut generating GAMS model. The solver will move to the next node if no cutting planes are found. Moreover, it is worthwhile to note that the MIP cuts generation is assigned to an automatic option in the branch and cut algorithm. The computational results were performed on a personal computer with an Intel Core(TM) i7 CPU 3 GHz and 4 GB RAM.

3.5. Procedure of the presented solution approach

The presented solution approach, which is implemented to solve the proposed model, is depicted in Figure 4.

1. Initialization of the $MILP-CMS^0$
 - 1.1. Set the active nodes: $S = \{MILP - CMS^0\}$;
 - 1.2. Set the upper bound: $OFV^U = +\infty$;
 - 1.3. Set the upper bound: $OFV_s^L = 0 \forall s$;
2. Termination:
 - 2.1. If $S = \phi$, then x^* is optimal for OFV^U
 - 2.2. Else if $OFV^U = +\infty$ or 0, then MILP-CMS is infeasible.
3. Problem selection:
 - 3.1. Delete a problem of $MILP-CMS^s$ from S
4. Relaxation: Solve the linear programming relation of $MILP-CMS^s$.
 - 4.1. While the relaxation is infeasible, do
 - 4.1.1. Set $OFV_s^L = \infty$
 - 4.1.2. If $OFV_s^L \geq OFV^U$
 - 4.1.2.1. If $S = \phi$, then x^* is optimal for OFV^U
 - 4.1.2.2. Else if $OFV^U = +\infty$ or 0, then MILP-CMS is infeasible.
 - 4.1.3. If $OFV_s^L < OFV^U$ and x^{LR} is integrally feasible
 - 4.1.3.1. Set $OFV_s^L = OFV^U$
 - 4.1.3.2. Delete all problems with $OFV_s^L \geq OFV^U$ from S ; and do
 - 4.1.3.1. If $S = \phi$, then x^* is optimal for OFV^U
 - 4.1.3.2. Else if $OFV^U = +\infty$ or 0, then MILP-CMS is infeasible.
 - 4.1.4. End While.
 - 4.2. If OFV_s^L is finite
 - 4.2.1. Let x^{LR} be an optimal solution
 - 4.2.2. Let OFV_s^L be an optimal objective value
 - 4.2.3. Otherwise $OFV_s^L = 0$
5. Add cutting planes: if desired, do
 - 5.1. Add a cutting plane which is violated by x^{LR}
 - 5.2. Return to (4).
6. End solution procedure.

Algorithm 1. The branch and cut algorithm procedure.

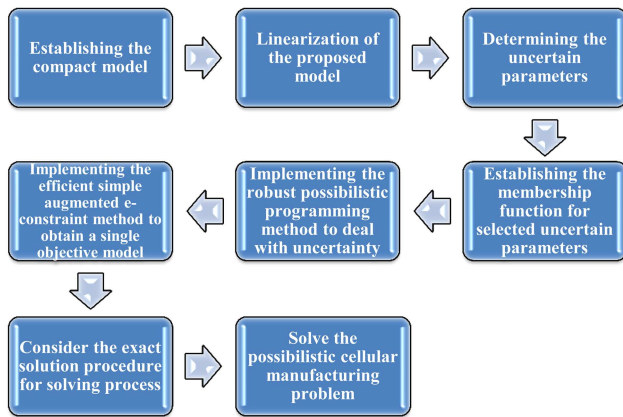


Figure 4. Hierarchical structure of the presented solution approach.

4. Case study

In this section, a real case study is provided to show the validity and applicability of the proposed model. To this end, the performance of the proposed model is indicated during the four periods. In the following, the outline of the case study is provided and then, the results obtained from applying the proposed model are discussed.

4.1. Outline of the case study

The case study is the assignment of different machines to cells along four periods in an XYZ company. Due to limitation in implementation, the managers of the company cannot reconfigure cells during planning periods. In this way, products should be produced in designed cells based on customers' demand and requested qualities through four periods. According to the XYZ's documents, three types of machines and workers are available with three levels of harnesses and skills, respectively. To illustrate the interaction between workers' skills, machine hardness, and quality of products, the managers and directory board members of XYZ company have defined the following rules:

Rule 1. If hardness of a job j on a machine m is low and the worker w is beginner, then the output of job j has medium (q_2) quality;

Rule 2. If hardness of a job j on a machine m is low and the worker w is semi-skilled, then the output of job j has high (q_1) quality;

Rule 3. If hardness of a job j on a machine m is low and the worker w is expert then the output of job j has high (q_1) quality;

Rule 4. If hardness of a job j on a machine m is moderate and the worker w is beginner, then the output of job j has low (q_3) quality;

Rule 5. If hardness of a job j on a machine m is moderate and the worker w is semi-skilled, then the output of job j has medium (q_2) quality;

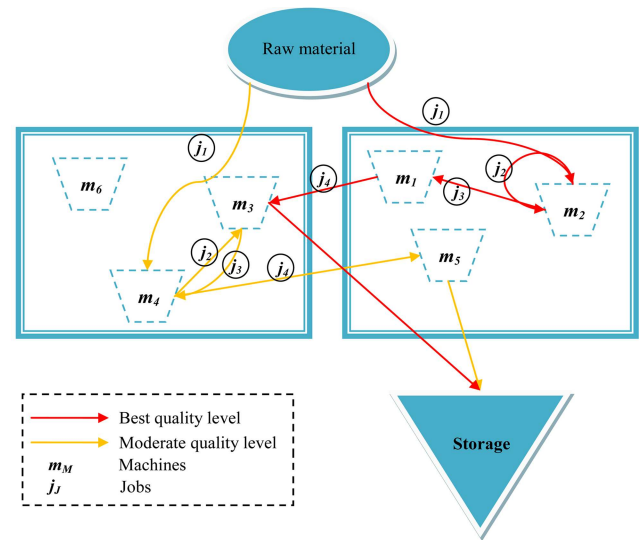


Figure 5. The process of the 4th product with the best and moderate quality levels regarding the required jobs on each machine.

Rule 6. If hardness of a job j on a machine m is moderate and the worker w is expert, then the output of job j has high (q_1) quality;

Rule 7. If hardness of a job j on a machine m is high, then the beginner worker cannot be assigned to it;

Rule 8. If hardness of a job j on a machine m is high and the worker w is semi-skilled, then the output of job j has low (q_3) quality;

Rule 9. If hardness of a job j on a machine m is high and the worker w is expert, then the output of job j has high (q_1) quality.

Other parameters of the proposed model are gathered by interviewing XYZ managers from different departments, and considering company's documents. For instance, the skill level of each worker on each machine is defined as fuzzy input parameters in Table 3.

4.2. Obtained results

In this section, the results obtained from the proposed bi-objective possibilistic nonlinear mixed-integer programming model are presented. The proposed model is solved using the exact solution procedure. The results show that two cells should be formed; assignments of each machine (X_{mk}) to these two cells are presented in Table 4.

In addition, the total demand of customers is satisfied during the planning horizon and demonstrated in Table 5. Furthermore, the production process for each product with a specific quality level (Y_{jpm}^{kq}) regarding the required jobs and machines is determined. In this respect, Figure 5 shows the production process of the

Table 3. The skill levels of each worker on each machine (S_{wm}^s).

Skills level	Machines	Workers	
		$w = 1$	$w = 2$
Expert	$m = 1$	$\tilde{S}_{11}^1 = (U[0.6, 0.65], U[0.7, 0.8], U[0.85, 0.95])$	$\tilde{S}_{21}^1 = (U[0.05, 0.15], U[0.15, 0.2], U[0.2, 0.35])$
Semi-skilled		$\tilde{S}_{11}^2 = (U[0.3, 0.35], U[0.4, 0.45], U[0.5, 0.6])$	$\tilde{S}_{21}^2 = (U[0.35, 0.45], U[0.5, 0.6], U[0.65, 0.75])$
Beginner		$\tilde{S}_{11}^3 = (U[0.0, 0.15], U[0.2, 0.25], U[0.25, 0.3])$	$\tilde{S}_{21}^3 = (U[0.7, 0.75], U[0.75, 0.8], U[0.9, 0.95])$
Expert	$m = 2$	$\tilde{S}_{12}^1 = (U[0.0, 0.05], U[0.1, 0.15], U[0.25, 0.3])$	$\tilde{S}_{22}^1 = (U[0.8, 0.825], U[0.85, 0.9], U[0.9, 0.95])$
Semi-skilled		$\tilde{S}_{12}^2 = (U[0.35, 0.4], U[0.4, 0.45], U[0.50, 0.6])$	$\tilde{S}_{22}^2 = (U[0.4, 0.45], U[0.5, 0.6], U[0.65, 0.75])$
Beginner		$\tilde{S}_{12}^3 = (U[0.65, 0.75], U[0.75, 0.8], U[0.80, 0.95])$	$\tilde{S}_{22}^3 = (U[0.1, 0.15], U[0.15, 0.2], U[0.25, 0.35])$
Expert	$m = 3$	$\tilde{S}_{13}^1 = (U[0.55, 0.60], U[0.65, 0.75], U[0.80, 0.95])$	$\tilde{S}_{23}^1 = (U[0.30, 0.45], U[0.5, 0.6], U[0.65, 0.75])$
Semi-skilled		$\tilde{S}_{13}^2 = (U[0.25, 0.30], U[0.35, 0.45], U[0.50, 0.55])$	$\tilde{S}_{23}^2 = (U[0.65, 0.75], U[0.75, 0.8], U[0.8, 0.9])$
Beginner		$\tilde{S}_{13}^3 = (U[0.05, 0.10], U[0.15, 0.2], U[0.20, 0.25])$	$\tilde{S}_{23}^3 = (U[0.35, 0.45], U[0.55, 0.6], U[0.65, 0.70])$
Expert	$m = 4$	$\tilde{S}_{14}^1 = (U[0.2, 0.3], U[0.35, 0.45], U[0.5, 0.55])$	$\tilde{S}_{24}^1 = (U[0.0, 0.05], U[0.1, 0.25], U[0.25, 0.3])$
Semi-skilled		$\tilde{S}_{14}^2 = (U[0.60, 0.7], U[0.7, 0.8], U[0.80, 0.95])$	$\tilde{S}_{24}^2 = (U[0.25, 0.35], U[0.35, 0.40], U[0.45, 0.55])$
Beginner		$\tilde{S}_{14}^3 = (U[0.3, 0.35], U[0.35, 0.4], U[0.4, 0.55])$	$\tilde{S}_{24}^3 = (U[0.6, 0.65], U[0.7, 0.8], U[0.85, 0.95])$
Expert	$m = 5$	$\tilde{S}_{15}^1 = (U[0.2, 0.3], U[0.35, 0.55], U[0.55, 0.65])$	$\tilde{S}_{25}^1 = (U[0.6, 0.75], U[0.75, 0.8], U[0.8, 0.9])$
Semi-skilled		$\tilde{S}_{15}^2 = (U[0.7, 0.75], U[0.75, 0.8], U[0.85, 0.95])$	$\tilde{S}_{25}^2 = (U[0.275, 0.35], U[0.35, 0.45], U[0.45, 0.6])$
Beginner		$\tilde{S}_{15}^3 = (U[0.2, 0.25], U[0.35, 0.5], U[0.55, 0.60])$	$\tilde{S}_{25}^3 = (U[0.05, 0.1], U[0.1, 0.2], U[0.2, 0.3])$
Expert	$m = 6$	$\tilde{S}_{16}^1 = (U[0.05, 0.15], U[0.15, 0.2], U[0.25, 0.3])$	$\tilde{S}_{26}^1 = (U[0.75, 0.8], U[0.8, 0.85], U[0.85, 0.95])$
Semi-skilled		$\tilde{S}_{16}^2 = (U[0.4, 0.45], U[0.5, 0.6], U[0.65, 0.75])$	$\tilde{S}_{26}^2 = (U[0.35, 0.425], U[0.45, 0.5], U[0.5, 0.55])$
Beginner		$\tilde{S}_{16}^3 = (U[0.65, 0.75], U[0.75, 0.8], U[0.85, 0.9])$	$\tilde{S}_{26}^3 = (U[0.1, 0.15], U[0.2, 0.25], U[0.25, 0.325])$
		$w = 3$	$w = 4$
Expert	$m = 1$	$\tilde{S}_{31}^1 = (U[0.25, 0.4], U[0.4, 0.45], U[0.45, 0.6])$	$\tilde{S}_{41}^1 = (U[0.05, 0.15], U[0.15, 0.25], U[0.25, 0.3])$
Semi-skilled		$\tilde{S}_{31}^2 = (U[0.75, 0.8], U[0.8, 0.85], U[0.85, 0.9])$	$\tilde{S}_{41}^2 = (U[0.35, 0.45], U[0.5, 0.6], U[0.65, 0.75])$
Beginner		$\tilde{S}_{31}^3 = (U[0.35, 0.4], U[0.4, 0.5], U[0.50, 0.6])$	$\tilde{S}_{41}^3 = (U[0.7, 0.75], U[0.75, 0.8], U[0.8, 0.9])$
Expert	$m = 2$	$\tilde{S}_{32}^1 = (U[0.25, 0.3], U[0.35, 0.55], U[0.55, 0.65])$	$\tilde{S}_{42}^1 = (U[0.0, 0.15], U[0.15, 0.25], U[0.25, 0.3])$
Semi-skilled		$\tilde{S}_{32}^2 = (U[0.65, 0.75], U[0.75, 0.8], U[0.85, 0.90])$	$\tilde{S}_{42}^2 = (U[0.3, 0.4], U[0.4, 0.45], U[0.45, 0.6])$
Beginner		$\tilde{S}_{32}^3 = (U[0.2, 0.3], U[0.35, 0.5], U[0.55, 0.60])$	$\tilde{S}_{42}^3 = (U[0.50, 0.60], U[0.65, 0.75], U[0.80, 0.95])$
Expert	$m = 3$	$\tilde{S}_{33}^1 = (U[0.6, 0.7], U[0.7, 0.8], U[0.85, 0.90])$	$\tilde{S}_{43}^1 = (U[0.25, 0.3], U[0.3, 0.45], U[0.5, 0.55])$
Semi-skilled		$\tilde{S}_{33}^2 = (U[0.3, 0.35], U[0.35, 0.45], U[0.45, 0.55])$	$\tilde{S}_{43}^2 = (U[0.65, 0.7], U[0.7, 0.8], U[0.80, 0.95])$
Beginner		$\tilde{S}_{33}^3 = (U[0.0, 0.05], U[0.1, 0.15], U[0.25, 0.3])$	$\tilde{S}_{43}^3 = (U[0.3, 0.35], U[0.35, 0.5], U[0.5, 0.55])$
Expert	$m = 4$	$\tilde{S}_{34}^1 = (U[0.65, 0.75], U[0.7, 0.8], U[0.80, 0.95])$	$\tilde{S}_{44}^1 = (U[0.7, 0.75], U[0.85, 0.9], U[0.9, 0.95])$
Semi-skilled		$\tilde{S}_{34}^2 = (U[0.35, 0.4], U[0.4, 0.45], U[0.50, 0.6])$	$\tilde{S}_{44}^2 = (U[0.3, 0.35], U[0.45, 0.55], U[0.55, 0.65])$
Beginner		$\tilde{S}_{34}^3 = (U[0.05, 0.15], U[0.15, 0.2], U[0.25, 0.3])$	$\tilde{S}_{44}^3 = (U[0.0, 0.05], U[0.05, 0.25], U[0.25, 0.3])$
Expert	$m = 5$	$\tilde{S}_{35}^1 = (U[0.1, 0.15], U[0.15, 0.25], U[0.25, 0.3])$	$\tilde{S}_{45}^1 = (U[0.65, 0.75], U[0.75, 0.8], U[0.85, 0.9])$
Semi-skilled		$\tilde{S}_{35}^2 = (U[0.35, 0.4], U[0.4, 0.45], U[0.45, 0.6])$	$\tilde{S}_{45}^2 = (U[0.3, 0.35], U[0.35, 0.4], U[0.4, 0.55])$
Beginner		$\tilde{S}_{35}^3 = (U[0.65, 0.75], U[0.7, 0.8], U[0.80, 0.95])$	$\tilde{S}_{45}^3 = (U[0.05, 0.15], U[0.15, 0.2], U[0.25, 0.3])$
Expert	$m = 6$	$\tilde{S}_{36}^1 = (U[0.25, 0.35], U[0.35, 0.45], U[0.45, 0.55])$	$\tilde{S}_{46}^1 = (U[0.2, 0.4], U[0.4, 0.5], U[0.5, 0.6])$
Semi-skilled		$\tilde{S}_{36}^2 = (U[0.60, 0.75], U[0.75, 0.8], U[0.80, 0.95])$	$\tilde{S}_{46}^2 = (U[0.7, 0.8], U[0.8, 0.85], U[0.85, 0.95])$
Beginner		$\tilde{S}_{36}^3 = (U[0.3, 0.35], U[0.35, 0.4], U[0.45, 0.55])$	$\tilde{S}_{46}^3 = (U[0.3, 0.4], U[0.45, 0.5], U[0.50, 0.6])$

forth product with the best and moderate quality levels regarding inter-/intra-cell movements, schematically.

Moreover, assignment of workers to perform each job on each machine with a specific skill level (ϖ_{wjm}^s) is performed. For further convenience, assignment of workers regarding their skill levels to the production process of the forth product is demonstrated in Figure 6.

Meanwhile, objective function values of the proposed model reveal that there is a conflict between minimizing the total cost and inaction of workers and machines, simultaneously. A survey of the proposed model indicated that minimizing inactive workers and machines led to increased cost of employment of work-

ers and processing cost of machines, respectively. The conflict between the two considered objective functions is shown in Figure 7, and the obtained Pareto optimal points are presented in Table 6. Therefore, decision makers can select one of the obtained Pareto optimal points, which is the best solution for them.

Table 4. Machine assignment to cells.

Machine	Cell	
	$k = 1$	$k = 2$
$m = 1$	0	1
$m = 2$	0	1
$m = 3$	1	0
$m = 4$	1	0
$m = 5$	0	1
$m = 6$	1	0

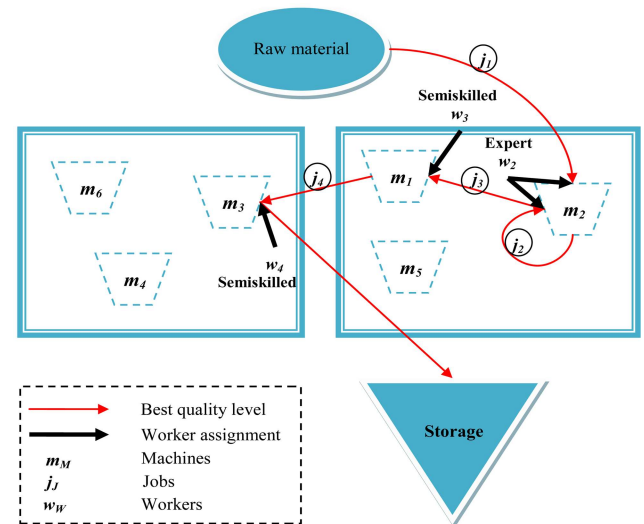


Figure 6. Worker assignment to each machine and job regarding their skill level.

Table 5. Number of products produced with a specific quality level in each period.

Quality level	Products	Period			
		$t = 1$	$t = 2$	$t = 3$	$t = 4$
Best quality	$p = 1$	14	20	11	11
Moderate quality		36	35	39	18
Worst quality		7	5	14	19
Best quality	$p = 2$	10	11	7	9
Moderate quality		79	82	45	29
Worst quality		35	45	19	5
Best quality	$p = 3$	8	9	8	6
Moderate quality		37	10	17	19
Worst quality		79	53	53	41
Best quality	$p = 4$	94	28	49	26
Moderate quality		59	7	39	13
Worst quality		86	35	18	17
Best quality	$p = 5$	13	14	6	7
Moderate quality		29	54	16	10
Worst quality		11	8	6	9
Best quality	$p = 6$	6	16	14	11
Moderate quality		47	97	45	16
Worst quality		25	9	11	13

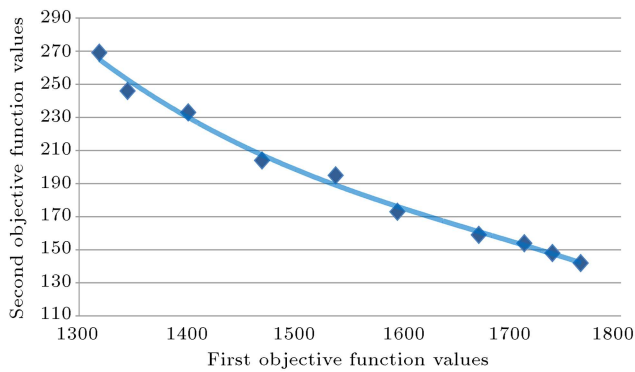


Figure 7. Schematic representation of the conflict between the objective functions.

Table 6. The best values of the objective functions.

Pareto optimal point	The values of objective functions	
	Objective 1	Objective 2
1	1319	269
2	1345	246
3	1401	233
4	1469	204
5	1537	195
6	1594	173
7	1669	159
8	1711	154
9	1737	148
10	1763	142

The obtained Pareto optimal points of objective functions have been approved by experts. In this respect, considering the worst Pareto optimal points of the first and second objective functions shows that the proposed approach can reduce the total costs by 23.6% and the total inaction of workers and machines by 11.7%.

5. Sensitivity analysis

A sensitivity analysis is provided to clarify the robustness and sensitiveness of the proposed possibilistic mixed integer programming model regarding important parameters for managing CMS based on product quality level, worker's skill level, and machine hardness level in real cases. Here, considering different workers with various skill levels as well as different machines with various hardness levels could lead to different values for objective functions.

In this respect, the number of workers with various skill levels is recognized as an important parameter to identify its effects on the objective functions. Meanwhile, the effects of changing the employed workers

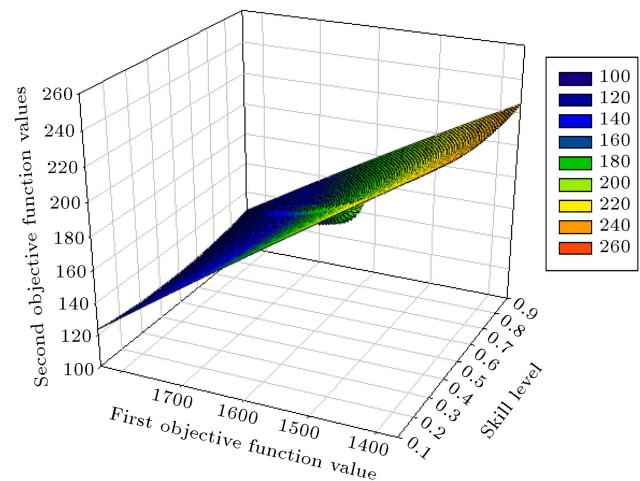


Figure 8. The effect of different skill levels of workers on the objective functions.

with various skill levels (i.e., expert, semi-skilled, and beginner) on the values of the objective functions are examined. The results show that considering workers with beginner and expert skill levels leads to the minimum and maximum values of the objective functions, respectively.

Therefore, the skill level of workers is changed to represent its effects on both the objective functions. As indicated in Figure 8, by increasing workers' skill level, the total costs of CMS problems increase. Moreover, the value of the second objective function for minimizing the inactive workers and machines is obtained lower than the determined Pareto optimal points from solving the case study. Although the cost of employing workers with high skill level increases, lower value for workers' inactivation is obtained. In addition, it is clear that a company with highly skilled workers could manufacture products with the best quality. Moreover, such workers could appropriately operate jobs on different machines with various hardness levels. Thereby, the hole in Figure 8 indicates that selecting the Pareto optimal midpoints may be a suitable decision for minimizing both the objective functions by ensuring the CMS problem competencies.

Furthermore, one of the main parameters is jobs with various hardness levels on each machine, which could lead to different costs. Accordingly, the number of machines with different job hardness levels (i.e., low, moderate, and high) are changed so that their effectiveness on both the objective functions of the proposed possibilistic mixed integer programming model could be determined. The results show that the trend of the cost variation with regard to change in the number of machines with various job hardness levels is increasing. On the other hand, job hardness level for machines is increased to identify the robustness or sensitiveness of both the objective functions. As indicated in Figure 9, the total cost of the CMS problem (Z_{TC}) increases

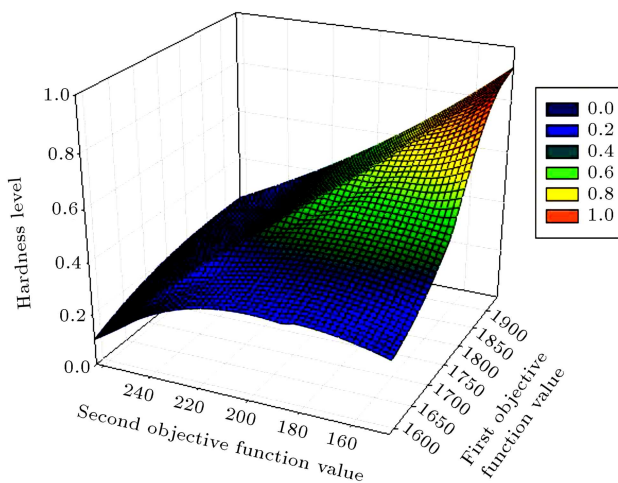


Figure 9. The effect of different jobs' hardness levels on the objective functions.

with high job hardness level. In contrast, the second objective function values (Z_{IA}) change around the obtained values for the case study. It is shown that job hardness level of machines cannot directly affect inactivation of workers and machines. To address the issue, the Hamming or Euclidean distance measure could be considered. These measures show how much the Pareto optimal points obtained from the second objective function for the case study and the sensitivity analysis are close to each other.

However, considering the output quality of the manufactured product is more important with regard to lowering of the total costs and inactivation of workers or machines. This is because the customer satisfaction could directly lead the company towards a successful business. To address the issue, simultaneous consideration of workers with different skill levels and machines with different hardness levels is more significant. Indeed, skill levels of workers and hardness levels of machines could affect the output quality. Therefore, considering the optimum combination of workers with suitable skill levels and machines with appropriate hardness levels could decrease the total costs and inactivation of workers and machines as well as preserve the required quality level of manufactured products. Ultimately, this study could assist decision makers to overcome this challenge by selecting the appropriate Pareto optimal point.

6. Conclusions and future directions

Design of appropriate Cellular Manufacturing Systems (CMSs) involves many operational and structural issues. In this respect, some significant issues such as product quality level, worker's skill level, and machine hardness level should be taken into consideration to help companies in the current competitive environment. In this study, a novel bi-objective pos-

sibilistic nonlinear mixed-integer programming model under imprecise condition was presented in order to minimize the total costs and total inaction of workers and machines. The proposed model was incorporated into dynamic cell formation, worker and machine assignments, machine hardness level, route and worker flexibility, operation sequence, product quality level, worker and machine capacity, and worker's skill level under uncertainty. Then, some important parameters were considered for fuzziness based on literature survey and the nature of the parameters. In this respect, the robust possibilistic programming approach was utilized to address the uncertain parameters in the proposed model. Hence, the presented model was implemented for a real case study to show the capability and efficiency of the proposed novel possibilistic mathematical model. Comparing the results obtained from the proposed model and the current actual practice showed that the presented model could help companies minimize their costs and appropriately manipulate workers and machines. Furthermore, the sensitivity analysis showed that changing workers' skill level could affect both the objective functions of the proposed approach. In contrast, the first and second objective functions were sensitive and robust to different job hardness levels of machines, respectively. For future research, considering the inventory level, lot splitting, and flexible reconfiguration features can enhance the performance of the proposed model. In addition, developing heuristic algorithms to solve large-size problems is suggested.

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