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A Bi-objective Model for Cellular Manufacturing System Considering Worker Skills, Part Priorities, and Equipment Levels

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Here, a new mathematical model for cellular manufacturing systems considering three important features of part priority, levels of machine's technology, and the operator's skill is developed. Simultaneous consideration of these features provides a more realistic analysis of the problems in cellular manufacturing systems. A model with multiple design features including cell formation, human resources flexibility with different skills, machines flexibility, operational sequence, processing time, and the capacity of machine and manpower is proposed in this article. Our focus is on the design of cells to implement two dissimilar goals. The first goal is the reduction of inter-cellular movements of parts and workers. The second goal is the creation of efficient cells by making cell's quality level identical for produced products so that the production of all the different parts have good quality. Two approaches of augmented ε-constraint and non-dominated sorting genetic algorithm II (NSGA-II) are used to solve this model. By comparison of these two approaches, we realize that the multi-objective evolutionary optimization algorithm creates a Pareto-optimal front in a reasonable amount of time for large-scale problems.

Keywords*: Cellular manufacturing system; Worker skills; Equipment levels; Part priorities; Augmented ε-constraint; NSGA-II.*

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1. Introduction

Cell manufacturing (CM) is the process of a group of similar parts on a certain group of machines and manufacturing processes. The main objectives of cellular manufacturing systems (CMSs) are the reduction of lead time, material handling cost, setup time, and production costs [1]. Here, three elements of part, machine, and worker are considered along with the technology level of machines and skill level of employees engaged in working on parts with different priorities and degrees to design cells. Thus, we consider relationships of part-operation–machine, part-operation–worker, machine–technology level, the worker–skill level, and part-priority level as effectiveness criteria in cell formation. Simultaneous consideration of three factors of part, machine, and worker is important

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because workers in a cell should be able to carry out all the operations of the allocated parts by using the machines in mentioned cell.

On the other hand, the relationship between the machine–technology level and worker–skill level is significant because there must be a mutual balance between workers and machines. In simple terms, skilled workers have a higher capability in working with high-tech machines in comparison with novice workers and therefore, it is preferred that skilled workers work with high-tech machines to create a uniform cell with a minimal difference in terms of technology between machines and skills of workers. The main objective of our work here is to present a more realistic viewpoint of cellular manufacturing by paying attention to quality derived from the cooperation of machines and workers to produce parts, given that some of the parts ordered by customers are more important in many cases and must be processed by high-tech machines and skilled workers. Parts are prioritized based on opinions of customers and by factors such as safety, the specificity of an order or in terms of the amount of order.

The first objective of this study is to minimize the number of movements of human resources and parts between cells. Reliability of a cell increases when workers of that cell can work with all machines assigned to their cell and when levels of expertise of workers in cells increase. The increasing level of expertise of workers and thereby improved reliability of cells creates a situation that if a worker is inadvertently removed from the cell, other workers can continue working on the related machine. One way to show the dependency of machines, operations, and parts is a binary three-dimensional matrix of part–operation–machine. If a particular element of the matrix is 1, it means that the corresponding operation of the intended part can be processed with that corresponding machine. There are parts with different qualities in case of having machines with different technology levels and workers with different levels of expertise. The poor quality of parts produced by some machines and workers may sometimes lead to dissatisfaction of customers and specialized machines and skilled workers are sometimes inefficiently used to produce a part which is not of great importance to the customer. This only makes the valuable resources unavailable for processing of the parts that essentially should be processed on the specified machines. The categorization of parts plays an important and useful role in solving this problem. We consider three categories to classify the level of technology of machines and workers as follows:

- The first level represents a specialized level of machines, skilled workers and high-priority parts.
- The second level represents the semi-specialized level of machines, semi-skilled workers and medium-priority parts.
- The third level represents general machines, ordinary workers and low-priority parts.

Balance of quality level of cells and output parts, as the second objective of our work, is obtained by minimizing the difference between the highest quality level of a cell and the lowest quality level of a cell. This balancing forms cells with identical levels in which there exist machines, parts, and workers at each level. This creates an opportunity to transfer skills and experience among skilled, semi-skilled and normal workers which in turn reduces training costs for workers to upgrade their skill levels. The opinions of experts are utilized to convert levels of quality to quantities and place those in the machine-worker quality matrix. Numbers in this matrix represent the quality factor of workers when working with the machines.

2. Literature Review

Various methods have been proposed for cell formation. A comprehensive summary of the studies focused on the cell formation problem (CFP) can be found in papers published by Heydari et al. [2], Paydar and Saidi-Mehrabad [3], and Yin and Yasuda [4].

Mahdavi et al. [5, 6] proposed a mathematical model to solve the cell formation problem based on the cell application concept in a cellular manufacturing system. The purpose of their model was to minimize the number of exceptional elements and intercellular voids. Also, they proposed an efficient method based on a genetic algorithm to solve the mathematical model. Paydar et al. [7] reformulated CFP as a multiple departures single destination multiple traveling salesman problem. They also developed a solution approach based on simulated annealing. Mahdavi et al. [8] adressed a multi-objective mathematical model for a cellular manufacturing system that included layout design and cell formation problems considering inter- and intra-cell layouts. They applied a fuzzy goal programming method to deals with their multi-objective problem and the model was verified using some numerical examples. Paydar and Saidi-Mehrabad [3] proposed a hybrid genetic- neighborhood search algorithm to solve cell formation problems to minimize the number of exceptional elements and voids. They compared their computational results with grouping efficacy of 35 various methods gathered from the literature and concluded the superiority of their hybrid method. Manpower played an important role in their model for formation of manufacturing cells.

Nowadays, human resources play an important role in cellular manufacturing systems. Min and Shin [9] created the prototype of a three-dimensional group technology system for the first time. Their method added workers to the part-machine incidence matrix as an element. Parkin and Li [10] proposed an algorithm for n-dimensional group technology problems. Their algorithm separately focused on each of the incidence matrices and sorted them. Li [11] presented a method to solve multi-dimensional group technology problems. This method simultaneously considered all incidence matrices. Mahdavi et al. [12] provided a mathematical model to solve cell formation problems based on a three-dimensional machine-part-worker incidence matrix to minimize exceptional elements and voids in a cellular manufacturing system. Saidi-Mehrabad et al. [13] provided a linear programming model for dynamic cellular manufacturing systems according to worker training and production planning. Bootki et al. [14] provided a three-dimensional CFP with the objectives of maximizing the total quality index of parts and minimizing the intracellular movements. Bootki et al. [15] studied two different aspects of human resources: (1) skill of worker to work with different machines and (2) preference of workers to choose co-workers. The former minimizes workers' movements between manufacturing cells and the latter may improve CMS acts in the long run through creating a friendly environment, cooperation, and coordination of workers, the balance of experiences and collaboration systems. Liu et al. [16] presented a bacteria foraging algorithm for cell formation and planning problems for the assignment of workers and machines. Liu [17] considered a common model of allocation of workers and production planning in a dynamic cellular manufacturing system. The objective was to minimize costs of backorders and cost of material handling. They provided a hybrid bacteria foraging algorithm to solve the problem.

Chu et al. [18] formulated a novel mathematical model for mutual training with learning and overlooking properties to assign labors in various cells. Due to the NP-hardness of the suggested model, a swarm intelligence metaheuristic was utilized to solve and analyze the problem. Finally, the computational results showed robustness and efficiency of the applied framework. Therefore, the authors recommended the obtained results to be used by managers for enhancing their organizations. Besides, Mejía-Moncayo and Battaia [19] proposed a cellular manufacturing system to enhance the designed problem's effectiveness and using several utilized optimization problems considered some key assumptions such as cell layout, workload balancing, and cell formation issues. They used a hybrid evolutionary algorithm to solve and assess performance of the suggested model and verified the problem by several numerical examples. Furthermore, Méndez-Vázquez and Nembhard [20] designed a cellular manufacturing system to assign cell and incoherent labors. Also, several organizational features were applied to measure their effects on system performance. They used a linear model, ANOVA, to evaluate the behavior of their proposed framework and achieved several managerial insights.

Recently, Sadeghi et al. [21] attempted to design a blood glucose strips supply chain network and considered cellular manufacturing systems and inventoried quantities as the main steps of the framework. The study developed a mathematical model to optimize the needed number of cells using some features of strong simulation software. Finally, their framework was evaluated using a sensitivity analysis and several key directions were proposed that could be useful for the blood glucose strips supply chain. On the other hand, Kesavan et al. [22] in a study addressed several issues such as inventory lot sizing, machine layout, and cell formation in their cellular manufacturing systems to attain useful results. Due to the NP-hardness of their proposed model, several meta-heuristic and heuristic algorithms were applied to solve the problem, specially in large dimensions, and the approaches were validated using an exact solution approach. They used a real-world case study in the electronic manufacturing industry and several significant results were obtained.

The novelty in the present work can be viewed in two respects: (1) problem modeling and formulation, and (2) the solution method. Here, we present a bi-objective mathematical model for cellular manufacturing systems considering concepts such as machine capacity with no machine duplication, the capacity of workers, operator skills, the priority of parts and levels of technology of machines with the objectives of reducing the cost of inter-cellular movements of workers and parts and balancing the quality level of the cells. A non-dominated genetic algorithm is utilized as the solution method for large-scale problem instances and an augmented ε-constraint method is used for obtaining Pareto-optimal solutions, specially for comparison purposes.

3. Modeling the Problem

A bi-objective mixed-integer mathematical model for cellular manufacturing systems considering operator skills, part priority, and technology of machines to reduce the cost of inter-cellular movements for workers and parts and to balance the quality level of the cells is presented in this section. Assumptions of the model are as follows:

- ✓ The number of cells are known
- ✓ Machine duplication is not allowed; i.e. there is only one type of machine for the processing of operations
- ✓ The lower and upper limits for the number of machines in each cell are known
- ✓ The number of workers, number of machines and number of parts are known
- ✓ Three levels are considered for each one of the parts, machines and workers elements
- ✓ The ability for processing of parts operation by the worker is expressed by a three-dimensional part-operation-worker incidence matrix
- ✓ The ability for processing of parts operation by machine is expressed by three-dimensional part-operation-machine incidence matrix
- ✓ The ability for a worker to work with a machine is expressed by worker-machine incidence matrix which is called the task matrix

- ✓ Duration of availability of machines and workers is fixed
- ✓ Quality of produced parts depends on the priority of part, the technology level of machines and the level of skills of workers being used to complete the operations and is measured through the opinions of experts
- ✓ The quality obtained from the working of workers by machines is expressed by a matrix called the quality matrix of worker–machine.

Indices:

i	Index for the set of parts ($i = 1, 2, \dots, I$)
j	Index for the set of machines ($j = 1, 2, \dots, J$)
c, c'	Index for the set of cells ($c, c' = 1, 2, \dots, K$)
s	Index for the set of operations of each part ($s = 1, 2, .., OP_i$)
w	Index for the set of workers ($w = 1, 2, \dots, W$).

Parameters:

a_{isj}	1, if operation s of part i is to be processed on machine j; 0, otherwise
r_{isw}	1, if operation s of part i needs worker w; 0, otherwise
B_{wj}	1, if worker w is able to operate machine j; 0, otherwise
U_{wj}	Quality obtained from the work of worker w with machine j
LB_c	Lower bound for the number of machines in cell c
UB_c	Upper bound for the number of machines in cell c
t_{isw}	Processing time of operation s of part i for worker w
A_1	Part intercellular movement cost
A_2	Worker intercellular movement cost
D_i	Demanded quantity of part i
MC_j	Time-capacity of machine j
WC_w	Time-capacity of worker w
M	A sufficiently large positive number.

Decision variables:

v_{wc}	1, if worker w is assigned to cell c; 0, otherwise
k_{ic}	1, if part i is assigned to cell c; 0, otherwise
y_{jc}	1, if machine j is assigned to cell c; 0, otherwise
x_{iswjc}	1, if operation s of part i is processed on machine j by worker w in cell c; 0, otherwise
Q_{max}	The maximum quality level of cells
Q_{min}	The minimum quality level of cells
q_c	The quality level of cell c

Objective Functions:

$$\min z_1 = A_1\left(\sum_i^I \sum_c^C k_{ic} - 1\right) + \frac{1}{2} \times A_2\left(\sum_w^W \sum_c^C \sum_{c'}^C v_{wc} . v_{wc'}\right) \tag{1}$$

$$\min z_2 = Q_{max} - Q_{min} \tag{2}$$

Expressions (1) and (2) are the first and second objectives, respectively. Specifically, the first objective function is for minimizing the cost of inter-cellular movements of workers and parts and the second one is to balance the quality level of cells.

Constraints:

$$\sum_{j}^{J} y_{jc} \leq UB_c\,, \ \ \forall c \tag{3}$$

$$\sum_{j}^{J} y_{jc} \geq LB_c\,, \ \ \forall c \tag{4}$$

$$\sum_{c}^{C} y_{jc} \leq 1\,, \ \ \forall j \tag{5}$$

$$\sum_{i}^{I}\sum_{s}^{S}\sum_{w}^{W} x_{iswjc} \leq M \cdot y_{jc}, \ \ \forall j, c \tag{6}$$

$$\sum_{c}^{C} x_{iswjc} \leq M \times r_{isw} \times a_{isj} \times B_{wj}\,, \ \ \forall i, s \in op_i, w, j \tag{7}$$

$$\sum_{w}^{W}\sum_{j}^{J}\sum_{c}^{C} x_{iswjc} = 1, \ \ \forall i, s \in op_i \tag{8}$$

$$\sum_{s}^{S}\sum_{w}^{W}\sum_{j}^{J} x_{iswjc} \geq k_{ic}, \ \ \forall i, c \tag{9}$$

$$\sum_{s}^{S}\sum_{w}^{W}\sum_{j}^{J} x_{iswjc} \leq M \times k_{ic}, \ \ \forall i, c \tag{10}$$

$$\sum_{i}^{I}\sum_{s}^{S}\sum_{j}^{J} x_{iswjc} \geq v_{wc}, \ \ \forall w, c \tag{11}$$

$$\sum_{i}^{I}\sum_{s}^{S}\sum_{j}^{J} x_{iswjc} \leq M \times v_{wc}, \ \ \forall w, c \tag{12}$$

$$q_c = \sum_{i}^{I}\sum_{s}^{S}\sum_{w}^{W}\sum_{j}^{J} u_{wj} \times x_{iswjc}\,, \ \ \forall c \tag{13}$$

$$Q_{min} = \min(q_1, q_2, \dots, q_c) \tag{14}$$

$$Q_{max} = \max(q_1, q_2, \dots, q_c) \tag{15}$$

$$\sum_{i}^{I}\sum_{s}^{S}\sum_{w}^{W}\sum_{c}^{C} x_{iswjc} \times t_{isw} \times D_i \leq MC_j\,, \ \ \forall j \tag{16}$$

$$\sum_{i}^{I}\sum_{s}^{S}\sum_{j}^{J}\sum_{c}^{C} x_{iswjc} \times t_{isw} \times D_i \leq WC_w\,, \ \ \forall w \tag{17}$$

$$v_{wc}, k_{ic}, x_{iswjc}, y_{jk} \in \{0,1\}, \ \ \forall i,s,j,c,w \tag{18}$$

$$Q_{max} \geq 0, Q_{min} \geq 0, q_c \geq 0, \forall c. \tag{19}$$

Constraints (3) and (4) determine the upper and lower limits of the number of machines in the cells. Constraint (5) prevents machine duplication. Constraint (6) ensures having machine j in cell c if operation s should be done by worker w on machine j in cell c. Constraint (7) guarantees that if a worker w is chosen to process operation s of part i on machine j in cell c, then she/he has the required ability. Constraint (8) ensures that each operation of each part is processed by one worker on one machine in one cell. Constraints (9) and (10) are for determining the cells between which part i moves for processing of its operation. Constraints (11) and (12) are for determining the cells between which worker w moves for processing of operations. Constraint (13) expresses the method of calculating the quality level of manufacturing parts in each cell. Constraints (14) and (15) represent the lowest and highest levels of quality of cells, respectively. Constraints (16) and (17) ensure that the duration of using machine j and worker w are not more than their availability time. Finally, constraints (18) and (19) specify the type of decision variables as binary and positive.

3.1. Linearization of the model

The proposed model is a nonlinear integer programming model due to the multiplication of variables in the second term of the first objective function; i.e. equation (1), and in constraints (14) and (15). We define an auxiliary variable as $N_{wc\acute{c}} = v_{wc}v_{w\acute{c}}$ to linearize the objective function. The following constraints should be added to the mathematical model:

$$N_{wcc'} - v_{wc} - v_{wc'} + 1.5 \geq 0, \ \ \forall w,c,c' \tag{20}$$

$$1.5N_{wcc'} - v_{wc} - v_{wc'} \leq 0, \ \ \forall w,c,c'. \tag{21}$$

Also, the following constraints should be added to make constraint (14) linear:

$$q_c - q_{c'} > M \times -Z_{cc'}, \ \ \forall c, \mathrm{c}', c \neq c' \tag{22}$$

$$q_c - q_{c'} > M \times (1 - Z_{cc'}), \ \ \forall c, c', c \neq c' \tag{23}$$

$$\sum_{\substack{c'=1 \\ c' \neq c}}^{C} Z_{cc'} \geq (c-1) \times q_c^{min}, \ \ \forall c \tag{24}$$

$$\sum_{c=1}^{C} q_c^{min} = 1 \tag{25}$$

$$Q_{min} = \sum_{c=1}^{C} q_c^{min} q_c. \tag{26}$$

The right-hand side of (26) is still a non-linear expression due to the multiplication of a binary variable by a continuous variable. We define the auxiliary variable as $E_c = q_c^{min} q_c$ to linearize (26). The following constraints should be added to the mathematical model:

$$Q_{min} = \sum_{c=1}^{C} E_c \tag{27}$$

$$E_c \le M \times q_c^{min}, \;\; \forall c \tag{28}$$

$$E_c \ge q_c - M \times \left(1 - q_c^{min}\right), \;\; \forall c \tag{29}$$

$$E_c \le q_c, \;\; \forall c. \tag{30}$$

Similar to what was done for linearizing constraint (14), the following constraints should be added to linearize constraint (15).

$$q_c - q_{c'} \ge M \times \left(F_{cc'} - 1\right), \; \forall c, c', c \ne c' \tag{31}$$

$$q_c - q_{c'} < M \times F_{cc'}, \;\; \forall c, c', c \ne c' \tag{32}$$

$$\sum_{\substack{c'=1 \\ c' \ne c}}^{C} F_{cc'} \ge (c - 1) \times q_c^{max}, \;\; \forall c \tag{33}$$

$$\sum_{c=1}^{C} q_c^{max} = 1 \tag{34}$$

$$Q_{max} = \sum_{c=1}^{C} q_c^{max} \, q_c. \tag{35}$$

Equation (35) is nonlinear similar to equation (26). Therefore, similar to the discussion presented for linearization of (26), we define the auxiliary variable as $G_c = q_c^{max} q_c$ to linearize (35). The following constraints should be added to the mathematical model:

$$Q_{max} = \sum_{c=1}^{C} G_c \tag{36}$$

$$G_c \le M \times q_c^{max}, \;\; \forall c \tag{37}$$

$$G_c \ge q_c - M \times (1 - q_c^{max}), \;\; \forall c \tag{38}$$

$$G_c \le q_c, \;\; \forall c. \tag{39}$$

According to what was discussed in the previous subsection, we present the linear model as follows:

$$\min z_1 = A_1\Big(\sum_{i}^{I} \sum_{c}^{C} k_{ic} - 1\Big) + \frac{1}{2} \times A_2\Big(\sum_{w}^{W} \sum_{c}^{C} \sum_{c'}^{C} N_{wcc'}\Big) \tag{40}$$

$$\min z_2 = Q_{max} - Q_{min} \tag{41}$$

Subject to

(3)-(13) and (16)-(17) and (20)-(25) and (27)-(34) and (36)-(39)

$$v_{wc}, k_{ic}, x_{iswjc}, y_{jk}, N_{wcc'}, Z_{cc'}, q_c^{min}, F_{cc}, q_c^{max} \in \{0,1\}, \;\; \forall i, s, j, c, w, c' \tag{42}$$

$$Q_{max} \ge 0, Q_{min} \ge 0, q_c, E_c, G_c \ge 0, \quad \forall c. \tag{43}$$

4. Multi-objective Solutions

In this section, two different approaches are introduced to solve the aforementioned model are presented. Here, ε-constraint is considered as a multi-objective decision-making (MODM) method for solving the model resulting in a Pareto-optimal front. Although MODM methods, such as ε-constraint, provide Pareto-optimal solutions, they are very time-consuming. Besides, NSGA II, as one of the most-widely used multi-objective evolutionary optimization algorithm is an approximate method with low computational time, is utilized. In the following, the achieved results will show that the NSGA-II algorithm behaves like the augmented ε-constraint method, specially for small size problems. So, comparing the NSGA-II algorithm with the augmented ε-constraint method verified the efficiency of the proposed meta-heuristic. Several works such as [23, 24] used only the NSGA-II algorithm as their solution approach, without comparing it with other approaches. Also, a number of researchers working with several algorithms reported the NSGA-II algorithm to be the best algorithm. For example, Azadeh et al. [25] applied NSGA-II and MOPSO for solving their problem and the results showed the superiority of NSGA-II over MOPSO. Therefore, we consider NSGA-II to be a proper approach for cellular manufacturing system problems and we compare it with the augmented ε-constraint method (a strong MODM method) to verify its efficiency.

4.1. Augmented ε-constraint

The ε-constraint method is considered as one of the best methods for solving discrete multi-objective optimization problems. A multi-objective optimization problem is defined by p objective functions $f_i(x)$, $(i = 1, \dots, p)$ in which $x \in X$ is a vector of decision variables and X is the feasible space of the problem determined by constraints of the problem. Here, we assume that all the objective functions are to be minimized. One objective function is chosen arbitrarily to be used in the "ε-problem" as the chosen objective function to be optimized considering all the other objective functions as constraints. The ε-constraint problem is shown below assuming the first objective function as the chosen one:

$$\begin{aligned} &\min f_1(x) \\ &\text{Subject to} \\ &f_2(x) \le \varepsilon_2, \qquad f_3(x) \le \varepsilon_3, \dots, f_p(x) \le \varepsilon_p. \end{aligned} \tag{44}$$

Pareto edge of the problem is obtained by changing values on the right side of new constraints, i.e. $\varepsilon_2, \dots, \varepsilon_p$. Problem (45) is the result of the application of the ordinary ε-constraint method in solving the problem.

$$\begin{aligned} &\min z_1 = A_1\Big(\sum_{i}^{I}\sum_{c}^{C} k_{ic} - 1\Big) + \frac{1}{2} \times A_2\Big(\sum_{w}^{W}\sum_{c}^{C}\sum_{c'}^{C} v_{wc} \times v_{wc'}\Big) \\ &\text{Subject to} \\ &\qquad z_2 = Q_{max} - Q_{min} \le \varepsilon \\ &\text{(3)-(13) and (16)-(17) and (20)-(25) and (27)-(34) and (36)-(39) and (42) and (43),} \end{aligned} \tag{45}$$

Here, z_1 is selected as the primary objective function and z_2 is added to other constraints of the problem as an ε-constraint. The conventional ε-constraint method does not ensure having efficient Pareto-optimal solutions. Mavrotas [26] presented the augmented ε-constraint method in 2009 to deal with this problem. In the augmented ε-constraint method, inequalities of constraints related to the objective functions are initially turned into equality using slack or surplus variables which are then considered as a part of the objective function. Augmented ε-constraint for our proposed model is:

$$\min z_1 = A_1(\sum_{i}^{I}\sum_{c}^{C} k_{ic} - 1) + \frac{1}{2} \times A_2(\sum_{w}^{W}\sum_{c}^{C}\sum_{c'}^{C} v_{wc} \times v_{wc'}) - eps \times s$$

Subjectto

$$z_2 + s = \varepsilon \tag{46}$$

(3)-(13) and (16)-(17) and (20)-(25) and (27)-(34) and (36)-(39) and (42) and (43),

where eps is a sufficiently small number (usually between 10^{-3} and 10^{-6}). Given that the measuring unit of the slack variable is the same as the second objective function and may be different from that of the first, s/r, where r is the range of the second objective function, is suggested to be used instead of s as the expression subtracted from the first objective to prevent scaling problems [27]. Thus, the objective function of the augmented ε-constraint problem is expressed as:

$$\min z_1 = A_1(\sum_{i}^{I}\sum_{c}^{C} k_{ic} - 1) + \frac{1}{2} \times A_2(\sum_{w}^{W}\sum_{c}^{C}\sum_{c'}^{C} v_{wc} \times v_{wc'}) - eps \times \left(\frac{s}{r}\right). \tag{47}$$

4.2. Non-dominated sorting genetic algorithm II

NSGA-II is considered to be an elitist multi-objective evolutionary optimization algorithm, known as the concept of non-dominated sorting [28]. The main priority for the formation of Pareto fronts in future iterations in NSGA-II is the selection of solutions in the better Pareto front and when solutions are in one front, priority is with the solutions in areas with the lower density of solutions. In fact, after the non-dominant sorting concept, the concept of crowding distance is also considered to be a key point in the NSGA-II algorithm.

4.2.1. Scheme for coding

The most important step in solving problems using meta-heuristic methods is the choice of solution representation [29, 30]. A series of solutions in the genetic algorithm is called a chromosome and each member in the chromosome is called a gene. Here, one of our chromosomes is adopted from Chu and Tsai [31]. The sequences of genes together are shown in this method and the value of each gene represents cell number and machine related to that gene is placed in that cell. An example of a chromosome used in this study is depicted in Figure 1, where M_j determines cells corresponding to machines.

M_1	M_2	M_3	M_4	M_5	M_6	M_7
For Example:						
3	2	1	2	3	1	3

Figure 1. Sample solution representation for machine- cell

There are three cells and seven machines in the example in Figure 1. Therefore, the length of the chromosome is equal to 7 and it can be seen from the above chromosome that machines 1 is placed in cell 3, machines 2 is related to cell 2 and so on. Thus, cell 1 includes machines {3, 6}, cell 2 includes machines {2, 4}, and cell 3 includes machines {1, 5, 7}. An issue needed to be dealt with is the way of representing solutions such that all constraints of the problem are satisfied as much as possible. For example, constraints (3), (4) and (5) are in from of assignment where the former two represent the upper and lower limits of cell and the latter states that each machine must be assigned exactly to one cell. These three constraints are met by the type of solution representation in Figure 1. Another chromosome used in our work is the part-operation-worker chromosome. A table of genes is used for representation in which the value of each gene represents the number of the worker who processes the operation of the part according to the worker's ability to operate and the worker capacity constraint. This chromosome is shown in Figure 2.

	S_1	S_2	S_3	S_4
P_1	W_2	W_2	0	0
P_2	W_1	W_1	W_2	0
P_3	W_1	W_1	W_3	W_3
P_4	W_3	W_3	W_3	W_3

Figure 2. Sample solution representation for part-operation-worker assignments

The part-operation-machine chromosome is another chromosome represented by a table of genes. The value of each gene represents the number of the machine which processes the operation of the part according to the machine's ability to operate and the machine capacity constraint. This chromosome is depicted in Figure 3.

	S_1	S_2	S_3	S_4
P_1	M_1	M_1	0	0
P_2	M_5	M_5	M_3	0
P_3	M_1	M_1	M_4	M_2
P_4	M_4	M_4	M_4	M_8

Figure 3. Sample solution representation for part-operation-machine assignments

We follow a repair strategy to satisfy constraints (3) and (4) and constraints (16) and (17) which relate to using machines and workers according to their available times. Chromosomes are usually repaired when infeasible chromosomes can be altered so to represent feasible solutions with the least amount of coding, which requires simplicity of constraints associated with this amendment. For example, constraints related to lower limits of cells in terms of the number of machines can be ignored during cross-over and mutation operations. Modification of chromosome to resolve this deficiency can be paved without heavy coding by checking the number of duplicate numbers representing the cells in the section related to machines in the first chromosome to see whether it is larger than the lower limit or not. We randomly select genes according to the number of machines lacked and replace those with the number of the intended cell if the lower limit of the cell is violated.

4.2.2. Crossover

Crossover operator transfers the characteristics of parents to offspring. Each individual in the offspring population inherits some of its characteristics from each parent. Here, one point crossover is utilized because of its simplicity, ease of use and satisfactory results. The random number in one point crossover is created in a range of (1, *length*-1) in which *length* means the length of the chromosome. Then, two parent chromosomes are cut from the mentioned point and combined. Figures 4 to 6 show the method of a one-point crossover operator for the three chromosomes introduced for solving our problem.

M r Parent A

2	1	2	1	3	2	3

M r Parent B

2	3	3	1	2	1	1

M r Offspring A

2	1	2	1	2	1	1

M r Offspring B

2	3	3	1	3	2	3

Figure 4. One-point crossover for machine-cell chromosome

Parent A

	s_1	s_2	s_3	s_4
p_1	W_2	W_2	0	0
p_2	W_1	W_1	W_2	0
p_3	W_1	W_1	W_3	W_3
p_4	W_3	W_3	W_3	W_3

Parent B

	s_1	s_2	s_3	s_4
p_1	W_1	W_1	0	0
p_2	W_2	W_1	W_2	0
p_3	W_3	W_3	W_1	W_3
p_4	W_1	W_4	W_1	W_1

Offspring A

	s_1	s_2	s_3	s_4
p_1	W_2	W_2	0	0
p_2	W_1	W_1	W_2	0
p_3	W_3	W_3	W_1	W_3
p_4	W_1	W_4	W_1	W_1

Offspring B

	s_1	s_2	s_3	s_4
p_1	W_1	W_1	0	0
p_2	W_2	W_1	W_2	0
p_3	W_1	W_1	W_3	W_3
p_4	W_3	W_3	W_3	W_3

Figure 5. One- point crossover part-operation-machine chromosome

Parent A

	s_1	s_2	s_3	s_4
p_1	M_1	M_1	0	0
p_2	M_5	M_5	M_3	0
p_3	M_1	M_1	M_4	M_2
p_4	M_4	M_4	M_4	M_8

Parent B

	s_1	s_2	s_3	s_4
p_1	M_3	M_3	0	0
p_2	M_1	M_1	M_3	0
p_3	M_4	M_4	M_4	M_2
p_4	M_1	M_4	M_6	M_7

Offspring A

	s_1	s_2	s_3	s_4
p_1	M_1	M_1	0	0
p_2	M_5	M_5	M_3	0
p_3	M_1	M_1	M_4	M_2
p_4	M_1	M_4	M_6	M_7

Offspring B

	s_1	s_2	s_3	s_4
p_1	M_3	M_3	0	0
p_2	M_1	M_1	M_3	0
p_3	M_4	M_4	M_4	M_2
p_4	M_4	M_4	M_4	M_8

Figure 6. One-point crossover for part-operation-worker chromosome

4.3.3. Mutation

The mutation operator is used to improve upon the exploration of solution space. This operation changes chromosomes completely randomly and is usually done with a very low probability. We use a new method for mutation operation for our problem. In this method, one of the three chromosomes, i.e., machine-cell, part-operation-worker, and part-operation-machine, is selected randomly after the selection of a member of the initial population. Then, one of the followings is performed.

(1) If a machine-cell chromosome is selected, one of its genes which represents the number of cells in which that gene (machine) exists is selected randomly and is replaced by a randomly selected but different cell number. An example of a mutation for the machine-cell chromosome is shown in Figure 7.
(2) If a part-operation-machine chromosome is chosen, one of the operations of part is randomly selected and the machine used for that operation is randomly replaced by another one capable of processing that operation of that part. An example of a mutation for the part-operation-machine chromosome is depicted in Figure 8.
(3) When a part-operation-worker chromosome is chosen, one of the operations of part is randomly selected and the worker who does the operation is randomly replaced by another one able to perform that operation of that part. An example of a mutation for the part-operation-worker chromosome is shown in Figure 9.

2	1	2	1	3	2	3

2	1	1	1	3	2	3

Figure 7. Sample of mutation for machine-cell chromosome

	S_1	S_2	S_3	S_4
P_1	M_1	M_1	0	0
P_2	M_5	M_5	M_3	0
P_3	M_1	M_1	M_4	M_2
P_4	M_4	M_4	M_4	M_8

	S_1	S_2	S_3	S_4
P_1	M_1	M_1	0	0
P_2	M_5	M_5	M_3	0
P_3	M_1	M_1	M_2	M_2
P_4	M_4	M_4	M_4	M_8

Figure 8. Sample of mutation for part-operation machine chromosome

	S_1	S_2	S_3	S_4
P_1	W_2	W_2	0	0
P_2	W_1	W_1	W_2	0
P_3	W_1	W_1	W_3	W_3
P_4	W_3	W_3	W_3	W_3

	S_1	S_2	S_3	S_4
P_1	W_2	W_2	0	0
P_2	W_1	W_1	W_2	0
P_3	W_1	W_2	W_3	W_3
P_4	W_3	W_3	W_3	W_3

Figure 9. Sample of mutation for part-operation worker chromosome

5. Computational Results

A small numerical example is presented and solved to verify the proposed model. The numerical example is using an augmented ε-constraint method to illustrate the conflict between the inter-cellular movements of parts and workers and the balance of quality level of cells. Then, five randomly generated examples are used to compare the performance of the NSGA-II algorithm and the augmented ε-constraint as an MODM method in terms of the quality of obtained Pareto fronts and computational times.

5.1. A comprehensive example

In this example, there are 5 machines, 3 workers and 4 parts each of which has three levels and 3 cells are to be formed. Information about the demands of parts, the number of operations for each part, upper and lower limits of the number of machines in each cell, available capacities of machines and workers as well as the cost of intercellular movement of parts and workers are known. Also, Table 1 shows the levels of parts, machines, and workers. According to Table 1, part 1 and part 2 are at the first level, part 4 is at the second level and part 3 is at the third level. Machine 1 and machine 2 are at the first level, machines 4 and 5 are at the second level and machine 3 is at the third level. Also, worker 1 is at the first level and an expert, worker 2, is at the second level and worker 3 is at the third level. The data for the part-operation-machine incidence matrix and part-operation-worker incidence matrix are shown in tables 2 and 3. For example, in Table 2, the first level operation of part 3 can be done by the first level machine 1 and the third level machine 3. This table also shows the flexibility of machines in the processing of parts. Besides, in Table 3, for example, worker 2 and worker 3 who are at the second and third levels, respectively, can process the second operation of part 4 which is at the second level. This table also shows the flexibility of workers in the processing of parts. Thus, according to Table 4, carrying out the second operation of part 4, which is at the second level by the semi-skilled worker 2, takes 7 time units and it takes 10 time units by the normal worker 3. Table 5 shows the ability of workers to work with different machines. For example, worker 1, who is an expert, can work with all the machines while worker 2, who is a semi-expert, can only work with semi-specialized machines, i.e., machine 4 and machine 5, and the normal machine 3; however, she/he cannot operate machine 1 and machine 2 since they are specialized machines. Also, worker 3 can only work with machine 3 which is a normal machine. Table 6 shows the quality obtained from the work of workers with different levels of machines. By solving the proposed model using the augmented ε-constraint method, four Pareto solutions were obtained: (0, 536), (50, 488), (10050, 256) and (16200, 216). Each of these 4 solutions can be chosen by the decision-maker and has no advantage over any other. Table 7 and Table 8 are the results of solving this example. Table 7 depicts the association of cells, operation of parts, machines, and workers. For example, in (10050, 256) Pareto solution, for operation 2 of part 2, the part should move from cell 2 to cell 1 and worker 1 moves between cells 1 and 2. Table 8 determines which machine and worker process the operation of which part and which part and which worker should move between which cells. For example, in (10050, 256) Pareto solution, both workers and the part are moved between cells to process the operation of part 2. All cells are expected to have the same level of quality and all of their operations of parts are preferred to be done in their cells and movements of parts and workers between cells for processing of the operations are not favorable; however, constraints such as capacity limitation of machines and workers, upper and lower cell limit for the number of machines, level of parts, machines and workers compromise these goals. Sometimes some workers or parts must be transferred from one cell to another for making cell quality level identical and this will create a contradiction in the first objective which is minimizing the inter-cellular movements of parts and workers. Thus, our bi-objective model is to optimize simultaneously these conflicting objectives.

Table 1. Parameters for the comprehensive example

Parameter name		value
Demand [D_1, D_2, D_3,D_4]		[100, 100, 40, 60]
OP_i[p_1,..,p_n]		[1,2,2,2]
Level 1	[p_1,..,p_n]	[1,2]
	[M_1,…,M_n]	[M_1,M_2]
	[W_1,…,W_n]	[W_1]
Level 2	[p_1,..,p_n]	[4]
	[M_1,…,M_n]	[M_4,M_5]
	[W_1,…,W_n]	[W_2]
Level 3	[p_1,..,p_n]	[3]
	[M_1,…,M_n]	[M_3]
	[W_1,…,W_n]	[W_3]
$\text{Uper\_bound}_{\text{cell}}$[$C_1$, C_2,C_3]		[1,1,1]
$\text{Lower\_bound}_{\text{cell}}$[$C_1$, C_2,C_3]		[2,2,2]
CM[M_1, M_2,…,M_n]		[1100, 800, 1000, 500, 800]
CW[W_1, W_2,…,W_n]		[2000,1100,1100]
A_1		100
A_2		50

Table 2. Part-operation-machine incidence matrix

a_{isj}	M_1		M_2		M_3		M_4		M_5	
	S_1	S_2	S_1	S_2	S_1	S_2	S_1	S_2	S_1	S_2
P_1	1	0	0	0	0	0	0	0	0	0
P_2	0	1	1	0	0	0	0	0	0	0
P_3	1	0	0	0	1	1	0	0	0	0
P_4	0	0	0	0	0	0	1	0	0	1

Table 3. Part-operation-worker incidence matrix

r_{isw}	W_1		W_2		W_3	
	S_1	S_2	S_1	S_2	S_1	S_2
P_1	1	0	0	0	0	0
P_2	1	1	0	0	0	0
P_3	1	0	0	0	1	1
P_4	0	0	1	1	0	1

Table 4. Processing time for part-operation-worker incidence matrix

t_{isw}	W_1		W_2		W_3	
	S_1	S_2	S_1	S_2	S_1	S_2
P_1	6	0	0	0	0	0
P_2	6	4	0	0	0	0
P_3	8	0	0	0	10	10
P_4	0	0	7	7	0	10

Table 5. Binary matrix for the possible worker-machine assignments

B_{wj}	M_1	M_2	M_3	M_4	M_5
W_1	1	1	1	1	1
W_2	0	0	1	1	1
W_3	0	0	1	0	0

Table 6. Quality index for possible machine- worker assignments

U_{wj}	M_1	M_2	M_3	M_4	M_5
W_1	200	200	80	120	120
W_2	0	0	48	72	72
W_3	0	0	32	0	0

Table 7. Operation of part, machine and machine assignments into the cells for the Pareto solution

Index		**Seed(0,536)**			**Seed(50,488)**			**Seed(10050,256)**			**Seed(16200,216)**		
		$Cell_1$	$Cell_2$	$Cell_3$	$Cell_1$	$Cell_2$	$Cell_3$	$Cell_1$	$Cell_2$	$Cell_3$	$Cell_1$	$Cell_2$	$Cell_3$
P_1	S_1	1			1			1				1	
P_2	S_1	1			1				1		1		
	S_2	1			1			1[a]				1[a]	
P_3	S_1		1			1			1				1
	S_2		1			1			1				1
P_4	S_1			1			1			1	1		
	S_2			1			1			1			1
W_1		1			1	1[b]		1	1[b]		1[b]	1	1[b]
W_2				1			1			1	1		1[b]
W_3			1			1			1				1
M_1		1			1			1				1	
M_2		1			1				1		1		
M_3			1			1			1				1
M_4				1			1			1	1		
M_5				1			1			1			1

Table 8. Processing of operations of parts on different machines and workers

		P_1			P_2						P_3						P_4					
		S_1			S_1			S_2			S_1			S_2			S_1			S_2		
$W_i \rightarrow$		1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Seed(0,536)	M_1	1							1													
	M_2				1																	
	M_3												1			1						
	$M4$																	1				
	M_5																				1	
Seed(50,488)	M_1	1						1														
	M_2				1																	
	M_3										1^{b}					1						
	$M4$																	1				
	M_5																				1	
Seed(10050,256)	M_1	1						$1^{a,b}$														
	M_2				1^{b}																	
	M_3										1^{b}					1						
	$M4$																	1				
	M_5																				1	
Seed(16200,216)	M_1	1						$1^{a,b}$														
	M_2				1^{b}																	
	M_3										1^{b}					1						
	$M4$																	1				
	M_5																				$1^{a,b}$	

a=Part movement between cells b=Worker movement between cells

5.2. Tuning algorithm parameters

To calibrate the NSGA-II and achieving the best performance, its parameters are tuned using a well-known DOE approach, called Taguchi [32]. By adapting relevant literature such as [23, 25] the values of the parameters at various levels for NSGA-II are presented in Table 9. Since the proposed model has two objective functions, MCOV is used as the response of the Taguchi method and shown in equation (48). Since the minimum amount of MCOV is the best value, so "Smaller-the-better" is used for the Taguchi method in Minitab software with the following formula ($F = -10Log10\ [\Sigma Y^2/n]$):

$$MCOV = \frac{MID}{MS}. \tag{48}$$

Table 9. The parameters values for various levels for NSGA-II

Parameters	Levels			Tuned level
	1	2	3	
No. of population (*Npop*)	50	100	200	100
Number of generations (*Maxgen*)	50	100	150	50
Mutation rate (*Pm*)	0.4	0.5	0.6	0.5
Crossover rate (*Pc*)	0.5	0.7	0.9	0.7

After performing the Taguchi method in Minitab software, the orthogonal array L^9 for tuning the NSGA-II is given in Table 10. After running the NSGA-II for these 9 experiments for the first example, the values of MCOV were obtained as reported in the last column of Table 10. It should be noted that each experiment is performed 30 times and the average of the results is considered as an MCOV for each experiment.

Table 10. The orthogonal array L9 for tuning the NSGA-II by Taguchi method

Experiment	Parameters				MCOV
	Npop	*Maxgen*	*Pm*	*Pc*	
1	50	50	0.4	0.5	0.29015
2	50	100	0.5	0.7	0.28704
3	50	150	0.6	0.9	0.29957
4	100	50	0.5	0.9	0.28206
5	100	100	0.6	0.5	0.30479
6	100	150	0.4	0.7	0.28490
7	200	50	0.6	0.7	0.29088
8	200	100	0.4	0.9	0.29751
9	200	150	0.5	0.5	0.30114

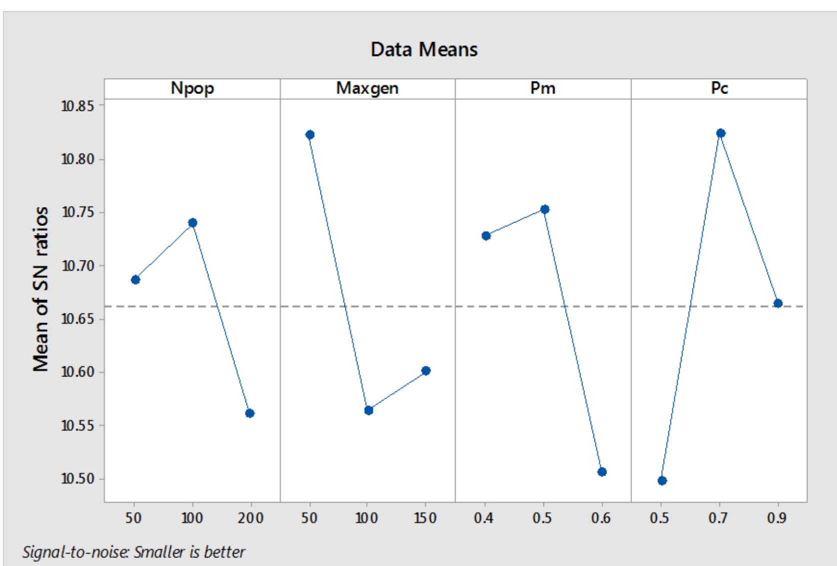

Figure 10. The signal-to-noise plot for an orthogonal array of Table 10

Finally, the signal-to-noise plot is illustrated in Figure 10 and based on this plot, the best or tuned values of parameters are selected. These selected values are also reported in the last column of Table 9. These tuned values are applied for running NSGA-II for all examples in various dimensions.

5.3. Solving the problems and comparing the performance of NSGA-II

Five randomly generated problems are created and solved. The first problem is the comprehensive example presented in sub-section 6.1. These five problems are solved using both augmented ε-constraint and NSGA-II. Table 11 summarizes the results of the augmented ε-constraint method. The values P, OP, M, W, and C, respectively, show the number of parts, operations of parts, machines, workers and cells. Two comparison criteria, which are the mean ideal distance (MID) and the maximum spread of the non-dominated solutions (MS) [33,34], along with computational time for the Pareto points of each example are also shown in Table 11. According to the obtained results, the NSGA-II algorithm for small size problems leads to efficient fronts in a way that they converge to Pareto- optimal front for the first three examples. Percentage differences between the results of the two algorithms are calculated by equation (49) and are reported in the last column of Table 11. By relying on the convergence of these three examples by the NSGA-II algorithm and the Pareto-optimal solutions, we trust the solutions of examples 4 and 5 by the NSGA-II algorithm. The summary of the obtained results is reported in Table 11, with GAP calculated as follows:

$$GAP = \frac{NSGAII(MID/MS) - AUGMECON(MID/MS)}{AUGMECON(MID/MS)} \times 100. \quad (49)$$

6. Conclusion

We considered the level of technology of machines, skills of workers and level of importance of parts. We proposed two disparate criteria of cost minimization of inter-cellular movement of parts and workers and the balance of the qualitative level of cells concerning existing relations among parts, workers, and machines in cells. The MODM and meta-heuristic approaches were utilized to solve the bi-objective model. Augmented ε-constraint presented the Pareto-optimal front requiring a long running time, while NSGA-II results in the Pareto-optimal front in a very short time. According to the available studies in the literature, the following subjects can be useful for future work:

- Use of the non-binary concept of mutual interest between workers concerning three levels of interested, not interested and indifferent or even in the form of fuzzy relations.
- Considering the intracellular movements of parts and workers and their significant impact on the cost of intercellular movements and backward movements.
- Considering the problem to be dynamic, i.e., multi-period.
- Parameters such as demand of parts or processing time of parts can be considered as fuzzy/stochastic numbers to make the problem more realistic.
- Use of other multi-objective evolutionary optimization algorithms such as the MOSA algorithm, MOPSO algorithm and comparing the performance of those algorithms with that of NSGA-II.

Table 11. Performance of the proposed NSGA-II algorithms compared to AUGMECON

No.	P (op)	M	W	C	Constraints	Decision variable	Ɛ-constraint			NSGA-II			GAP	
							CPU (sec)	MID	MS	CPU (sec)	MID	MS	MID	MS
1	4 (2)	5	3	3	179	228	411	4570.3	16203.1	300	4570.3	16203.1	0	0
2	5 (2)	3	3	2	298	447	506	1696.1	4094.7	400	1696.1	4094.7	0	0
3	10 (2)	7	6	3	1132	2655	1320	996.9	1650.6	489	1026.67	1719.1	2.9	4.1
4	25 (14)	17	12	5	42301	179056	N/A	N/A	N/A	569	80100	48521	N/A	N/A
5	50 (20)	25	17	6	224307	1101332	N/A	N/A	N/A	703	440032	39622	N/A	N/A

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