Machine Reliability in a Dynamic Cellular Manufacturing System: A Comprehensive Approach to a Cell Layout Problem

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ABSTRACT

The fundamental function of a cellular manufacturing system (CMS) is based on the definition and recognition of a type of similarity among parts that should be produced in a planning period. Cell formation (CF) and cell layout design are two important steps in implementation of the CMS. This paper represents a new nonlinear mathematical programming model for dynamic cell formation that employs the rectilinear distance notion to determine the layout in the continuous space. In the proposed model, machines are considered unreliable with a stochastic time between failures. The objective function calculates the costs of inter- and intra-cell movements of parts and the cost due to the existence of exceptional elements (EEs), cell reconfigurations, and machine breakdowns. Due to the problem's complexity, the presented mathematical model is categorized in NP-hardness; thus, a genetic algorithm (GA) is used for solving this problem. Several crossover and mutation strategies are adjusted for GA and parameters are calibrated based on Taguchi experimental design method. The great efficiency of the proposed GA is then demonstrated by drawing a comparison between particle swarm optimization (PSO) and the optimum solution via GAMS considering several small/medium- and large-sized problems..

1. Introduction

In today's world, due to the enhancements in the customer's power of choice and extension of competitive markets, organizations are required to reform their structures. Group technology (GT) is a production philosophy that aims to determine, categorize, and assign parts to groups and part families; also, it assigns machines to cells to produce these part families. This process is based on the part characteristics and their similarities in the production process, design and geometrical characteristics.

A cellular manufacturing system (CMS), which is the most important application of GT, overcomes the inefficiency of traditional approaches through reduction in transportation time and distance. A flow shop layout has high

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efficiency in a mass production system, while a job shop is a very flexible system for producing various parts. In fact, each of these systems does not have any other benefits. The CMS is an approach between these two manufacturing systems that aims to improve flexibility and efficiency to produce manufacturing groups in different sizes.

In a CMS, machines and parts assignment to cells must impose minimum cost on the system. After determining the assignment to machines and parts, machines' locations must be determined. This issue is referred to as cell layout (CL).

However, the layout design in a CMS has not been paid much attention, since most of the relevant studies in the literature only investigate the CFP [1, 2]. As stated by Alfa et al. [3], facility layout and CF problem decisions are interrelated, and addressing them simultaneously is very important for a successful CMS design. However, each of these decisions is proven to be complex [4, 5]. Therefore, the simultaneous addressing of these decisions is a more difficult issue.

On the other hand, it seems that demand and product mix will continuously change with a lower product lifecycle and shorter time distances to present the product [6]. Wemmerlov and Hyer [7] stated that a demand for the products, produced in manufacturing cells, is not so much predictable. As a result, planning horizon can be segmented to smaller periods. Therefore, each period has its own demand and product mix. In this situation, we are faced with dynamic manufacturing or dynamic environment requirements. It has to be said that, in a dynamic situation, the demand and product mix in each period can be different and certain.

For a prosperous design, planning must be done over time for all the periods with respect to the variations. Variations in cell structure within planning periods may include exchanging the machines between the cells, adding new machines to the cells, eliminating the machines from the cells, and relocating the machines in the cells. In previous studies, for locating the machines in manufacturing cell space, line formed locations were the only consideration and the machines were assigned to these positions. It is obvious that if assigning

the number of machines to a cell cannot be formed, it turns into a U form that imposes additional costs on the system. With respect to this point, using the concept of distance in order to calculate the amount of parts' relocations between two or more machines in a cell rather than considering positions for assigning the machines to manufacturing cells can make the problem actual and can ease the costs calculation.

Furthermore, traditionally, CF problems are performed assuming that all the machines are 100% reliable. However, machines that are the key elements in manufacturing systems break down most of the times, and it is not possible to repair them as quickly as the production requirements dictate. Their breakdown can affect system performance and cause some manufacturing problems. Machine failures should, hence, be taken into account during the design of CMS to improve the overall performance of the system. However, any attempt at improving the reliability of a system results in higher costs. Therefore, an optimization approach that integrates cost and reliability considerations is the most appropriate policy to achieve an optimum balance [8].

This paper proposes a model that concurrently considers cell formation and facility layout problems that incorporates machine reliability and cost considerations to develop an effective CMS in dynamic conditions. To achieve this, a new mathematical nonlinear programming model for dynamic cell formation, employing the rectilinear distance concept to determine layout in a continuous space, is presented in this study. To increase the accuracy of the inter- and intra-cell layouts, the material handling cost is calculated based on the actual location of machines and cells on the shop floor considering machine dimensions and aisle widths. A target function accurately calculates the costs of inter- and intra-cell relocation for parts. In addition, the cost of cell reconfiguration and EEs is calculated. In an accurate cellular layout, cells and machines should not be overlapped. However, in a number of research bodies, machines located in each position can be assigned to any of the cells without any restrictions [9]. The model proposed in this paper prevents cells and

machines from being overlapped by imposing some restrictions on assigning machines to cells and cells to shop floor. Furthermore, machine reliability and cost considerations are incorporated in the proposed model. Since machine reliability has a probabilistic nature, it is assumed that time between failures follows an exponential distribution. Therefore, the number of breakdowns for each machine follows a Poisson distribution with a known failure (i.e., breakdown) rate.

The remainder of the paper is organized as follows. In the next section, the relevant literature is reviewed. Section 3 describes proposed model and explains reliability considerations in the design of CMS. In Section 4, the proposed genetic algorithm is introduced. The PSO is introduced in Section 5. Some numerical examples and comparing the results are presented in Section 7 in order to demonstrate the methodology. Finally, conclusion and future research are given in section 8.

Literature Review

Studies conducted in dynamic cell formation can be categorized as follows:

- ✓ Studies that propose appropriate models in cellular manufacturing systems with respect to production information and solve the model by employing accurate or heuristic algorithms.
- ✓ Studies that attempt to propose new approaches including existing accurate or heuristic models and comparing different solving methods.
- ✓ Studies incorporating reliability consideration in designing CMS.

2-1. Studies based on the proposing models

The most popular studies conducted in designing dynamic CMS (DCMS) are as follows. Kannan and Ghosh [10] examined a DCMS in terms of scheduling, and illustrated that simpler scheduling can be achieved thorough DCMS. They also examined the impacts of the DCMS on preparation time, flow time, and work-in-process. Balakrishnan and Cheng [11] proposed a flexible two-step method to solve the cell formation problem with respect to demand variations using dynamic programming and machine assignment. The first phase contains assigning machines to each period, and the second phase of the method is to employ dynamic programming for designing within planning periods. Rheault et al. [12] proposed the idea of dynamic cell manufacturing to overcome the flexibility reduction in designing a CMS. They considered the demand and product mix in each period as a constant and certain value. Their objective function is to minimize the total inter-cell relocation costs and cell restructuring with constraints of capacity of cell space and common quadratic assignment problem (QAP) constraints. Bulgak et al. [13] proposed a new mathematical model for designing a DCMS. In addition to considering inter-cell relocation, cell restructuring, and cell capacities, this model considers assumptions, such as level of inventory in each period, intra-cell relocation, maintenance costs, and subcontracting. Schaller [14] proposed a mathematical model for a CF problem considering demand variations within the periods.

Wicks and Reasor [15] proposed a mathematical model for designing a dynamic manufacturing cell system based on part family and machine grouping. The objective function is to minimize the total inter-cell relocation costs, fix costs of machine purchasing and cell restructuring costs with constraints of machine capacity and lower bound of cells capacity. Chen [16] presented the DCMS model to minimize material relocation costs, cell restructure, and fix machine cost with constraints of lower and upper bounds of cells capacity and constant number of cells. Mungwattana [17] examined the cell formation problem in his thesis. In his study, he considered a number of assumptions, such as multiple operational paths, batch movements of the parts, variable production costs, machine time capacity constraints, lower and upper bounds for cells capacity, number of cell constraint, demand variations, machine purchasing costs, cell restructuring cost, inter-cell relocating cost and multi-task machines. Safaei and Tavakkoli-Moghaddam [18] developed a new model for solving the dynamic cell formation problem considering subcontracting with some assumptions, such as batch movement of the parts, inter-cell relocating, demand variations in different

periods, machine time capacity, maximum capacity of cells, existence of multitask machines, and parts returns by customers. They solved the proposed model after linearization by a branch-and-bound (B&B) algorithm. Arkat et al. [19] proposed a mathematical model to simultaneously determine the formation of cells, cellular layout, and the operations sequence. The objective of the model was to minimize the total transportation cost of parts as well as minimizing makespan. In their approach, cells are prevented from being overlapped by imposing some restrictions on assigning machines to cells. Mahdavi et al. [20] examined an integrated mathematical model considering CF and cell layout simultaneously. In their paper, machine cells are allocated to a set of predetermined positions in the shop floor, and the machines are arranged in a linear form in each cell.

Mohammadi et al. [21] presented a multi-row layout and developed a GA to solve an integrated CF and layout problem. They calculated the material handling cost on the basis of the actual location of machines on the shop floor regarding machine dimensions and aisle widths. In their approach, machines assigned to the same cell are arranged through a linear flow line, and the machine cells are placed on the shop floor as a multi-row layout. A few years later, these authors introduced a new layout framework called S-shaped layout that is a modified version of the multi-row layout [22]. They proposed a bi-objective model for integrated cell formation and layout problem. In their approach, machines are arranged through an S-shaped form according to their assignment to the cells considering machine dimensions, the width of the shop floor, and the aisle widths. A hybrid solution method, combining simulated annealing and dynamic programming, is developed for solving the problem [22].

2-2.   Studies based on the solving methods
Among the studies done in proposing different solving methods in a dynamic cell formation system design, the following studies are mentioned:
Safaei et al. [23] proposed a nonlinear integer mathematical model for a CMS in a dynamic condition to overcome demand variations and

product mix. The advantages of this model include the consideration of inter and intra-cell batch relocation, operational sequence, multiple paths, and multiplicity in a machines type. The main constraints in this model are the upper bound of cells capacity and time capacity of machines. They solved their model by merging a mean field annealing (MFA) algorithm with the simulated annealing (SA) algorithm, namely MFA-SA. They examined the obtained findings with SA and B&B methods, and demonstrated that the MFA-SA algorithm achieved better results. Askin et al. [24] proposed a four-step algorithm for solving the CF problem considering demand variations and product mix. In the proposed model, existence of multiple operational paths is considered as an assumption. Phase 1 is related to assigning the activities to specific types of machines. Phase 2 is about assigning parts activity to a specific machine. Phase 3 is related to candidate cell determination to locate the machine. Phase 4 is about cell design enhancement and completion.

Safaei et al. [25] solved the integer mathematical model related to the CF problem with a dynamic and uncertain environment employing fuzzy programming. In this model, the demand and time capacity of machines are considered as fuzzy forms. The objective function of the proposed model is to minimize the total inter- and intra-cell relocating costs, fixed and variable costs of machines, and cell restructuring costs. Tavakkoli-Moghaddam et al. [26] proposed a multi-criteria linear-integer model that includes information, such as cell capacity constraints, inter-cell relocation, multi operational paths, machines reestablishment in planning periods, existence of several single type machines, and operation sequence. The objective function for their model is to minimize the machine purchasing costs, inter-cell relocation cost, part production cost and cell restructuring cost. They solved the model by SA, and demonstrated that, through sufficient time, more appropriate solutions are obtained by the B&B algorithm. Tavakkoli-Moghaddam et al. [27] solved the Mungwattana's proposed model by meta-heuristic algorithms, such as SA, GA, and tabu search (TS) and, then, compared it with the B&B method. They demonstrated that SA

generated more appropriate solutions for solving this particular model. Bajestani et al. [28] proposed a multi-criteria programming model for a dynamic CF. They solved the proposed model employing a scatter search (SS) algorithm, and demonstrated that, for this problem, the SS algorithm outperformed multi-criteria GA. Saidi-Mehrabad and Safaei [29] developed the dynamic CF model by considering the number of variable cells for sequential planning periods and, then, solved the model by the neural network in a deterministic condition.

Bagheri et al. [30] developed a new mathematical model to simultaneously solve the cell formation, inter-cell layout problems, and operator assignment. The objectives included the minimization of inter- and intra-cell movements, machine relocation cost, and operator-related issues. They employed an LP-metric approach to obtaining the preferred solution and solved the problem using the B&B technique. Forghani et al. [31] formulated a simultaneous CF and layout problem and combined the quadratic assignment problem (QAP) with the two-dimensional facility layout problem. The QAP was employed to specify the intra-cell layout. while the inter-cell layout was represented by the continuous layout problem. They used a GA for solving the problem. Deep et al. [32] examined an integrated mathematical model for multi-period cell formation and part operation tradeoff in a dynamic cellular manufacturing system considering multiple part process route. Their approach concurrently generated machine cells, part families, and the optimum process route. They employed a simulated annealing-based genetic algorithm to solve the proposed problem.

2-3. Studies considering the reliability

The importance of appropriate reliability planning on CMS output performance has been studied by a number of researchers. Logendran et al. [33] compared both mean work in-process and mean throughput time in a CMS and job shops considering machine breakdown. Their study indicated that performance at mean throughput time was better in the CMS only when preventive maintenance was performed. Therefore, it was concluded that reliability was

an important design factor in the CMS. Das et al. [8] proposed a bi-objective model to incorporate reliability considerations into the CF problem. They assumed that each machine had a number of similar copies. When machine breakdowns occur, each machine type is replaced with another similar copy. In their approach, minimization of the total costs and maximization of the system reliability are considered as two objective functions. Saeed et al. [34] developed a binary integer programming model to deal with the CF problem considering alternative process routings for part types, configuration of machine cells, and machine reliability. They showed that the consideration of the machine reliability could make undesirable changes in the block diagonal machine-part matrix; however, it could reduce the overall cost of the cellular system. Chung et al. [35] proposed an efficient TS algorithm to solve the CF problem with alternative process routings and machine reliability considerations.

Rafiee et al. [36] proposed an integrated cell formation and inventory lot-sizing problem to minimize some CMS costs. Furthermore, the process deterioration and machine breakdowns are considered in their approach to make the model more practical and applicable. Arkat et al. [37] used chance-constrained programming (CCP) to model cell formation problem considering machine reliability. Their proposed model minimizes the total CMS costs, consisting of intercellular and intracellular movement costs and machine breakdown costs. Alhourani [38] considered alternative process routings for parts and machines reliability together to solve the generalized GT problem; they can be of help in realistic selection of process routings for parts. In addition, other important production parameters, such as operations' sequence, production volumes, machines' capacities, duplicate machines, machine reliability and alternative preprocessing routing for parts should be considered all together in the machine cell formation problem.

Reviewing the previous studies indicates that there is no paper to consider the simultaneous formation of cells and layout using exact information of inter- and intra-cell layouts under a dynamic condition and reliability

consideration. Therefore, using the notion of distance, a new establishment design in continuous space for machine arrangement in manufacturing cells and cells layout in a job shop level, considering cells reconfiguration and machines reliability in a dynamic condition, is presented in this paper.

3. The Proposed Model

The presented model with a number of assumptions, parameters, decision variables, objective function, and constraints is discussed below.

3-1. Model assumption

- Flow between machines in each period is determined. This number is obtained from the parts demand, operational paths for parts, and also batch size of parts transportation.
- Parts are moved between and in the cells in batches. Largeness of the batches per product is known and constant for all periods. In addition, the size of the part batches for inter- and intra-cell relocations is assumed the same.
- Time between failures follows exponential distribution. Therefore, the number of breakdowns for each machine follows a Poisson distribution with a known failure (i.e., breakdown) rate.
- Machine breakdown cost is assumed to be known in advance and is based on its repair, install/uninstall costs.
- The inter-cell relocation cost is based on the unit of distance and remains constant over time.
- The machine relocation cost during the periods is constant and known for per machine. This cost includes opening, transferring, and resetting the machine.
- The number of cells is known and constant over time.
- There is one from each type of machine.
- The maximum capacity of cells is known and remains constant over time.
- The distance between two machines is calculated through a rectilinear distance.
- Machines are considered as squares of equal area and supposed to have a unit dimension.

- Excess inventory between the periods is zero; delayed orders are not allowed and demands per period must be supplied in that period.

3-2. Sets

$i, i' = \{1,2,\dots,,m\}$	Index set of machines
$j = \{1,2,\dots,,n\}$	Index of parts
$l, k, k' = \{1,2,\dots,c\}$	Index set of cells
$h = \{1,2,\dots,,H\}$	Index set for time periods

3-3. Model parameters

D_{jh}	Demand for part type j in period h
B_j	Largeness of batch for transportation of part type j
C_{intra}^j	The intra-cell material handling cost for transporting part j per unit distance (\$/unit)
C_{inter}^j	The inter-cell material handling cost for transporting part j per unit distance (\$/unit)
C_i	Cost of relocation for machine i
R_{ij}	The operation number done on part j using machine i
E	Horizontal length of the job shop (i.e., length of the job shop)
F	Vertical length of the job shop (width of the job shop)
SP	Set of (i, j) pairs when $a_{ij} \geq 1$ (set of elements for part-machine matrix that are not equal to zero)
NM	Maximum number of machines relocated per period.
ϑ_j	Coefficient of cost (or penalty) due to the existence of each exceptional part type j per period.
N	Very large number
$f_{ii'h}$	Number of trips for moving part type j between machines i and i' in period h
N	Positive big number
A_{kl}, B_{kl}	Binary random values
λ_i	Failure rate for machine i
β_i	Breakdown unit cost for machine i
α	Pre-specified confidence level
θ_{ih}	Number of breakdowns occurring for machine i in period h
$f_{ii'h}^j$	Number of travels for transferring

part type j between machines i and i' in period h which is calculated as follows:

$$f_{ii'h}^{j} = \begin{cases} \left[D_{jh} \middle/ B_j \right] & if \quad R_{i'j} - R_{ij} = 1 \\ 0 & if \quad R_{i'j} - R_{ij} \neq 1 \end{cases}$$

3-4. Decision variables

$X_{ikh} = \begin{cases} 1 & \text{If machine } i \text{ in period } h \text{ is assigned to cell } k, \\ 0 & \text{Otherwise} \end{cases}$

$Y_{ikh} = \begin{cases} 1 & \text{If part } j \text{ in period } h \text{ is assigned to cell } k, \\ 0 & \text{Otherwise} \end{cases}$

$Z_{ih} = \begin{cases} 1 & \text{If machine type } i \text{ relocates in periods } h \text{ and } (h+1) \\ 0 & \text{Otherwise} \end{cases}$

$U_{ijkh} = \begin{cases} 1 & \text{If } Y_{jkh} = 0 \text{ and } X_{jkh} = 1 \\ 0 & \text{Otherwise} \end{cases}$

$V_{ijkh} = \begin{cases} 1 & \text{If } Y_{jkh} = 1 \text{ and } X_{jkh} = 0 \\ 0 & \text{Otherwise} \end{cases}$

$\zeta_{ij} = \begin{cases} 1 & \text{If part } j \text{ requires machine } i \\ 0 & \text{Otherwise} \end{cases}$

x_{ih} Horizontal component of machine type i in period h

y_{ih} Vertical component of machine i in period h

p_{kh}^{1} Left side horizontal component of cell k in period h

p_{kh}^{2} Right side horizontal component of cell k in period h

q_{kh}^{1} Bottom side vertical component of cell type k in period h

q_{kh}^{2} Top side vertical component of cell type k in period h

If both machines i and i' are located in cell k in period h ($X_{ikh}, X_{i'kh} > 0$), then an intra-cell movement will happen. Regarding distance between machine i (x_i, y_i) and machine j (x_j, y_j), which is calculated by:

$$|x_{ih} - x_{i'h}| + |y_{ih} - y_{i'h}|$$

The relocation cost of part j between machines i and i' in period h can be determined as follows:

$$C_{ii'h}^{j} = (|x_{ih} - x_{i'h}| + |y_{ih} - y_{i'h}|)C_{intra}^{j}$$

On the other hand, if machines i and i' are not located in the same cell in period h

($X_{ikh}X_{i'kh} = 0$ and $X_{ikh}X_{i'k'h} > 0$) and in period h machine i was in cell k and machine i' was in cell k', then an inter-cell movement will happen and the relocation cost of part j between machines i and i' in period h can be determined by:

$$C_{ii'h}^{j} = (|x_{ih} - x_{i'h}| + |y_{ih} - y_{i'h}|)C_{inter}^{j}$$

3-5. Reliability of the CMS design

As mentioned before, most of the studies exising in the literature assumed that machines are reliable and can process parts without any breakdown. However, one of the most important factors influencing the performance of the CMS is machine breakdowns that result in some manufacturing problems such as higher production costs and longer production period. Since machine reliability has a probabilistic nature, it is assumed that machines reliability follows an exponential distribution with a known failure (breakdown) rate. In addition, machine breakdown cost is assumed to be known in advance and is based on its repair, install/uninstall costs.

Herein, in order to calculate the total breakdown cost, we define λ_i as failure rate for machine i, β_i as the breakdown unit cost for machine k, and α as the pre-specified confidence level. Moreover, ζ_{ij} is defined as follows:

$$\zeta_{ij} = \begin{cases} 1 & \text{If part } j \text{ requires machine } i \text{ for processing} \\ 0 & \text{Otherwise} \end{cases}$$

Considering θ_{ih} as the number of breakdowns occurring for the ith machine in period h, the total breakdown cost (TBC) is calculated as follows:

$$TBC = \sum_{h=1}^{H} \sum_{i=1}^{m} \sum_{j=1}^{n} \zeta_{ij} \theta_{ih} \beta_i \tag{1}$$

In the proposed model, it is assumed that the time between failures follows exponential distribution. Hence, the number of breakdowns for each machine follows a Poisson distribution as follows where T_{ij} represents the process

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time of machine i for part j, and D_{jh} shows the amount of demand j in period h.

$$\Pr\left(\theta_{ih} = \phi_{th}\right) = \frac{\exp\left(\lambda_i D_{jh} T_{ij}\right).\left(\lambda_i D_{jh} T_{ij}\right)^{\phi_{th}}}{\phi_{th}!} \tag{2}$$

Due to the probabilistic nature of the time between machine breakdowns, calculating the exact amount of θ_{ih} is impossible. Hence, based on the concept of CCP, stochastic variable θ_{ih} in equation (1) can be replaced by φ_{ih} as a new deterministic variable, and the following chance constraint will be added to the model to ensure that the number of breakdowns never exceeds φ_{ih} in at least α of time. Hence, the following constraint can be defined below.

$$\Pr\left(\theta_{ih} \leq \varphi_{ih}\right) \geq \alpha \tag{3}$$

Considering Eq. (2), Eq. (3) can be rewritten by:

$$\sum_{\omega=0}^{\varphi_{ih}} \frac{exp(-\lambda_i D_{jh} T_{ij}).(\lambda_i D_{jh} T_{ij})^\omega}{\omega!} \geq \alpha \quad \forall i, j \tag{4}$$

where φ_{ih} is an integer variable.

On the other hand, as Eq. (1) related to the total breakdown cost is a nonlinear one, the following equation is defined to simplify the term of the problem:

$$Q_{ijh} = \zeta_{ij} \times \varphi_{ih} \tag{5}$$

where ζ_{ij} is a binary variable and φ_{ih} is an integer variable. Hence, Q_{ijh} is an integer

variable. The newly defined equation is equivalent to the following equation:

$$Q_{ijh} \geq \varphi_{ij} - \left(1 - \zeta_{ij}\right).N \tag{6}$$

where N is a large positive number. If ζ_{ij} takes 1, this constraint becomes $Q_{ijh} \geq \varphi_{ij}$, and due to the minimized form of the objective function, Q_{ijh} will equal $\geq \varphi_{ij}$. Similarly, if ζ_{ij} is 0, the constraint becomes $Q_{ijh} \geq -N$ and again, because of the minimization of the objective function, Q_{ijh} becomes 0. Therefore, TBC is rewritten as follows:

$$TBC \tag{7}$$
$$= \sum_{h=1}^{H} \sum_{i=1}^{m} \sum_{j=1}^{n} Q_{ijh}\,\beta_i$$

Furthermore, Eq. (4) is a non-linear one and, in order to simplify the problem, this constraint is linearized. To do so, considering the left-hand side of this constraint is the cumulative Poisson probability with parameter λ_i, the inverse form of the cumulative Poisson distribution function is used. Thus, this constraint is rewritten by:

$$\varphi_{ih} \geq \tag{8}$$
$$F^{-1}(\lambda_i D_{jh} T_{ij}, \alpha)$$

where F^{-1} is the inverse of the cumulative Poisson distribution function and can be computed with the parameters of λ_i, $D_{jh}, T_{ij}, and\ \alpha$ using Poisson tables.

3-6. Mathematical formulation
With respect to the input parameters and variables, the presented nonlinear model for this problem is as follows:

$$\text{Min} \sum_{h=1}^{H} \sum_{j=1}^{n} \sum_{i=1}^{m} \sum_{i'=1}^{m} f_{ii'h}^{j} C_{ii'h}^{j} + \sum_{h=2}^{H} \sum_{i=1}^{m} C_i Z_{ih} + \sum_{h=1}^{H} \sum_{k=1}^{C} \sum_{(i,j)\in sp} \vartheta_j.\frac{(U_{ijkh} + V_{ijkh})}{2}$$
$$+ \sum_{h=1}^{H} \sum_{i=1}^{m} \sum_{j=1}^{n} Q_{ijh}\beta_i \tag{9}$$

$$\sum_{k=1}^{C} X_{ikh} = 1 \ , \ i = 1,2,\dots,m \ , \quad \forall h \tag{10}$$

$$\sum_{k=1}^{C} Y_{jkh} = 1 \ , \ j = 1,2,\dots,n \ , \quad \forall h \tag{11}$$

$$1 \leq \sum_{i=1}^{m} X_{ikh} \leq NM \quad , \ k = 1,2,\dots,C \ , \ \forall h \tag{12}$$

$$NZ_{ih} \geq |x_{ih} - x_{i(h+1)}| + |y_{ih} - y_{i(h+1)}| \quad \forall i, h < H \tag{13}$$

$$|x_{ih} - x_{i'h}| + |y_{ih} - y_{i'h}| \geq 1 \tag{14}$$

$$\begin{cases} x_{ih} \geq p_{kh}^1 - N(1 - X_{ikh}) \\ x_{ih} \leq p_{kh}^2 + N(1 - X_{ikh}) \\ y_{ih} \geq q_{kh}^1 - N(1 - X_{ikh}) \\ y_{ih} \leq q_{kh}^2 + N(1 - X_{ikh}) \end{cases} \quad \forall i, k, h \tag{15}$$

$$\begin{cases} p_{kh}^1 \geq 0 \\ q_{kh}^1 \geq 0 \\ p_{kh}^2 \leq E \\ q_{kh}^2 \leq F \end{cases} \quad \forall k, h \tag{16}$$

$$\begin{cases} p_{kh}^1 - p_{lh}^2 + NA_{kl} + NB_{kl} \geq 0 \\ p_{kh}^2 - p_{lh}^1 - NA_{kl} - N(1 - B_{kl}) \leq 0 \\ q_{kh}^1 - q_{lh}^2 + N(1 - A_{kl}) + NB_{kl} \geq 0 \\ q_{kh}^2 - q_{lh}^1 - N(1 - A_{kl}) - N(1 - B_{kl}) \leq 0 \\ \qquad 0 \leq k < l \leq C \end{cases} \tag{17}$$

$$Q_{ijh} \geq \varphi_{ij} - (1 - \zeta_{ij}).N \tag{18}$$

$$\varphi_{ih} \geq F^{-1}(\lambda_i D_{jh} T_{ij}, \alpha) \tag{19}$$

The objective in the presented model is simultaneous decision-making to specify a cell for machines, part families, and facility layout under a dynamic condition. The model is a nonlinear model that aims to minimize the cost of inter- and intra-cell relocations of the parts, the relocation costs of the machines during periods, the costs related to the existence of exceptional parts, and the total breakdown cost. The third phase of the objective function attempts to minimize the number of exceptional parts. The quantity of 1/2 in this relationship is due to double calculation of decision variables when they are equal to 1. Finally, the last phase in the objective function attempts at minimizing the total breakdown cost due to the existence of unreliable machines described in detail in the previous section.

The set of constraint (10) in the mathematical model leads to the assignment of per machine to a single cell. The set of constraint (11) leads to the assignment of each part to a single part family. The set of constraint (12) demonstrates the capacity of per cell that puts the number of machines in each cell in the quantity between 1 and NM. The set of constraint (13) ensures that, by relocating machine type i during periods h and $(1+h)$, variable Z_{ih} obtains the quantity one. The set of constraints (14) prevents machines from overlapping. As mentioned before, the machines are assumed as squares with a unit dimension. The set of relationships (15) ensures that each machine must relocate the space of its corresponding cell. The set of relationships (16) ensures that cells are located in the space of a job shop; moreover, to control the cells which are in the space of the job shop, the set of relationships (17) is developed to control the cells which are in space of the job shop. The set of Constraints (18) and (19) is related to reliability consideration in CMS, as explained before in Section 3.5.

4. The Proposed Genetic Algorithm

Several algorithms have been applied in the context of a DCMS design to approach the appropriate design. One of the most popular forms of these designs is the genetic algorithm (GA). This section attempts to examine some aspects of this algorithm and demonstrates its

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application in a DCMS design. The GA is known as the most popular meta-heuristic algorithm and is a component of evolutionary calculation and is a subset of artificial intelligence. The primary idea of this algorithm is derived from the Darwin's evolutionary theory and its application is based on natural genetics.

In a way that the GA searches the solution space, not only the better quality solutions are acceptable, but also the solutions with lower fitness are acceptable, leading the algorithm to escape from local optimum points. The GA varies in many ways with traditional optimization methods. In this algorithm, design space should be converted to genetic space. Therefore, we deal with a series of coded variables. Another major difference between the GA and other optimization methods is that the GA works with a population or a set of points at a certain moment, while traditional optimization methods operate only in a particular point. A distinguishing feature of the GA is that the principle of processing in this algorithm is random and is guided towards the optimum place. Generally, the differences between the GA and other optimization methods can be expressed as follows:

- ✓ The GA does not search the solution in a single point and searches the solution in parallel.
- ✓ The GA does not use the deterministic rules and uses probabilistic rules.
- ✓ The GA is based on coded variables, unless in cases whose variables are illustrated as real numbers.
- ✓ The GA does not require backup information. It only determines the members of objective function and the fitness of path in the search space.

By applying the GA, the following steps are necessary:

- Representing an appropriate solution structure.
- Obtaining appropriate initial solutions in a population size.
- Employing appropriate genetic operators (i.e., mutation and crossover) to obtain new solutions.
- Selecting population of the next generation from parent and offspring chromosomes.

- Evaluating chromosome measure (i.e., fitness function)
- Specifying the stopping criteria

The algorithm in two phases is used to solve the model of this problem. The first phase is related to machine assignment to manufacturing cells and layout determination, and the second phase is about determination of part assignment to part families. The flowchart process of the algorithm is provided in Fig. 1.

4-1. Parameter tuning

In this paper, the Taguchi experimental design method is applied to calibration of the parameters of meta-heuristic algorithms. Taguchi introduced this method in early 1960s. The orthogonal arrays of the method are used for the evaluation of a large number of factors with a few experiments. In the current problem, the L9 design of the Taguchi method is applied to the algorithms by using the Minitab 16.2 software. The Taguchi method aims to minimize variances of quality characteristics obtained from S/N ratio (Taguchi et al., 2000). The quality characteristic of this paper is considered as a relative percentage deviation (RPD), which is considered to exchange objective function values to non-scale. Hence, "The smaller-the better" type is chosen. The RPD is computed as follows:

$$RPD = \frac{|Obj_i - Obj_{best}|}{|Obj_{best}|} \times 100 \qquad (20)$$

where Obj_{best} and Obj_i are the best achieved objective value for a special instance and the objective value obtained for the *i*-th experiment, respectively.

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$$RPD = \frac{|Obj_i - Obj_{best}|}{|Obj_{best}|} \times 100 \qquad (20)$$

where Obj_{best} and Obj_i are the best achieved objective value for a special instance and the objective value obtained for the *i*th experiment, respectively.

Also, the signal-to-noise ratio for "the smaller-the better" characteristic is calculated by:

$$S/N = -10 \log(\frac{1}{n}\sum_{i=1}^{n} y_i^2) \qquad (21)$$

where y_i denotes the response value in the i-th replication and n denotes the number of replications in experiments' replications. We incorporate three factors that can have significant effects on the proposed evolutionary algorithms. The considered levels of the parameters are listed in Table 1.
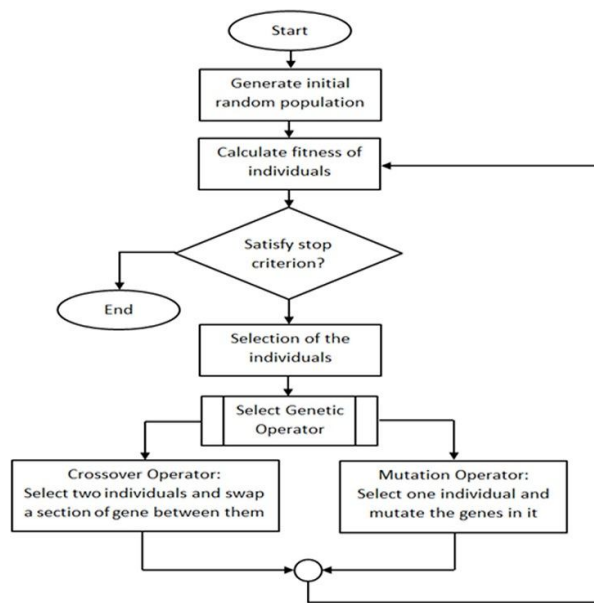

Fig. 1. Flowchart of the genetic algorithm

Tab. 1. Considered levels of parameters of the modified GA

	Parameter	Level 1	Level 2	Level 3
Modified GA	Crossover	0.60	0.70	0.80
	Mutation	0.10	0.15	0.20
	Population size	50	70	90

Fig. 2 shows the level of control factors versus control factors. A larger value of the S/N ratio in the graphs is more desirable.
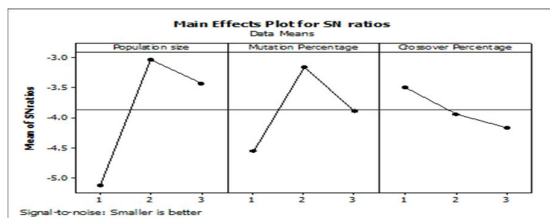

Fig. 2. Mean S/N ratios for the proposed GA

4-2. Solution view

One chromosome coding is required for the GA to point to solutions to the problem. The way that chromosomes are viewed determines how a problem is formulated in a form of an algorithm and what genetic operators are applied. Each chromosome is formed from genes that can be shown as binary and integer numbers or combination of characters that is a

coded form of a feasible solution (appropriate or inappropriate) from the problem.

The considered chromosome for the first step of this problem includes a matrix with H rows and M columns that can be divided into the following sub-matrix.

- Sub-matrix of Z is related to assignment of machines to manufacturing cells. This sub-matrix consists of H (i.e., number of periods) rows and M (i.e., number of machines) columns. Each element of this matrix is a number between 1 and C (i.e., number of cells), and element Z_{ih} represents the number of cells that includes machine type i in period h.

- Sub-matrix X is related to the horizontal component of machines' location. This sub-matrix also consists of H rows and M columns. With respect to the machines'

dimension (1×1), one integer is sufficient to familiarize each of horizontal and vertical components of the machines. Each element of this matrix is a number between 1 and E (i.e., length of the job shop), and element x_{ih} represents the horizontal component of location that includes machine i in period h.

- Sub-matrix Y is related to the vertical component of machines' location. This sub-matrix also consists of H rows and M columns. Each element of this matrix is a number between 1 and F (i.e., width of the job shop) and element y_{ih} represents the vertical component of location that includes machine i in period h.

Figs. 3 and 4 illustrate the general and detailed views of the chromosome structure related to machines alignment to manufacturing cells, respectively.

$$[[Z] \quad [X] \quad [Y]]$$

Fig. 3. General view of the chromosome structure

Z_{11} Z_{12} ... Z_{1M} $\vdots$ $\vdots$ $\vdots$ Z_{h1} Z_{h2} ... Z_{hM}	x_{11} x_{12} ... x_{1M} $\vdots$ $\vdots$ $\vdots$ x_{h1} x_{h2} ... x_{hM}	y_{11} y_{12} ... y_{1M} $\vdots$ $\vdots$ $\vdots$ y_{h1} y_{h2} ... y_{hM}
This part assigns machines to cells	This part represents the x components of machines	This part represents the y components of machines

Fig. 4. Detailed view of the chromosome structure.

The considered chromosome for the first second of this problem includes a matrix with H rows and N columns. Its detailed structure related to parts alignment to part families is shown in Fig. 5.

$$\begin{matrix} Z'_{11} & Z'_{12} & ... & Z'_{1M} \\ \vdots & \vdots & & \vdots \\ Z'_{h1} & Z'_{h2} & ... & Z'_{hM} \end{matrix}$$

Fig. 5. Detailed view of the chromosome structure

4-3 Obtaining the primary solutions

The elements of matrix Z are obtained randomly from within the numbers of 1 to C. The elements of matrices X and Y are selected in a way that machines are not overlapped; in this way, numbers of a column from X and Y are not simultaneously equal to another column of X and Y. The elements of matrix z' are also obtained randomly from within the numbers of 1 to C.

4-4 Genetic operators

A genetic operator is used to produce a new generation of offspring.

4-4-1. Mutation

In the proposed GA, in sections of machine assignment to manufacturing cells, five types of the operator are used simultaneously. These operators are as follows:

- *Machine relocation in cells:* This operator is on matrix *Z,* that is, substituting two numbers from two columns in a row of matrix *Z*.
- *Relocation of two machines:* This operator is on matrices *X* and *Y* simultaneously. Selecting two columns from a row of matrices *X* and *Y* and substituting the numbers of these columns in the same row, the location of those machines in considered period will change.
- *Relocation and cell change of two machines:* This operator is on matrices *Z, X* including two previous operators simultaneously.
- *Approaching one machine to another:* This operator is on matrix *X* or *Y*. One of the columns from matrix *X* or *Y* is selected and changes to the numbers of another column from the same matrix with one unit difference.
- *Assigning the machines with more flow to a single cell:* This operator is on matrix *Z*. With respect to the numbers of flow matrix, machines with more relations are assigned to a single cell.

In the section concerning part assignment to part families in this algorithm, substitution of two numbers from two columns of a row in matrix Z' is done.

In both parts of the solution view in this algorithm, the selected crossover means substitution of a part of a row from parent with the same part of the same row of another parent and generation of two offspring similar to the two parents.

4-4-2.Crossover

In the crossover operator, two individuals are randomly chosen to act as parents so as to create one or more offspring. There are different methods to combine variable values of given parents. The current study applies parameterized uniform crossover. It selects the first parent amongst the best individuals in the population, while the other one is chosen from the whole population, randomly. Then, a real random number at the interval [0,1] for each row is produced. If the random number is larger than a predetermined threshold value, called crossover probability (CProb), then the allele of the first parent is applied. Otherwise, the allele of the second parent is applied to the offspring generation. An example process of crossover is provided in Fig. 6.

In this example, offspring 1 inherits the gene of parent 1 with probability of 0.5 and inherits the gene of parent 2 with probability of 0.5.
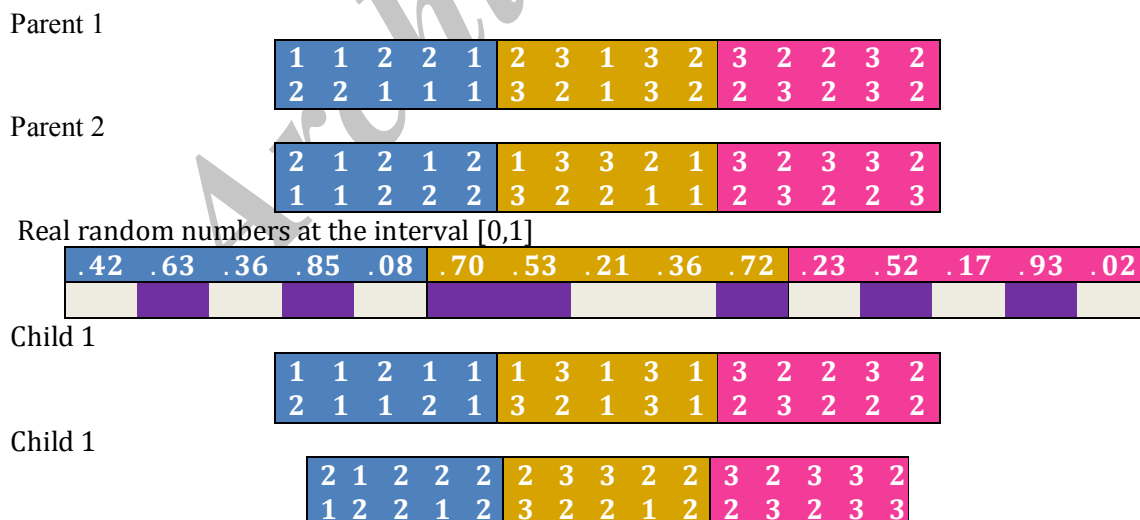
Parent 1

Parent 2

Real random numbers at the interval [0,1]

Child 1

Child 1

Fig. 6. Example process of the crossover

4-5. Selecting the next generation

Selecting the parents for producing next generation plays a major role in the genetic algorithm. The aim is to select the best chromosomes (i.e., the solutions that are better than others) for entering to the next generation or producing new generation. Generally, each chromosome with a particular probability has

an opportunity to produce or enter to the next generation. Therefore, chromosomes with high fitness should have more probability to be selected. Several methods have been proposed for selecting the next generation that are in two categories: probabilistic and non-probabilistic. Probabilistic methods contain roulette wheel selection, scaling, and grouping. Non-probabilistic methods include competitive selection and elite models. Roulette wheel mechanism is used in this study. In this method, members are selected based on their relative consistency. In other words, a roulette wheel method selects the next generation's members to the number of population, giving more probabilities to more appropriate chromosomes and generating the random number between zero and one.

4-6. Criterion for evaluating chromosomes
The fitness function is an implication of the objective function. In the GA, the fitness value for each chromosome is equivalent to the value of the objective function for a solution. For instance, if the objective in a cellular manufacturing problem is to minimize the sum of costs according to the problem model, an offspring will be acceptable when it more minimizes the cost function relative to its parents. Also, in this problem, fitness for each chromosome is calculated based on an objective function.

4-7. Stopping condition
To stop the GA and present a final solution, stopping criterion should be considered. The stopping criteria that are mainly used are as follows:

- The maximum specified numbers of generation: if the number of generations passes the maximum specified numbers of generation, algorithm will end.
- Convergence of population: in broad terms, GA attempts to converge the population to a single population. If the current population converges to a single solution, algorithm will end.
- Reaching a specified solving time.

The criterion of the maximum specified numbers of the generation is used here.

5. Particle Swarm Optimization (PSO)
PSO is an evolutionary computation technique developed by Kennedy and Eberhart [39]. This particle swarm concept was inspired via social behavior of bird flocking and fish schooling. The social behavior is modelled as a PSO algorithm to guide a population. This population consists of a set of particles moving towards the most promising region of the search space which is called swarm. The general procedures of PSO are as follows:

5-1. Initialization
A population (A) of potential solutions is randomly generated which is called particles, and each particle is assigned to a randomized velocity. The population size is dependent on the problem.

5-2. Evaluating and updating the best positions
The desired optimization fitness function is computed as follows:
- Compare the fitness of each particle with its best position, if the current is better, update the best position.
- Compare the best position of each particle with the best global one, if the best position is better, update the best global one.

5-3. Velocity update
The particles are flown through a hyperspace via updating their own velocities. The velocity update of a particle is dynamically adjusted based on its own past best path and those of its companions. Furthermore, the particle updates its velocity and position by the following equations:

$$\begin{bmatrix} V_{id}^{new} = W \times V_{id}^{old} + c_1 \times rnd_1 \times \left(P_{id} - X_{id}^{old} \right) \\ + c_2 \times rnd_2 \times \left(P_{gd} - X_{id}^{old} \right) \end{bmatrix} \quad (22)$$

$$X_{id}^{new} = X_{id}^{old} + V_{id}^{new} \quad (23)$$

where V_{id}^{new} is the particle new velocity, V_{id}^{old} represents the current particle velocity, P_{id} shows the best previous position of particle i in dimension d, and P_{gd} is the best position in dimension d found by all particles till now. W indicates the inertia weight; c_1 and c_2 are

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learning factors. X_{id}^{new} is the new particle (solution) position, and X_{id}^{old} is the current particle position in the d-th dimension. rnd_1 and rnd_2 are random numbers between 0 and 1 which indicate the stochastic element of the PSO.

In this paper, the Taguchi experimental design method, as explained before in section 5.1, is applied to calibrate the parameters of PSO according to Table 2. Fig. 7 shows the level of control factors versus control factors. A larger value of the S/N ratio in the graphs is more desirable.

Tab. 2. Considered levels of parameters of PSO

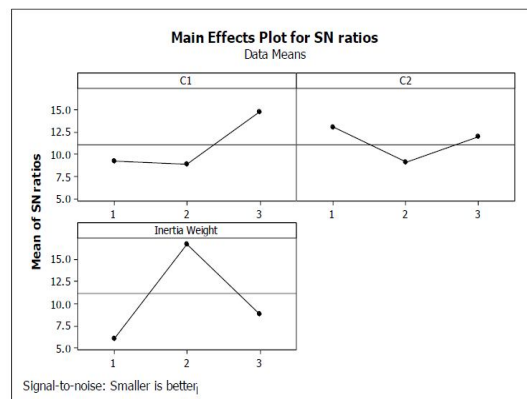|	Parameter	Level 1	Level 2	Level 3
PSO	C_1	1	1.5	2
	C_2	1	1.5	2
	Inertia weight	0.3	0.6	0.9

Fig. 7. Mean S/N ratios for the proposed PSO

5-4. Termination

Stop the algorithm if the stopping criterion is met; otherwise go to second step (5.2). In this paper, the stopping criterion is set when reading the maximum number of iterations.

6. omputational Results

In this section, in order to validate the proposed model, a numerical instance is represented and solved through GAMS. The information of the problem is given in Tables 3-5.

Tab. 3. Process of generating parameters for the problem

Parameters	value
B_j	U[10,30]
m	5
n	8
C_{intra}^{j}	U[5,10]
C_{inter}^{j}	U[20,40]
E	6
F	6
NM	4
$C_i = U[5000,7000]$	

After two hours of lunching the program, the solution has been obtained. In the first period, machines 1, 2, and 5 and parts 1, 2, 3, 5, and 8 are relocated in cell 1 and machines 2 and 4 and parts 4, 6, and 7 are relocated in cell 2. In the second period, machines 2 and 4 are relocated in cell 1 and machines 1, 3, and 5 are relocated in cell 2. In this period, parts 7, 2, and 8 are relocated in cell 1 and parts 1, 3, 4, 5, and 6 form the part family of cell 2. Layouts for machines are illustrated in Figs. 8 and 9. The special features of this algorithm make us

unable to consider this algorithm as a simple

random searcher.

Tab. 4. Demand of parts in the first and second periods

Part number	Demand of period 1 (D_{i1})	Demand of period 2 (D_{i2})
1	325	110
2	298	378
3	129	429
4	316	316
5	409	402
6	521	109
7	580	571
8	180	362

Tab. 5. Reliability information for machines

Machine	λ	Breakdown Cost
1	0.0239	1000
2	0.0317	1200
3	0.0204	1500
4	0.0018	1400
5	0.0112	1000
6	0.0264	1300
7	0.0029	1200
8	0.0175	1100

The part-machine matrix of the problem is given below, in which the average of operation for this matrix is set to 3.

$$
\begin{array}{c|cccccccc}
 & p_1 & p_2 & p_3 & p_4 & p_5 & p_6 & p_7 & p_8 \\
\hline
M_1 & 0 & 0 & 1 & 3 & 0 & 1 & 2 & 0 \\
M_2 & 3 & 2 & 0 & 0 & 0 & 2 & 1 & 3 \\
M_3 & 2 & 0 & 2 & 0 & 2 & 3 & 0 & 0 \\
M_4 & 0 & 1 & 3 & 1 & 1 & 0 & 0 & 2 \\
M_5 & 1 & 3 & 0 & 2 & 3 & 0 & 3 & 1 \\
\end{array}
$$

Machine-part matrix for problem 5×8
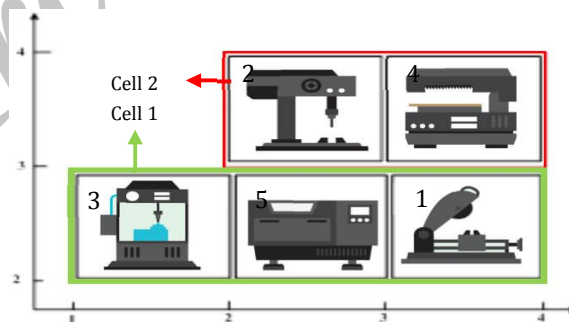
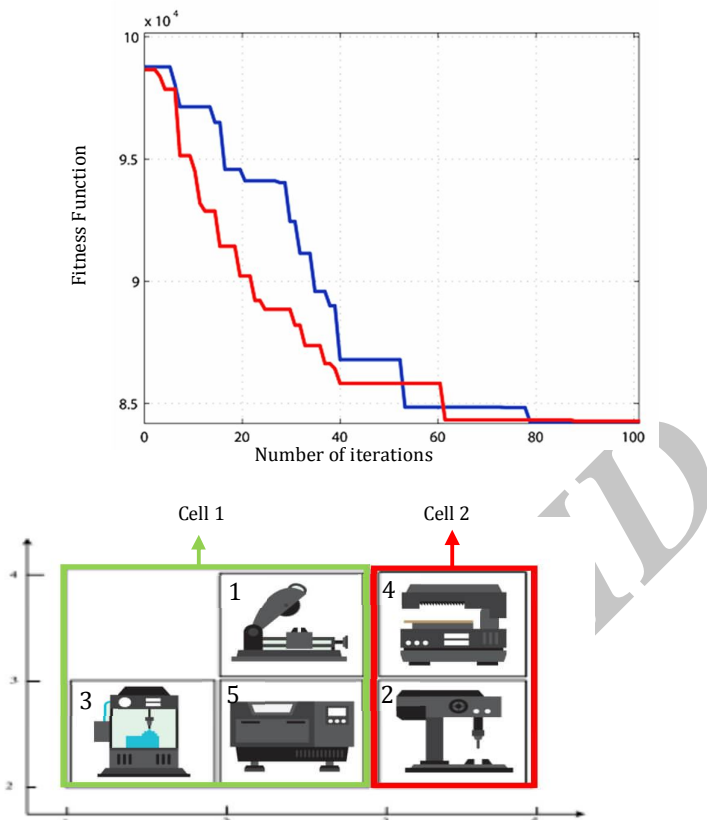**Fig. 8. Designed by solving the model in the first period**

Fig. 9. Designed by solving the model in the second period

7. Comparison of the Results

The proposed GA is coded by Visual Basic (VB) and run by a Pentium 4 personal computer (PC). The number of populations, number of replications for generations, mutation rate, and crossover rate for the proposed GA are considered 20, 100, 0.25, and 0.85, respectively. After two hours, the GA stops and the best obtained solution is reported. The number of cells for the problems with 3 to 7 machines is considered 2 and also considered 3 for the problems with 8 to 13 machines. In order to demonstrate the efficiency of our proposed GA, several small/medium- and large-sized problems are resolved via PSO and GAMS. Gap between the results, shown in Table 6, is calculated by:

$$\text{Gap} = \frac{|\text{Obj}_{\text{Meta-heuristic}} - \text{Obj}_{\text{solution.best}}|}{|\text{Obj}_{\text{solution.best}}|} \times 100$$

where $\text{Obj}_{\text{solution.best}}$ denotes the optimal solution of the mathematical programming model if it exists; otherwise; it is the best solution obtained from all meta-heuristic runs.

$\text{Obj}_{\text{Meta-heuristic}}$ shows the best obtained solution by each method.

For better understanding the differences between meta-GA, PSO, and GAMS, Fig. 10 represents the relative gap between the GA and PSO solutions, and Fig. 11 indicates fitness function trend lines; finally, Fig. 12 represents the growth of computational time for different method solutions. Considering these values, it can be concluded that GAMS solver cannot find feasible solutions to the large-sized problems. Furthermore, the proposed GA can obtain better solutions in shorter time in comparison with PSO.
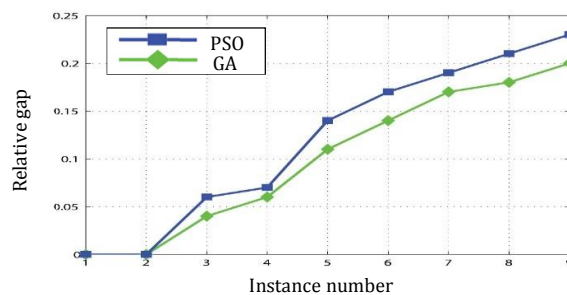

Fig. 10. Relative gap between the GA and PSO solutions

Tab. 6. Comparison of the obtained results

Dimensions of problem	Average of 10 genetics	Optimum Genetics	Time of Genetic	Gap_{GA}	Average of 10 PSO	Optimum PSO	Time of PSO	Gap_{PSO}	Solution of GAMS	*Time of B&C*
3*5	24283.36	24283.36	20.19	0	24283.36	24283.36	23.14	0	24283.36	18.99
4*6	28641.74	28641.74	27.11	0	28641.74	28641.74	30.09	0	28641.74	64.43
5*8	85620.59	84180.59	22.30	0	87520.01	84180.59	25.17	0	84180.59	201.71
6*9	120903.94	119046.75	35.17	0	121826.69	119058.65	35.15	0.01	119046.75	836.62
7*11	224095.13	218951.06	44.01	0.02	256011.10	218994.84	44.37	0.04	218907.28	1872.19
8*13	497882.65	476416.88	68.74	0.08	500284.22	476416.88	69.01	0.08	476036.01	3315.21
10*12	706813.47	694902.16	78.01	-	709804.19	695944.51	80.10	0.15	-	3600
11*13	972491.55	952906.25	90.51	-	993901.01	954716.77	91.01	0.19	-	3600
12*15	120265.16	120094.02	108.17	-	121147.33	120370.23	109.09	0.23	-	3600

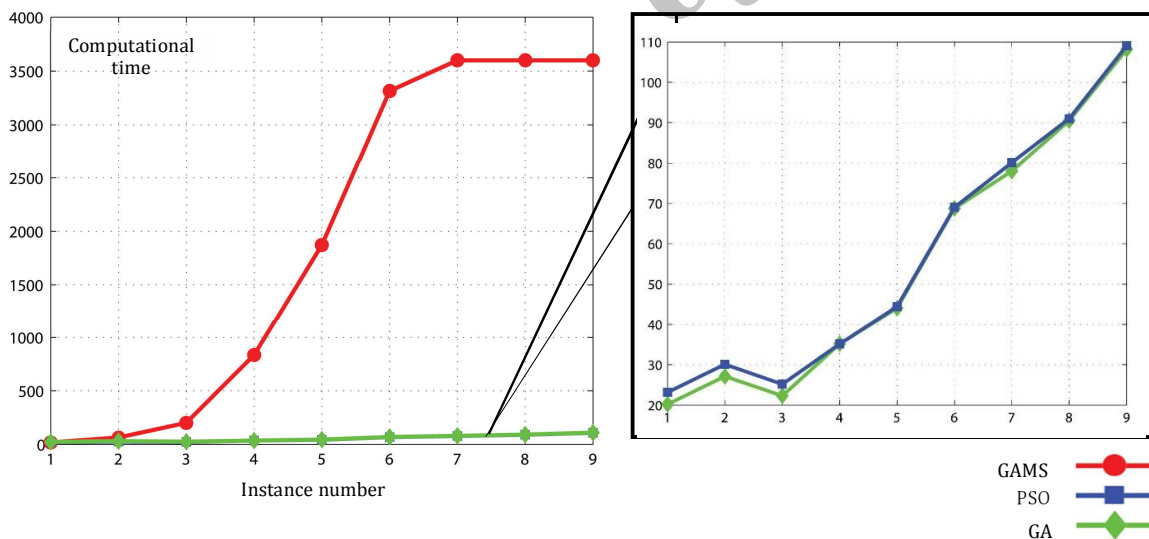*Time is based on seconds

Fig. 9. Growth of computational time for different method solutions

8.   Conclusion and Future Research

In this study, a new non-linear mixed integer programming model was proposed which considered the simultaneous cell formation and inter/intra cell layouts in continuous space in a dynamic environment. In the proposed model, machines were considered unreliable with an exponential distribution time between failures.

The purpose of the model was to determine the cell formation and the intra and inter-cell layout concurrently in a way that the total transportation cost of parts, the total breakdown cost, the reconfiguration cost of cells, and the number of EEs were minimized. The proposed model attempted at calculating the material handling costs realistically. The material

handling cost was obtained on the basis of the actual location of machines and cells on the shop floor regarding dimensions of equal-sized machines. Handling both inter- and intra-cellular materials using batch sizes for transferring parts was taken into account for calculating the transportation cost. The transportation cost is calculated on the basis of the distance traveled according to center-to-center interval among machines through a rectilinear distance. Furthermore, in the presented model, cells were configured in flexible shapes during the planning horizon considering the capacity of cells in each period. Due to NP-hardness of the problem, a genetic algorithm was then developed. The performance of GA was then demonstrated via comparing the results with those of PSO and GAMS considering several small/medium- and large-sized problems with respect to the computational time and objective value. The results demonstrated that the proposed GA could find better solutions in shorter time in comparison with PSO. In addition, finding the exact solution of the problems with more than 13 machines via GAMS solver is impossible. For future research, the following areas can be attractive and the present study can provide the necessary background for researchers who seek to work in these areas:

- Considering multi-operational paths in the model can provide a model close to the real situation of job shop; in the presented model, the operational paths are considered constant.
- Considering unequal dimensions for machines, in the proposed model, machines are considered as squares of equal area with unit dimension. In order to obtain more appropriate schema from the space of a job shop, dimensions of machines can be considered as input parameters.
- Developing probabilistic models and fuzzy models factors (e.g., available machines, operation time, costs, transportation time, and demand for each part) can be considered as fuzzy or probabilistic.
- Incorporating production data such as setup times and holding inventory between periods and also integrating the proposed

model with scheduling problem can make the model more realistic.

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