*Journal of Quality Engineering and Production Optimization*

*Vol. 4, No. 2, Summer & Autumn 2019*

*http://jqepo.shahed.ac.ir*

DOI: 10.22070/JQEPO.2020.3433.1071

# Analysis of Response Robustness for a Multi-Objective Mathematical Model of Dynamic Cellular Manufacturing

**Reza Ehtesham Rasi [1*], Akram Ali Kazemi [1]**

[1] *Department of Industrial Management, Qazvin Branch, Islamic Azad University, Qazvin, Iran*

**** Corresponding Author:** Reza Ehtesham Rasi (Email: ehteshamrasi@qiau.ac.ir)*

***Abstract*** *– The multi-objective optimization problem is the main purpose of generating an optimal set of targets known as Pareto optimal frontier to be provided the ultimate decision-makers. The final selection of point of Pareto frontier is usually made only based on the goals presented in the mathematical model to implement the considered system by the decision-makers. In this paper, a mathematical model is presented and analyzed to design manufacturing cells by considering two non-contiguous objectives and switch among cellular pieces. Cooperation among workers in a cell can have a significant effect on the operation completion time. Therefore, one of the important points of using the cellular manufacturing system is to control all system pieces during the manufacturing process. It implies that the number of labors, sorts of apparatus, and parts given to a cell must be at administrative level. It means that the number of workers, types of machinery, and parts devoted to a cell must be at managerial level. To analyze and evaluate the robustness of the manufactured solutions, Monte Carlo simulation as robustness analysis technique has been used. Finally, the result of solving and analyzing the problem is presented in the frame of the case study of Emersun Company.*

***Keywords****- Pareto frontier, Robustness, Cellular manufacturing, Mathematical model.*

## I. INTRODUCTION

In the early 1970s, a robust approach was proposed for solving the optimization problem since of the fast item changes and decreasing the life cycle. This issue leads to reorganizing cellular fabricating during planning horizons. On the other hand, in most cell arrangement strategies, the choice influences the reconfiguration of cells and definition of the part families' fair for single – period which might not be ideal in another period. In this manner, this reason persuades researchers and producers to study cellular manufacturing systems (CMS) under the dynamic condition that is named as dynamic cellular manufacturing system (DCMS) (Niakan et al., 2016). The structured management system leads to reduce significantly the time of manufacturing and system costs. The system should determine relations such as cooperation among workers, and the relation of workers with machinery based on expertise. Cooperation among workers in a cell can have a great effect on the time of operation completion. Therefore, one of the important points of using a cellular manufacturing system is to control all system pieces during the manufacturing process. The basis of the group manufacturing system is the division of the manufacturing facilities into several groups

*Manuscript Received:21-Aug-2019 & Revised: 28-Oct-2019 & Accepted: 23-Nov-2019*
*ISSN: 2423-3781*

of cell machinery each of which manufactures a piece of the family. Cell manufacturing is an approach aimed at increasing the manufacturing and flexibility of the system to meet industry need through utilizing the similarity of pieces. The advantages of implementing a cellular manufacturing system is to including reducing preparation time of pieces, costs and material transportation time, improving manufacturing programming, reduction of Work-In-Process (WIP), flow time and space utilization (Singh, 1993). Despite all the advantages of this system, the allocation of manufactured machinery to cells causes a workload imbalance on machinery in the manufacturing system. Jensen et al. (1996) and Adenso et al. (2001) offered to use alternative manufacturing pathways as an effective solution to solve this problem. Some disadvantages of CMS are also low flexibility toward rapid change of combining product and demand (Ang and Yale, 1984; Satog and Suresh, 2009).

In this paper, a bi-objective mathematical model is presented to create an appropriate manufacturing system focusing on the appropriate allocation of workers and machinery to cells and finally allocating pieces to cells. The concept of robustness in mathematical programming brings the consideration of the logical community to this viewpoint, and it is a rule known as robust optimization. In this paper, a concept is presented as non-contiguous. Non-contiguous is the concept which deals with the type of machines required to process pieces in a cell the same as the concept of heterogeneity of operations. The main objective of the research is to minimize the total non-contiguous of cells. If all types of machines are allocated to one cell, the non-contiguous will be maximized and when only one device is allocated to each cell, it will be minimized. Hence, minimizing cellular motion is also considered as the second objective in this model. In this study, the cell design approach is examined with two objectives, minimizing cellular motion and non-contiguous, that are opposite to each other. This paper studies the concept of robustness in multi-objective programming and examines the robustness of optimal responses of Pareto manufactured for the cell manufacturing model. In this type of problem, the objective is to present a set of optimal responses of Pareto. This paper is structured as follows: In the second part, the literature on the subject of this research is examined. In the third section, the Mathematical model of research is introduced i.e. parameters, objective functions and related restrictions also will be explained in this section. In section 4, a case study of Emersun Company is presented. The managerial insights have been explained and the conclusions and suggestions for future work are expressed in section 5.

## II. RELEVANT LITERATURE

The issues of CMS plan are combinatorial optimization and mathematical programming approach which gives superior arrangements in comparison with other methods. Kusiak and Chow (1978) developed P-Median model for cellular manufacturing system design in which the objective is to minimize the sum of the distance between each product/machine pair. Yasuda et al. (2005) developed a multi-objective model to design CMS which can present different solutions. Raflei and Ghodsi (2008) considered a dynamic cell formation problem as a multi-objective problem solved by the combinatorial optimization algorithm of ants and genetic. Sharda and Banerjee (2013) evaluated the configuration of considered machine cells in future programming periods by considering uncertainty in process time, equipment failure and product demand. The configuration design obtained at the end of the programming period reduces the total cost and leads to robust configuration that aims to minimize the manufacturing time and average work inflow and the number of machines. Kamal and Pardeep (2015) presented a comprehensive mathematical model to design robust machine cells in manufacturing dynamic segments. The presented model includes the problem of designing configuration cells for the device connected to the problems of machinery allocation, dynamic manufacturing and routing. Allahyari and Azzab (2015) developed a new continuous formula for job-shop manufacturing with horizontal and vertical corridors. Bulent et al. (2015) proposed a scientific programming approach to plan a layered cellular framework in an environment with non-deterministic demand. Luan et al. (2015) provided an integrated mathematical model for DCMS under multi-period planning horizons with distinctive demands. Hao et al. (2017) presented simulation results of an integrated mixed-integer programming model, including sensitivity analysis for numerical illustration. The comprehensive model includes cell arrangement, inter and intracellular materials handling, stock and backorder holding, administrative task (including asset alteration) and flexible production routing. The mentioned model considers multi-production planning with flexible resources (machines and operators) where each period has diverse demands. The results verify the validity and sensitivity of the proposed model using GA. Azadeh et al. (2017) presented multi-objective dynamic cellular manufacturing system (MDCMS) which considers human elements. Human elements are consolidated into the proposed demonstration in terms of human reliability and decision-making processes. According to Bortolini et al. (2019), mixed-model flexible manufacturing systems (FMSs) and, more as of late, reconfigurable manufacturing systems (RMSs) are broadly considered as diffuse arrangements for complex production environments, focusing on variable markets and profoundly dynamic production plans. Their plan and administration are challenging both in modern plants and for plant-redesign activities. This paper progresses the current literature showing and applying an ideal linear programming cost. Chu et al. (2019) presented a new model of cross-training with learning and overlooking impacts pointing at addressing the issue of labor task traversing numerous cells. Zhang et al. (2020) developed an efficient multiscale topology to optimize method for minimizing the recurrence reaction of cellular composites over recurrence interim, which comprises of spatially-varying connectable evaluated miniaturized scale structures.

Mulvey et al. (1995) described a robust solution, which measures robust optimization solutions of Pareto by having uncertainty resources and an accurate definition of weights. To do this, an integrated method is designed, which can be used in discrete multi-objective issues employing a combination of Mont Carlo simulation and optimization. Lahdelma et al. (1998) studied the stochastic multi-objective acceptability analysis method (SMAA) in arrange to go up against instability in multi-criteria problems with discrete options. SMAA can be considered as a robustness analysis within the multi-criteria decision-making method. It is assumed that the decision-maker has a set of weights for objective functions. Despite various studies in the past two decades, the objective of mathematical programming problems is to apply the robustness concept in multi-objective programming problems that have not been ever examined widely. Liesio et al. (2007 & 2008) focused on the robustness of venture choice utilizing mathematical programming. Wang and Zionts (2006) analyzed the robustness of the Aspiration-level Interactive Method (AIM). The robustness concept in multi-objective optimization was proposed by Figueira et al. (2008). In the recent study, Roy (2010) proposed the multi-dimensional robustness issue in the overall framework of an operational project. Some recent works also deal with multi-objective robustness and optimization such as Zhen and Chung (2012), in which robustness was examined as the second objective function in wharf allocation problem by the innovative solving method. Vitayasak et al. (2019) presented a robust machine layout plan apparatus that minimizes the fabric stream removal employing a Genetic Algorithm (GA), taking into account demand instability and machine maintenance. Tests were conducted utilizing eleven benchmark datasets that considered three scenarios: preventive maintenance (PM), corrective maintenance (CM) and both PM and CM. The results were analyzed measurably. The impact of a few maintenance scenarios including the ratio of the number of machines with period-based PM (PPM) to the number with production quantity-based PM (QPM), the rate of machines with CM (%CM), and a combination of PMM/QPM ratios and %CM on fabric stream separate were examined. Shen et al. (2019) considered the large-scale industries; optimization of multi-type vitality frameworks to minimize the entire vitality cost is of incredible significance and has received around worldwide consideration. In genuine mechanical plants, deterministic optimization may experience challenges since different vulnerabilities. Danilovic and Ilic (2019) proposed a new hybrid heuristic for cell arrangement problem. The objective of the work was to design the algorithm for the cell arrangement issue that is more effective at that point and the best-known algorithms for the same issue. The procedure of the new approach was to utilize the specificities of the input occasions to limit down the attainable set, and hence increment the productivity of the optimization process. Sadeghi et al. (2020) examined the integration of design and control stages in a three-echelon supply chain framework of a blood sugar strip producer. The primary step is fabricating framework plan based on layered Cellular Manufacturing System (CMS) for which a mixed-integer linear programming approach is proposed in order to minimize the required number of cells. The novelty of the proposed model is in incorporating shifts into layered CMS plan. In the second step of the plan stage stock parameters in numerous levels of the supply chain are assessed based on the continuous review, fixed order quantity (Q, r) model. Control stage is activated by discharging client order for numerous sorts of products and incorporates replenishments within the three echelons of the supply chain and planning in the layered CMS. Jeong and Lee (2020) presented a robust optimization model to secure flexibility under the high infiltration of renewable vitality frameworks in future lattice. An increment in renewable vitality into a control framework causes troubles and complexities with regard to control framework planning and operation owing to an increment in vulnerability. Ning and You (2020) presented a novel transformation-proximal bundle algorithm for multistage versatile robust optimization problems. By dividing recourse response choices into state and control choices, the proposed algorithm applies relative control approach as it were to state decisions and permits control decisions to be completely versatile, hence changing the first problem into a comparable two-stage versatile robust optimization (ARO) problem.

This paper studies the robustness concept in multi-objective programming and evaluates the robustness of Pareto optimal responses manufactured for the cellular manufacturing model. In such problems, the objective is to present a set of Pareto optimal response. Mixed multi-objective programming should be examined by two angles: optimization and decision-making back, so as in addition to identifying optimal responses, provides a view point for decision-makers to select the optimal model. In this study, researchers seek to look at the robustness of Pareto optimal solution (selection or more preference) and do not examine the total robustness of Pareto set. In addition, the first objective function of this paper minimizes the non-contiguous of cells and the second objective function minimizes the number of motions among cells in comparison last recent articles with considering constraints resources. This section is based on analyzing CMS problem and changing it to a multi-objective integer programming. Depicting the implementation method and then presenting a suitable index to measure the robustness of Pareto optimal solutions are as follows.

## III. PROBLEM STATEMENT AND MATHEMATICAL FORMULATION

In this part, the proposed model is considered. After that, uncertain angles of the problem are portrayed, and related mathematical programming model is defined.

### *A. Nomenclature*

In this section, indices, parameters and decision variables connected within the proposed mathematical model are displayed. The specified indices are illustrated in Table (1) and basic parameters and decision variables of the model are presented in Table (2) and Table (3).

**Table I. Indices in the mathematical model**

| ***Explanations*** | ***Symbols*** |
|---|---|
| Machines set; $m$=1,2,…8 | $m$ |
| Cells set ; $c$=1,2,3 | $c$ |
| Pieces set; $p$=1,2,…,20 | $p$ |
| Workers set; $w$=1,2,…,12 | $w$ |

**Table II. Parameters applied in the mathematical model**

| **Explanations** | **Symbols** |
|---|---|
| Is equal 1 if the piece $p$ is allocated to machine $m$ | $\boldsymbol{V_{mp}}$ |
| Is equal 1 if the labor $w$ is allocated to machine $m$ | $W_{wm}$ |
| Is equal 1 if worker $w$ is interested in cooperating with worker $w'$ | $LW_{ww'}$ |

**Table III. Decision variables applied in the mathematical model**

| Explanations | Symbols |
|---|---|
| Is equal 1 if machine *m* is allocated to cell *c* | $x_{mc}$ |
| Is equal 1 if piece *p* is allocated to cell *c* | $s_{pc}$ |
| Is equal 1 if labor *w* is allocated to cell *c* | $y_{wc}$ |

The formulation of bi-objective programming model for designing CMS problem is as following:

$$Min\ Z1 = \sum_{p}\left(\sum_{c} S_{pc} \sum_{m} x_{mc}\,(1 - V_{mp})\right) \quad (1)$$

$$Min\ Z2 = \sum_{p}\left(\sum_{c} S_{pc} - 1\right) \quad (2)$$

$s.t$

$$\sum_{c} x_{mc} = 1; \forall\, m \quad (3)$$

$$\sum_{m} x_{mc}\, V_{mp} \leq M\, S_{pc}; \forall\, p\,, c \quad (4)$$

$$\sum_{c} y_{wc} = 1; \forall\, w \quad (5)$$

$$x_{mc} \leq \sum_{w} y_{wc}\, W_{wm}\ ; \forall\, m\,, c \quad (6)$$

$$y_{wc} + y_{w'c} - 1 \leq \left(\sum_{r} y_{rc}\, LW_{rw}\right) + M\, lW_{ww'}; \forall w \neq w', c \quad (7)$$

$$y_{wc} + y_{w'c} - 1 \leq \left(\sum_{r} y_{rc}\, LW_{rw}\right) + M\, lW_{ww'}; \forall w \neq w', c \quad (8)$$

$$lW_{ww'} + y_{wc} + y_{w'c} - 2 \leq \left(\sum_{r} y_{rc}\, LW_{rw}\right); \forall w \neq w', c \quad (9)$$

$$lW_{ww'} + y_{wc} + y_{w'c} - 2 \leq \left(\sum_{r} y_{rc}\, LW_{rw}\right); \forall w \neq w', c \quad (10)$$

$$x_{mc}\,, S_{pc}\ \in\ \{0,1\}; \quad (11)$$

The first objective function minimizes the non-contiguous of cells and the second objective function minimizes the number of motions among cells. Constraint (2) expresses the unique allocation of each machine to a cell. Constraint (3) calculates the allocation of pieces to cells. Constraint (4) allocates uniquely the workers to cells and constraint (5) allocates workers to cells. Constraints (6 - 9) also assign workers interested in cooperating together. In fact, if two workers are interested in cooperating together, the model decides about whether or not their cooperation according to allocate machines used by them to cells and also the allocation of workers to cells.

### *B. Solving Mathematical Model*

Pareto optimal solution (POS) as the uppermost solution is used by multi-objective programming. This solution is considered as (POS*). The objective of the presented method is to assess the robustness of the Pareto set obtained in the CMS problem, while we face uncertainty in parameter values. The variation range in model parameters is expressed by small value $\alpha$, which shows the percentage of variation of each parameter. $\alpha$ is determined by decision-makers and its main value known as reference weight is shown by symbol $w^*p$ ($p$ is an index of the objective function). The variations are defined by neighborhood parameters of $\alpha$, which are in fact a percentage of initial weight. For example, an average neighborhood 10% corresponding weights $wp^*$ can be in the interval. In order to better evaluation of $\alpha$ values, we use them in cells and also allocate workers to cells, the model decides about whether or not their cooperation.

The decision-makers divide these weights variations using the number of points called $G$ (usually $G$ is a set between 5 to 10). Whatever the number of $G$ network points are more, the accuracy in robustness evaluation and also the time of calculations are increased. By starting from the reference weight $wp^*$, neighborhood weight gradually expand. If the point $G$ is in-network, the entire processes end after $G$ steps. When we are in the $G$-the point of the network, the weight variations are calculated as follows:

$$\left[W_p^* \times \left(1 - \frac{g}{G} \times a\right), W_p^* \times \left(1 + \frac{g}{G} \times a\right)\right] \tag{12}$$

$wp^*$ is the reference weight for objective function $p$ and $\alpha$ is the neighborhood parameter as a percentage of reference weight identifying the neighborhood borders of weight. At first, CMS model is solved by GAMS software and Pareto related responses are extracted, the Pareto manufactured front is shown in figure (1).

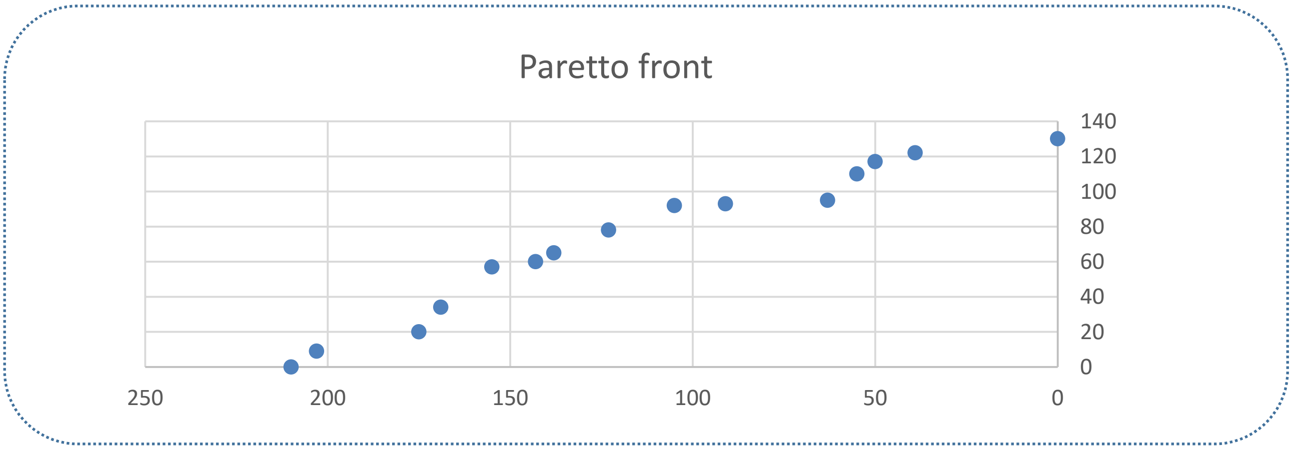



Figure 1. Pareto front points

### *C. Robustness Evaluation*

For each point of network $G$, Monte Carlo simulation is applied by using uniform distribution to manufacture weights of corresponding distances. Then, uniform vector is made by normalized weights distribution; the weights are examined versus their borders. The results of optimization (i.e. objective function and decision-making variables values) are saved and we continue to repeat Monte Carlo simulation. We finish *N* repetitions of Monte Carlo and obtain a set of *N* Pareto optimal solutions known as *sg*. Thereafter, the members of *sg* set are made which are the Pareto optimal responses of reference weight related to *wp**. In other words, frequency of each response is calculated. The frequency shows the uppermost solution robustness due to small perturbation in its weight. In fact, when we move to next points of network, the weight distance of random sampling is developing. Therefore, we expect that POS* decreases as we move towards wider distances. In order to measure the robustness degree due to decrease, we introduce an index known as robustness index (*RI*) which is introduced as follows: POS* frequency is calculated from solutions obtained from Monte Carlo simulation for *g* points of network. We plot the frequency diagram, which is the coordinates of each $\lambda g$ point and frequency POS* is in set of sg solutions and the sampling distance *wp**. This function is definitely a descending function and called robustness diagram. Robustness index can be calculated by robustness diagram as a criterion for measuring special POS robustness. Robustness index is obtained from the area under robustness curve made by $\lambda g$ points divided by total robustness area. So as the frequency is 100% for all intervals. The formula of calculating robustness index is as follows:

$$\mathrm{RI} = \frac{\frac{1}{2} + \sum_{g=1}^{G} \lambda_g + \frac{\lambda_G}{2}}{G} \tag{13}$$

The robustness index can be obtained from functional integral introducing POS* frequency related to the width of sample distance x ($x \leq a$) divided the maximum robustness($a \times 100\%$). In other words, the function *fq(x)* introduces POS* frequency of function *x*, its integral limits are 0 to *a* and is defined as follows in order to present robustness index of POS*:

$$RI = \frac{\int_0^a \mathrm{fq(x)dx}}{a} \tag{14}$$

### D. Robustness and Decision-Making Support

Pareto frontier robustness information is essential for decision-makers. As mentioned earlier, combinational multi-objective optimization has two important aspects: optimization and decision-making support. Decision-makers consider candidate solutions such as POS and choose based on more preference. The robustness of POS provides additional information to the decision-makers and shows good performance. When robustness is neglected, decision-makers may find sensitivity about small changes in initial assumptions. *RI* is the robustness index used to compare different POS*s on their robustness for a small change on parameter weights. Whatever *RI* increases, robustness corresponding to POS* increases. It is important to note that calculations are non-sensitive to the number of objective functions. It can indicate that we deal with the numerical property of objective functions, which leads to the solution for single-objective problems.

### E. Implementation of Algorithm

Today, new and efficient optimization algorithms with increasing calculation power help us to solve accurately (by identifying all POSs) more complex problems. We have 2 or 3 objectives to visualize the robustness of the Pareto frontier. Optimization is simulated at a proper time in order to obtain results of Monte Carlo simulation. For example, if the CMS problem related to the reference problem is solved in 7 seconds, it needs 33 hours for 1000 repetitions in 10 different intervals. If the number of objective functions and decision-making variables increases, the conclusion is difficult versus the robustness of the Pareto frontier. Since a large number of POSs made during the Monte Carlo simulation process and robustness index of POS converge to zero, it is difficult and may be impossible to use the presented method in major problems. The pseudo-code of the defined algorithm is as follows:

### *Algorithm*

1: start

2: define parameter *a*

3: Define the number of sub-interval

4: Initialize objectives weight parameter in considered interval.

5: solve the problem and save response in a set related to considered subinterval

6: repeat step 5 several specified times for Monte Carlo simulation

7: calculate the variable $\lambda_g$

8: add one unit to interval value and go to step 5

9: plot robustness diagram for responses

10: calculate robustness of responses

## IV. CASE STUDY OF EMERSUN COMPANY

This section, the case study of Emersun Company is presented in accordance with the real-world conditions in order to validate and ensure the accuracy of the presented model. Emersun Company has 8 production machines and 12 workers. This factory manufactures 20 different pieces. With regard to surveys conducted by workers in the system, Workers' desire for teamwork is determined. As previously mentioned, at first step the CMS model is solved by GAMS and Pareto related responses are extracted. This example is solved on one system (with RAM: 4GB, processor Core *i7* and processor power 3.2 GHz). The time required to accurately solve a problem once is about 7 seconds. With regard to the algorithm structure described in the previous section, the implementation of the entire algorithm took more than 40 hours. Some parameters used to solve the problem are listed as follows:

**Table IV. Piece matrix - numerical example machine**

| | $p_1$ | $p_2$ | $p_3$ | $p_4$ | $p_5$ | $p_6$ | $p_7$ | $p_8$ | $p_9$ | $p_{10}$ | $p_{11}$ | $p_{12}$ | $p_{13}$ | $p_{14}$ | $p_{15}$ | $p_{16}$ | $p_{17}$ | $p_{18}$ | $p_{19}$ | $p_{20}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $m_1$ | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | **0** |
| $m_2$ | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | **0** |
| $m_3$ | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | **1** |
| $m_4$ | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | **1** |
| $m_5$ | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | **1** |
| $m_6$ | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | **1** |
| $m_7$ | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | **1** |
| $m_8$ | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | **0** |

**Table V. Workers interest in teamwork**

| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $P_6$ | $P_7$ | $P_8$ | $P_9$ | $P_{10}$ | $P_{11}$ | $P_{12}$ | $P_{13}$ | $P_{14}$ | $P_{15}$ | $P_{16}$ | $P_{17}$ | $P_{18}$ | $P_{19}$ | $P_{20}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $W_1$ | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 |
| $W_2$ | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 1 |
| $W_3$ | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 |
| $W_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| $W_5$ | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 0 |
| $W_6$ | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |
| $W_7$ | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| $W_8$ | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 0 |
| $W_9$ | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 |
| $W_{10}$ | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 |
| $W_{11}$ | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 |
| $W_{12}$ | 1 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 |

**Table VI. Labor matrix - numerical example machine**

| | $W_1$ | $W_2$ | $W_3$ | $W_4$ | $W_5$ | $W_6$ | $W_7$ | $W_8$ | $W_9$ | $W_{10}$ | $W_{11}$ | $W_{12}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $W_1$ | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| $W_2$ | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| $W_3$ | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 |
| $W_4$ | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 1 |
| $W_5$ | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 0 |
| $W_6$ | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 1 |
| $W_7$ | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 |
| $W_8$ | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 |
| $W_9$ | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 |
| $W_{10}$ | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 |
| $W_{11}$ | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 |
| $W_{12}$ | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 |

It can be observed that the above matrix can be also presented in the form of asymmetric. In fact, the worker desires to cooperate together has an asymmetric structure and is completely one-sided. After solving the problem by CPLEX optimization software, the results are as follows. Now, it is worth noting that the results of the one-time implementation are examined in order to assess the accuracy of model performance. The overall structure of the system is shown in figure (2).

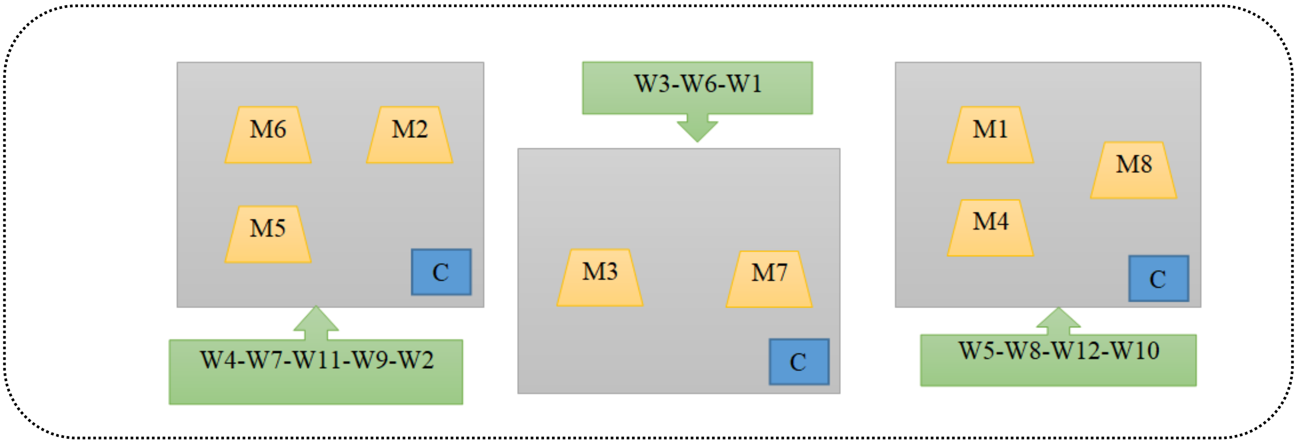



**Figure 2. Overall system structure**

There are more machines and also more workers in cells 1 & 3. This allocation obtains accomplishments of solving model and parameters of machine-pieced allocation based on workers' ability and tendency to cooperate together according to the following method. To allocate pieces to machines, the allocation of piece-machine can be obtained due to the responses obtained from solving models and parameters in accordance with the following method.

### *A. Piece- machine allocation method*

A piece may be transferred to several cells and does not allocate its mathematical model to all cells. Identifying a piece by its allocated family is necessary to program manufacturing design and control. In this study, pieces are allocated to machines after appropriate allocating machines to cells. Since the pieces allocation method does not affect the objective function value, so for this allocation, an algorithm is used according to the following steps. The quality of obtained responses is also calculated by efficient grouping, which its calculation method is described in the following. But the innovative algorithm steps for allocating pieces are as follows:

1. A piece is allocated to one cell, in which the most desired operations for a piece are conducted;

2. If there is an obstacle for this allocation, it is allocated to one cell that has the lowest non-contiguous;

3. If there is still an obstacle for allocation, it is allocated to one cell following steps 1 and 2.

### *B. Calculation of responses quality*

After allocating pieces to machines, we can calculate the manufacturing response quality to compare two similar responses or compare two or more special responses. The following formula is designed for quality calculation.

$$GE = \frac{(m-e)}{(m+v)} \tag{15}$$

In which, $m$ is the total number of 1 in piece- input machine matrix.

$e$ is the number of 1 in blocks (or active cells)

$v$ is the number of zero in blocks

The manufactured number is between 0 and 1 and whatever this number is closer to 1, the quality of manufactured response is more. Allocating pieces to machines is shown in table (7).

**Table VII. Final allocation of the piece – machines**

| | $p_1$ | $p_2$ | $p_3$ | $p_4$ | $p_5$ | $p_6$ | $p_7$ | $p_8$ | $p_9$ | $p_{10}$ | $p_{11}$ | $p_{12}$ | $p_{13}$ | $p_{14}$ | $p_{15}$ | $p_{16}$ | $p_{17}$ | $p_{18}$ | $p_{19}$ | $p_{20}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $m_1$ | **1** | **1** | **1** | **1** | **1** | **1** | **1** | **1** | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | **0** |
| $m_2$ | **1** | **1** | **1** | **1** | **1** | **1** | **1** | **1** | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | **0** |
| $m_3$ | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | **1** | **1** | **1** | **1** | 0 | 0 | 0 | **0** |
| $m_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | **1** | **1** | **1** | **1** | 0 | 0 | 0 | **0** |
| $m_5$ | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | **1** | **1** | **1** | 1 | 0 | 0 | 0 | 0 | 1 | 0 | **0** |
| $m_6$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | **1** | **1** | **1** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | **1** |
| $m_7$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | **1** | **1** | **1** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | **0** |
| $m_8$ | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | **1** | **1** | **1** | 1 |

The efficiency of allocations, according to the mentioned method is ***0.72***. After solving the problem by CPLEX software, which is one of the most powerful tools solving mixed-integer problems, the responses are extracted, and finally, the Pareto frontier is manufactured by one of the response points and the results are completely analyzed above. Then, the robustness of each point is calculated according to defined pseudo-code in solving the method section. The considered problem is solved for 20 different values. The number of sub-intervals for the problem is considered 11, and the number of Monte Carlo simulations for each sub-interval is 200. The results of calculating $\lambda g$ are shown in table (8).

**Table VIII. Repeat the initial answer in each interval by Monte Carlo simulation**

| ***P20*** | ***P19*** | ***P18*** | ***P17*** | ***P16*** | ***P15*** | ***P14*** | ***P13*** | ***P12*** | ***P11*** | ***P10*** | ***P9*** | ***P8*** | ***P7*** | ***P6*** | ***P5*** | ***P4*** | ***P3*** | ***P2*** | ***P1*** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| 56 | 56 | 55 | 43 | 60 | 44 | 52 | 52 | 44 | 44 | 40 | 60 | 55 | 60 | 42 | 53 | 43 | 40 | 40 | 41 |
| 17 | 27 | 28 | 24 | 25 | 25 | 27 | 30 | 16 | 15 | 16 | 18 | 26 | 26 | 23 | 30 | 29 | 17 | 27 | 28 |
| 19 | 21 | 17 | 22 | 18 | 17 | 24 | 14 | 16 | 21 | 14 | 19 | 15 | 20 | 25 | 15 | 22 | 15 | 22 | 18 |
| 15 | 10 | 13 | 9 | 15 | 9 | 9 | 14 | 15 | 11 | 15 | 10 | 11 | 14 | 11 | 12 | 10 | 12 | 9 | 14 |
| 12 | 7 | 7 | 6 | 12 | 7 | 11 | 7 | 9 | 9 | 12 | 11 | 10 | 12 | 9 | 11 | 11 | 11 | 7 | 6 |
| 6 | 7 | 8 | 5 | 6 | 10 | 5 | 6 | 7 | 9 | 8 | 10 | 10 | 7 | 9 | 7 | 10 | 5 | 9 | 6 |
| 5 | 9 | 7 | 5 | 7 | 7 | 7 | 6 | 7 | 5 | 8 | 8 | 9 | 5 | 6 | 5 | 8 | 9 | 9 | 6 |
| 8 | 5 | 8 | 8 | 6 | 7 | 5 | 5 | 5 | 6 | 4 | 7 | 6 | 6 | 4 | 7 | 8 | 8 | 6 | 7 |
| 7 | 7 | 5 | 7 | 7 | 4 | 4 | 4 | 4 | 6 | 5 | 3 | 6 | 3 | 5 | 3 | 6 | 3 | 4 | 3 |
| 4 | 2 | 4 | 4 | 3 | 2 | 5 | 4 | 5 | 2 | 5 | 3 | 3 | 4 | 4 | 3 | 4 | 2 | 4 | 4 |

Now, the robustness of each point is obtained according to the mentioned relations to calculate responses robustness and the necessary information about the most robust point to changes is provided for decision-makers. The diagram of responses robustness is shown in figure (3).

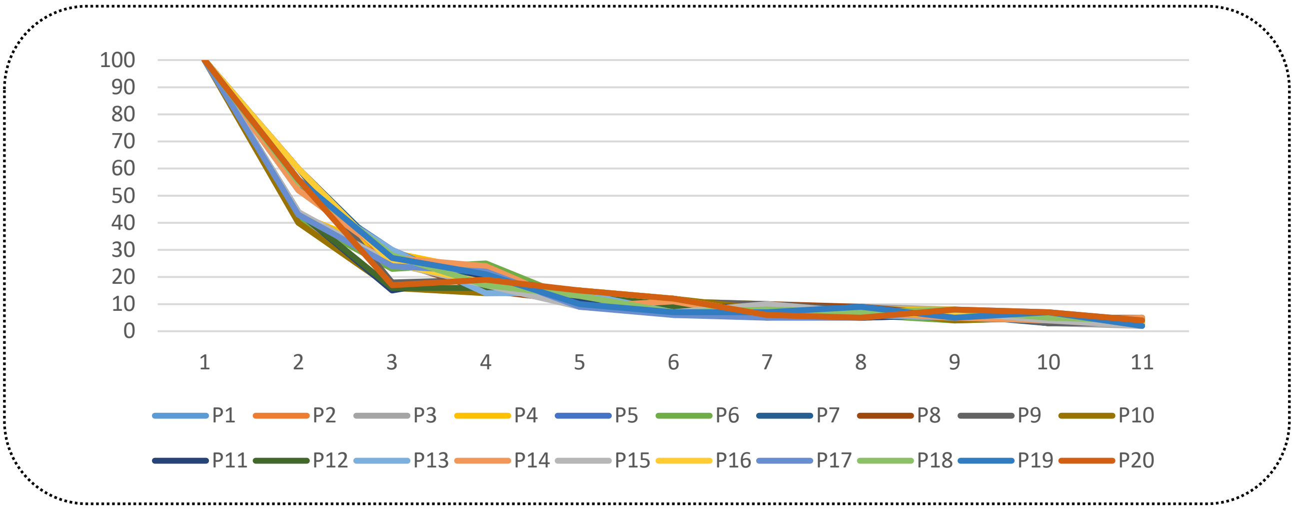



**Figure 3. Comparison of robustness of Pareto frontier points**

The area value under diagrams is more than others. This is consistent with the calculation of the defined method of more robust points and decision-makers are suggested to focus on these points and research more about other points. In an overview, we can observe all the diagrams in the following diagram and better compare it. In terms of dispersion of obtained responses during consecutive repetitions, it can be observed that in points near 0, in which the number of repetitions of accurate problem response is low, there is more density. This indicates that whatever the points are closer to the beginning and end of intervals, the probability of accurate problem response is less. This can be observed well in the diagrams. The responses robustness values are defined in the table (9). This value represents the ratio of area under the diagram to the entire area. If this value is closer to 1, the robustness of the point will be more.

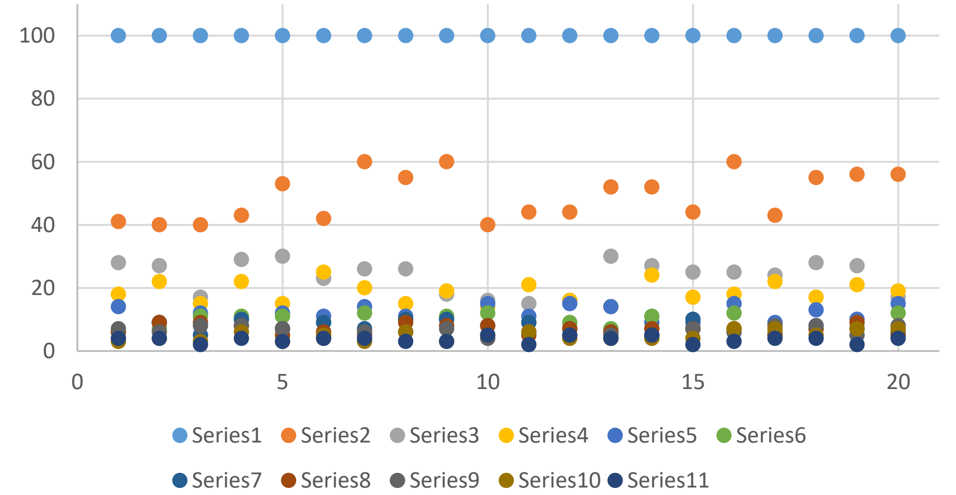
**Table IX. Stability of the received responses**

| | $p_1$ | $p_2$ | $p_3$ | $p_4$ | $p_5$ | $p_6$ | $p_7$ | $p_8$ | $p_9$ | $p_{10}$ | $p_{11}$ | $p_{12}$ | $p_{13}$ | $p_{14}$ | $p_{15}$ | $p_{16}$ | $p_{17}$ | $p_{18}$ | $p_{19}$ | $p_{20}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| RI | 0.5174 | 0.5602 | 0.4592 | 0.519 | 0.421 | 0.4981 | 0.4096 | **0.5928** | 0.5841 | 0.5066 | 0.5089 | 0.4807 | 0.5757 | 0.4571 | 0.5375 | 0.4845 | 0.4889 | 0.4396 | 0.5331 | **0/4057** |

It can be observed that the response ***p8*** has the most robustness, and the decision-maker is suggested to choose this point.

## V. MANAGERIAL INSIGHTS

This segment provides some insights, which managers have to be bear in intellect, whereas assessing the findings of the study. The proposed framework provides managers a robust scientific demonstration, which can be applied to any dynamic cellular manufacturing within the concept of robustness by applying little alterations. Since both deterministic and stochastic adaptations of the model are developed, directors are free to apply any of the two, whether having uncertain parameters or not. Clearly, based on the results, one can contend that this cellular fabrication is not beneficial under the current circumstances. In any case, we note that the dynamic cellular fabricating within the concept of robustness in Emersun Company is optimized (see Figure. 4). In this way, there is still space for cost improvement of the gotten reactions if more stability of the received responses enters into the cells and minimizes the non-contiguous of cells and the number of movements among cells. Another major issue influencing the benefit of the cells is the full development levels are compared in Emersun Company with regard to the formulated development scheme in table (IX). The results reveal that the model is able to move forward the advancement level dynamic cellular fabricating, and robustness can give more valuable managerial insights.



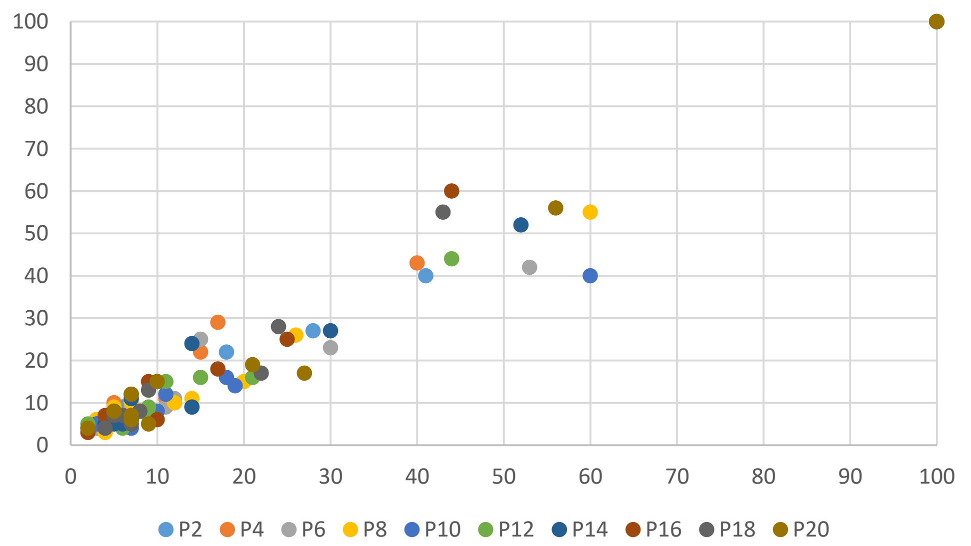




**Figure 4. Pareto optimization**

## VI. CONCLUSION AND FUTURE RESEARCH

Today, all great manufacturing centers benefit from cellular manufacturing systems; also in Emersun company group technology (GT) advantages are used simultaneously. More than one objective function is usually needed to design a system based on efficient cellular manufacturing by mathematical modeling. In fact, multi-objective problems are widely designed and used in this field. But for multi-objective problems, instead of an optimal point, a set of responses known as Pareto frontier are provided to decision-makers. Definitely, in order to use the model results in real-world problems only one point of Pareto frontier should be chosen to be implemented in the system. This choice is made by decision-makers and based on the objective of the mathematical model. In fact, the decision-maker chooses the final response only due to the model objectives. But in addition to these objectives, it is better to consider other criteria to choose the final response. One of the important criteria is the robustness of manufacturing responses against the changes of problem parameter. In this paper, Pareto responses are evaluated and analyzed after designing the bi-objective mathematical model in order to form a cellular manufacturing system by robustness analysis. In the presented model, the objectives are to minimize non-contiguous and intercellular displacements of pieces. These objectives, in addition to the appropriate allocation of machines to cells, cause the group technology feature efficient through the non-contiguous concept in the system. Also, with respect to the problem structure and input parameters, workers are allocated to cells in such a way that there is the most cooperation possibility among workers. Because of the high cooperation possibility among workers reduces the manufacturing time and costs. Finally, in order to evaluate Pareto frontier responses, a robust analysis technique is used based on Monte Carlo simulation by considering interval changes of non-contiguous value parameters against intercellular transitions. For validation of model, it is imperative that any mathematical model with expressed pressure-dependent compliance be approved through comparison with experimental data. The objective of the approval experiment is to be a physical realization of an initial-boundary esteem issue since an initial boundary is what the computational model was developed to solve it. In fact, the non-contiguous importance parameter is changed at a certain interval that these changes are divided into certain subintervals. For each subinterval, Monte Carlo simulation is performed, and the problem is solved. Finally, the response of robustness is calculated through relations defined in the problem definition section and is provided to the decision-makers. A case study is conducted to evaluate and examine model efficiency, and the results are presented.

Since algorithm implementation is time-consuming, it is practically impossible to use the algorithm for large-dimension problems, so as a suggestion for future researches; the robustness of the response can be analyzed by meta-heuristic algorithms and present an appropriate solution to ensure that responses are accurate. It is also suggested that other criteria should be presented to better choose the final response by decision-makers.

## REFERENCES

Ang, C. L., & Willey, P. C. T. (1984). A comparative study of the performance of pure and hybrid group technology manufacturing systems using computer simulation techniques. *International Journal of Production Research*, 22(2), 193–233.

Adenzo-Diaz B, Lozano S. (2008). A model for the design of dedicated manufacturing cells. *International Journal of Production Research*, 46(2):301–19.

Adenso-Diaz, B. Lozano, S. Racero, J.Guerrero, F. (2001).Machine cell formation in generalized group technology. *Computers and Industrial engineering*, 41(2), 227-240.

Allahyaria, Maral Zafar. Azabb, Ahmed. (2015).A Novel Bi-level Continuous Formulation for the Cellular Manufacturing *System Facility Layout Problem*, Procedia CIRP, 33, 87 – 92.

Azadeh,A.Ravanbakhsh,M.Rezaei Malek,M. Sheikhalishahi,M.Taheri Moghadam,A.(2017). Unique NSGA-II and MOPSO algorithms for improved dynamic cellular manufacturing systems considering human factors. *Applied Mathematical Modelling*, 48(3), 655-672.

Bertsimas, D., Sim, M. (2003).Robust discrete optimization and network flows. *Mathematical Programming (Series B)*, 98(3), 49–71.

Bertsimas, D. Sim, M. (2004). The price of robustness. *Operations Research*, 52(l),35–53.

Ben-Tal, A.Nemirovski,A.(1998).Robust convex optimization. *Mathematics of Operations Research*, 23(4), 769–805.

Ben-Tal, A. Nemirovski, A. (2000). Robust solutions of linear programming problems contaminated with uncertain data. *Mathematical Programming*, 88(3), 411–424.

Bortolini,Marco.Ferrari, Emilio, Gabriele Galizia,Francesco,Mora, Cristina, Pilati ,Francesco.(2019). Optimal redesign of Cellular Flexible and Reconfigurable Manufacturing Systems. *Procedia CIRP*, 81, 1435-1440.

Bulent Erenay, Gursel A. Suer, Jing Huang, Sripathi Maddisetty.(2015).Comparison of layered cellular manufacturing system design approaches. *Computers & Industrial Engineering*, 85(3), 346–358.

Chu,Xianghu. Gao,Du. Cheng,Shi.Wu,Lang. Chen, Jiansheng.Shi, Yuhui.Qin, Quande.(2019). Worker assignment with learning-forgetting effect in cellular manufacturing system using adaptive memetic differential search algorithm. *Computers & Industrial Engineering*,136(6),381-396.

Danilovic,Milos.Ilic, Oliver.(2019). A novel hybrid algorithm for manufacturing cell formation problem. *Expert Systems with Applications*,135(30),327-350.

Figueira, J. R., Greco, S., Mousseau, V., & Słowin´ ski, R. (2008).Interactive multi objective optimization using a set of additive value functions. *International Journal optimization LNCS*, 5252, 97–119.

Gokhan,Egilmeza. Bulent, Erenayb. Gürsel, A. Süer. (2014).Stochastic skill-based manpower allocation in a cellular manufacturing system. *Journal of Manufacturing Systems*, 33(4),578-588.

George, Mavrotas. Olena, Pechak. Eleftherios,Siskos. Haris,Doukas. John,Psarras.(2015).Robustness analysis in Multi-Objective Mathematical Programming using Monte Carlo simulation. *European Journal of Operational Research*, 240(1),193–201.

Hao, Chunfeng.Luan, Shichao. Kong,Lili.(2017). Simulation Analysis of an integrated model for Dynamic Cellular Manufacturing System. *AIP Conference Proceedings*, 1839,020162, https://doi.org/10.1063/1.4982527 Published Online.

Luan, Shichao, Jia Guozhul.(2015).An Model for Dynamic Cellular Manufacturing System Based on Multi-functional Machines and Multi-skilled Operators. *Industrial Engineering Journal*, 18 (4),112- 118.

Jensen, J.B. Malhotra, M.K. Philipoom, P.R. (1996).Machine dedication and process flexibility in a group technology environment. *Journal of Operations Management*, 14(3),19-39.

Jeong, Jinwoo.Lee,Byongjun.(2020). A framework for estimating flexible resources according to future Korean renewables scenario: Robust optimization approach considering multiple uncertainties. *International Journal of Electrical Power & Energy Systems*,118, Article in press.

Jeon G, Leep HR.(2006).Forming part families by using genetic algorithm and designing machine cells under demand change. *Computers & Operations Research*,33(3),263–283.

Kusiak, Chow W.(1987). Efficient solving of the group technology problem. *Journal Manufacturing System*, 6(2): 117–124.

Kamal Deepa, Pardeep K.(2015).Design of robust cellular manufacturing system for dynamic part population considering multiple processing routes using genetic algorithm. *Journal of Manufacturing Systems,* 35(2),155–163.

Liesio, J., Mild, P. Salo, A.(2007).Preference programming for robust portfolio modeling and project selection. *European Journal of Operational Research*, 181(3), 1488–1505.

Liesio, J., Mild, P. Salo, A. (2008).Robust portfolio modeling with incomplete cost information and project interdependencies. *European Journal of Operational Research*, 190(3), 679–695.

Mulvey, J. M., Vanderbei, R. J., & Zenios, S. A. (1995).Robust optimization of largescale systems. *Operations Research*, 43(2), 264–281.

Niakan,F.Baboli,A.Moyaux,T.Botta-Genoulaz,V.(2016).A Multi-objective Mathematical Model Considering Economic and Social Criteria in Dynamic Cell Formation. *IFIP International Conference on Advances in Production Management Systems*, 46-53. https://hal.inria.fr/hal-01387844.

Ning, Chao.You,Fengqi.(2020).A transformation-proximal bundle algorithm for multistage adaptive robust optimization and application to constrained robust optimal control. *Automatica,* In press, corrected proof, Available online 3 January 2020.

Raflei H, Ghodsi R.(2008).A bi-objective mathematical model toward dynamic cell for-mation considering labor utilization. *Applied Mathematical Modeling* ,37(4),2308–2316.

Roy, B. (2010).Robustness in operational research and decision aiding: A multifaceted issue. *European Journal of Operational Research*, 200(2), 629–638.

Lahdelma, R., Hokkanen, J. Salminen, P. (1998).SMAA – Stochastic multiobjective acceptability analysis. *European Journal of Operational Research*, 106(3), 137–143.

Pitombeira Neto AR, Goncalves Filho EV.(2010).A simulation-based evolutionary multi objective approach to manufacturing cell formation. *Computer Industrial Engneeering*,59(1),64–74.

Sadeghi,Azadeh.Suer,Gursel. Sinaki,R.Y.Wilson,Darin.(2020). Multiscale topology optimization for minimizing frequency responses of cellular composites with connectable graded microstructures. *Mechanical Systems and Signal Processing*,135(1),106-369.

Satoglu, S. I., & Suresh, N. C. (2009).A goal-programming approach for design of hybrid cellular manufacturing systems in dual resource constrained environments. *Computers and Industrial Engineering*, 56(2), 560–575.

Shiyas,C.R. Madhusudanan Pillai,V.(2014). A mathematical programming model for manufacturing cell formation to develop multiple configurations. *Journal of Manufacturing Systems*, 33 (1) 149– 158.

Srinivasan G, Narendran TT, Mahadevan B.(1990).An assignment model for the part-families problem in group technology. International Journal Production Research,28(l),145–152.

Singh, N.(1993).Design of cellular manufacturing systems: an invited review. *European Journal of Operational Research*, 69(4), 284-291.

Sharda B, Banerjee A. (2013).Robust manufacturing system design using multi objective genetic algorithms, pettiness Bayesian uncertainty representation. *Journal Manufacturing System*,32(3),315–324.

Shen, Feifei.Zhao,Liang.Du,Wenli. Zhong,Weimin.Q,Feng.(2019).Large-scale industrial energy systems optimization under uncertainty: A data-driven robust optimization approach. *Applied Energy,* in press, corrected proof, Available online 26 November 2019.

Suresh, N.C., and Slomp, J.(2001). A multi-objective procedure for labour assignment and grouping in capacitated cell formation problems. *International Journal of Production Research*, 39(2), 4103-4131.

Vitayasak, Srisatja. Pongcharoen, Pupong, Hicks, Christian.(2019).Robust machine layout design under dynamic environment: Dynamic customer demand and machine maintenance. *Expert Systems with Applications: X,3,* Article 100015.

Wang, J. Zionts, S. (2006).The aspiration level interactive method (AIM) reconsidered: Robustness of solutions. *European Journal of Operational Research*, 175(3), 948–958.

Yasuda K, Hu L, Yin Y. (2005).A grouping genetic algorithm for the multi-objective cell formation problem. *International Journal of Production Research*, 43(4):829–53.

Zhang,Yan.Xiao,Mi.Gao,Liang.Gao,Jie.Li,Hao.(2020).Multiscale topology optimization for minimizing frequency responses of cellular composites with connectable graded microstructures. *Mechanical Systems and Signal Processing*, 135(1), 26-49.

Zhen, L.Chang, D.-F.(2012).A bi-objective model for robust berth allocation scheduling. *Computers and Industrial Engineering*, 63(3), 263–272.