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A bi-objective Optimization Model for a Dynamic Cell Formation Integrated with Machine and Cell Layouts in a Fuzzy Environment

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ABSTRACT

In this paper, a bi-objective optimization model is developed to integrate the cell formation and inter/intra-cell layouts in continuous space by considering fuzzy conditions to minimize the total cost of parts relocations as well as cells reconfigurations. The intra- and inter-cell movements for both parts and machines using batch sizes for transferring parts are related to the distance traveled through a rectilinear distance in a fuzzy environment. To solve the proposed problem as a bi-objective mixed-integer non-linear programming model is NP-hard, four meta-heuristic algorithms based on a multi-objective optimization structure are tackled to address the problem. In this regard, not only Genetic Algorithm (GA), Keshtel Algorithm (KA) and Red Deer Algorithm (RDA) are employed to solve the problem, but also a novel hybrid meta-heuristic algorithm based on the benefits of aforementioned algorithms is developed. Finally, by considering some efficient assessment metrics of Pareto-based algorithms, the results indicate that the proposed hybrid algorithm not only is more appropriate than the exact solver but it also outperforms the performance of individual ones particularly in medium- and large-sized problems.

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Cellular manufacturing system; cell formation; inter/intra-cell layout; Pareto-based algorithms; hybrid meta-heuristic algorithm

1. Introduction and Literature Review

The facility design is a significant requirement in the field of manufacturing systems engineering. Approximately, $250 billion is spent annually in the U.S for the facility designing, planning, and re-planning [1–3]. Also, it is estimated that around 20–50% of the total cost of manufacturing systems is attributed to material handling. The same source also reports that effective planning can reduce such costs by over 10–30% [4–7]. Minimizing material movements may be among the initial reasons for developing a Cellular Manufacturing System (CMS) [5–8]. In general, the CMS based on Group Technology (GT) is an approach to apply the advantages of both flexible and mass production properties. The main role of the CMS is to assign a number of parts and machines to each other to produce some cells on the

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basis of their similarities in the production process, design and geometrical characteristics comprehensively [1,7–9].

Recent decades have seen a great deal of interest in employing different applications of CMSs. There are numerous advantages of using the CMS included but not limited to reduce the material transferring cost, the setup time, the delivery time, the lot size and the amount of the Work-In-Process (WIP) inventory. Another main benefit is to better cause the supervisory control and the improvement of the product quality and productivity [9–11]. These benefits can be accrued only if a cell configuration and a scheduling system of a CMS are effectively designed. One of the crucial steps in designing a CMS is the Cell Formation (CF) problem as a well-known work extensively studied in the literature [10–13]. Given a definition of a CF, it involves two fundamental tasks (i.e. part-family formation and machine-cell formation) to minimize some objectives, such as the inter- and intra-cell movements. As indicated by these factors, the Exceptional Elements (EEs) are a common issue in a CMS of manufacturing environments recognized as the major obstacle in the cell formation and its scheduling processes [12–15]. An EE can be defined generally as a product that needs to be produced in more than one cell and causes inter-cell transfer of materials. In conclusion, a well-known objective in a CF problem is to minimize the number of EEs. There are also other common objectives involving the minimization of the inter-cell material handling cost as well as the materials flow.

The facility layout is also a key element in designing a CMS considering the layout of machines within cells (intra-cell layout) and the layout of cells (inter-cell Layout) on the shop floor. An efficient facility layout can reduce the material handling cost, work-in-process, and throughput rate [13–17]. A competent layout not only enhances the system performance but also minimizes around 40–50% of the production costs on average [16–19]. Although minimizing the number of EEs or other common objectives (e.g. minimization of inter-cell movement cost) may reduce flows between cells, they do not necessarily lead to a minimum of the material handling cost since the real parameters related to the facility layout problem are ignored in the calculation of these objectives. Hence, incorporating the facility layout problem in the CMS design process is of high significance. However, the layout design in a CMS has not paid much attention since most of the relevant research only investigates the CFP [20–24]. As stated in Alfa et al. [2], facility layout and CF decisions are interrelated and tellingly addressing them simultaneously is important for the successful CMS design. However, each of these decisions is proven to be complex [21–25]. As a result, the simultaneous addressing of these decisions is a difficult issue.

There are some new trends (e.g. the reliability of CMS) in recent studies. Most of them either investigate some of these decisions or handle all of them, but in a sequential fashion [24–28]. On the other hand, a majority of approaches in the area of facility layout and CF problems to ease of making mathematical formulation usually consider the minimization of the number of inter- or intra-cell movements or both [26–29]. Accordingly, to minimize the material handling cost, the exact information about the facility layout design in addition to the notion of distance must be considered. Moreover, those approaches that aim at minimizing the material handling cost usually apply unrealistic assumptions, such as the fixed cells and machines locations in the layout problem. Based on this drawback, the layout may be inefficient. As such, for locating the machines in the manufacturing cell space, the line formed locations are the only consideration and the machines are assigned to these positions in the majority of previous studies. As it may be evident, if assigning the number of machines to a cell cannot be a line formed, it turns into a U-form imposing additional costs to the system [29–35].

Considering different real-life constraints and practical assumptions make the model difficult to solve. Due to decisions of the proposed system as a type of tactical and operational levels, the computational cost is very important for the decision-makers of a CMS to be less. Therefore, efficient solution algorithms are needed to address this dilemma. Meta-heuristics are the popular feasible alternatives to solve this complicated problem form the literature [33–39]. As one of the NP-hard problems, this chance even with low possibility always exists for a new meta-heuristic algorithm to better solve such a complicated model to get a near-optimal solution in less time [35–40]. This reason motivates several researchers to employ different types of meta-heuristics in this research area [37–43]. To cover the limitations of several meta-heuristics employed in the literature, this study not only uses Genetic Algorithm (GA) [27] as a well-known in the field and two recent meta-heuristics, namely, Red Deer Algorithm (RDA) [18] and Keshtel Algorithm (KA) [29] but also develops a new hybrid meta-heuristic algorithm to consider the benefits of these individual algorithms.

Given a general view of other sections of this paper, its remaining is structured as follows. Problem definition and formulation is discussed in Section 2. The proposed solution approaches including GA, RDA, KA and the developed hybrid meta-heuristic algorithm are given in Section 3. Computational results and analyses of the algorithms are explored in Section 4. Finally, concluding remarks and future research directions are provided in Section 5.

2. Proposed Model

The aim of this model is to determine concurrently the formation of cells, the layout of machines inside cells and the layout of cells on the shop floor in dynamic conditions in a way that the total transportation cost of parts and reconfiguration cost of cells and the number of EES are minimized. The proposed mixed-integer non-linear programming model with a number of assumptions, parameters, and decision variables are discussed below.

2.1. Assumptions

- The flow between machines in each period is determined. This number is obtained from the parts demand and parts operational paths as well as the batch size of parts transportation.
- The parts are moved within the batches, in which the largeness of the batches per product is known and constant for all periods. In addition, the size of the part batches is assumed the same for both inter and intra-cell relocations.
- The material handling cost is calculated according to center-to-center distance between machines through a rectilinear distance.
- The material handling cost of inter and intra-cell movements for both parts and machines is related to the distance traveled.
- The unit cost of inter and intra-cell movements for each part type is predetermined and remain the same planning horizon.
- The unit cost of machine relocation during the periods is constant and predetermined for each machine type. This cost includes opening, transferring, and resetting the machine.

- The number of cells to be formed in each period is determined in advance. This predetermined number of cells in the system is on the basis of the expected workload in each cell. However, the shape of the cells is not predetermined and cells are flexibly configured during the planning horizon.
- There is only one number of each machine type.
- The maximum capacity of cells is known and remains the same planning horizon.
- Machines are considered as squares of equal area and hence supposed to have a unit dimension. It is examined that the proposed considerations provide a suitable approximation to the real-world conditions where machines are not exact squares or rectangles [41–47]. The cells are considered in a rectangular shape.
- There is no excess inventory between the periods, delayed orders are not allowed and demands per period must be supplied in that period.
- The efficiency of machines and production is assumed to be 100%.

In the following section, the sets, parameters and decision variables of the proposed model are presented. It should be noted that the tilde sign ($\sim$) is utilized for fuzzy parameters as one of the main innovations of this study in this field.

Sets:

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

Parameters:

$\widetilde{D_{jh}}$	Demand for part type j in period h
B_j	Largeness of batch for the transportation of part type j
$\widetilde{C^{j}_{intra}}$	Intra-cell material handling cost for transporting part j per unit distance (\$/unit)
$\widetilde{C^{j}_{inter}}$	Inter-cell material handling cost for transporting part j per unit distance (\$/unit)
$\widetilde{C_i}$	Relocation cost of machine i(\$/unit)
R_{ij}	Operation number done on part j using machine i
E	Horizontal length of the shop floor (i.e. length of the shop floor)
F	Vertical length of the job shop (the width of the shop floor)
SP	Set of pairs (i, j) such that $a_{ij} \geq 1$ (the set of non-zero elements of a part-machine matrix)
NM	Maximum number of machines relocated in each cell per period.
N	Appropriate large positive number
A_{kl}, B_{kl}	Zero and one random variables
$A_{ii'h}, B_{ii'h}$	Zero and one random variables
$f^{j}_{ii'h}$	Number of trips for moving part type j between machines i and i' in period h

$$f^{j}_{ii'h} = \begin{cases} [\widetilde{D_{jh}}/B_j] \; if \; R_{i'j} - R_{ij} = 1 \\ 0 \; if \; R_{i'j} - R_{ij} \neq 1 \end{cases} \tag{1}$$

Decision variables:

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

Otherwise

$Y_{jkh} = \begin{cases} 1 \\ 0 \end{cases}$ If part j is assigned to cell k in period h

Otherwise

$Z_{ih} = \begin{cases} 1 \\ 0 \end{cases}$ If machine i relocates during periods h and $(h + 1)$

Otherwise

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

Otherwise

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

Otherwise

x_{ih} Horizontal coordinate of the center of machine i in period h
y_{ih} Vertical coordinate of the center of machine i in period h
p^1_{kh} Horizontal coordinate of the left side of cell k in period h
p^2_{kh} Horizontal coordinate of the right side of cell k in period h
q^1_{kh} Vertical coordinate of the bottom side of cell k in period h
q^2_{kh} Vertical coordinate of the top side of cell k in period h

Therefore, the relocation cost of part j between machines i and i′ in period h, regarding inter-cell or intra-cell movement can be determined below:

If $X_{ikh}, X_{i'kh} > 0$, this cost equals to Equation (2) as follows:

$$\widetilde{C^j_{ii'h}} = (|x_{ih} - x_{i'h}| + |y_{ih} - y_{i'h}|)\widetilde{C^j_{intra}} \tag{2}$$

If $X_{ikh}.X_{i'kh} = 0$ and$X_{ikh}.X_{i'k'h} > 0$, this cost equals to Equation (3) as follows:

$$\widetilde{C^j_{ii'h}} = (|x_{ih} - x_{i'h}| + |y_{ih} - y_{i'h}|)\widetilde{C^j_{inter}} \tag{3}$$

2.2. Mathematical Formulation

With respect to input parameters and variables, the presented nonlinear model for this problem is as follows:

$$\text{Min} \sum_{h=1}^{H} \sum_{j=1}^{n} \sum_{i=1}^{m} \sum_{i'=1}^{m} f^j_{ii'h} \widetilde{C^j_{ii'h}} + \sum_{h=2}^{H} \sum_{i=1}^{m} \widetilde{C}_i Z_{ih} \tag{4}$$

$$\text{Min}\sum_{h=1}^{H}\sum_{k=1}^{C}\sum_{(i,j)\in sp}\frac{(U_{ijk}+V_{ijk})}{2} \tag{5}$$

s.t.

$$\sum_{k=1}^{C}X_{ikh}=1, i=1,2,\ldots,m,\forall h \tag{6}$$

$$\sum_{k=1}^{C}Y_{jkh}=1, j=1,2,\ldots,n,\forall h \tag{7}$$

$$1\leq\sum_{i=1}^{m}X_{ikh}\leq NM, k=1,2,\ldots,C,\forall h \tag{8}$$

$$NZ_{ih}\geq|x_{ih}-x_{i(h+1)}|+|y_{ih}-y_{i(h+1)}|\forall i,h<H. \tag{9}$$

$$|x_{ih}-x_{i'h}|+|y_{ih}-y_{i'h}|\geq 1 \tag{10}$$

$$\begin{cases}x_{ih}\geq p^1_{kh}-N(1-X_{ikh})\\ x_{ih}\leq p^2_{kh}+N(1-X_{ikh})\\ y_{ih}\geq q^1_{kh}-N(1-X_{ikh})\\ y_{ih}\leq q^2_{kh}+N(1-X_{ikh})\end{cases}\forall i,k,h \tag{11}$$

$$\begin{cases}p^1_{kh}\geq 0\\ q^1_{kh}\geq 0\\ p^2_{kh}\leq E\\ q^2_{kh}\leq F\end{cases}\forall k,h \tag{12}$$

$$\begin{cases}p^1_{kh}-p^2_{lh}+NA_{kl}+NB_{kl}\geq 0\\ p^2_{kh}-p^1_{lh}-NA_{kl}-N(1-B_{kl})\ \leq\ 0\\ q^1_{kh}-q^2_{lh}+N(1-A_{kl})+NB_{kl}\geq 0\\ q^2_{kh}-q^1_{lh}-N(1-A_{kl})-N(1-B_{kl})\ \leq\ 0\\ 0\leq k<l\leq C\end{cases} \tag{13}$$

$$X_{ikh},Y_{jkh},Z_{ih},U_{ijkh},V_{ijkh}=0\text{ or }1 \tag{14}$$

$$x_{ih},y_{ih},p^1_{kh},p^2_{kh},q^1_{kh},q^2_{kh}\ \geq\ 0\text{ and Integer} \tag{15}$$

The first objective function represents the intra- and inter-cellular material transferring costs. The following term denotes the cells reconfiguration cost that may vary from period to period. The second objective function correlates with minimizing the number of exceptional parts. The coefficient of 1\2 in this relationship is due to the double calculation of decision variables when there are equal to 1. Constraint (6) guarantees that each machine allocated to only one cell. Constraint (7) shows that each part is allocated to a part family. The number of machines in a single cell is limited by Constraint (8). Constraint (9) shows that by relocating machine type i during periods h and $(h+1)$, variable Z_{ih} equals 1. Constraint

(10) according to the machine dimension is assumed to be 1×1, causes the machines do not overlap. Constraint (11) makes that each machine will be inside its corresponding cell space. Constraint (12) shows that the cells are placed inside the job shop space. Constraint (13) shows that the cells do not overlap. Constraints (14) and (15) determine the type of problem variables.

2.3. Proposed Fuzzy Circumstances

In this section, the mathematical model presented in this paper is a mixed-integer programming model. Since an inevitable factor is inevitable in the real world of uncertainty, most of the parameters used are considered triangular fuzzy numbers because of their uncertain nature. In general, the fuzzy programming problem must first be transformed into a definite equivalent problem and then solved with standard methods and the optimal answer is obtained. As a result, the final solution to the problem is obtained with respect to the fuzzy structure of the problem.

In the following section, a two-step approach is used to solve the model. In the first step, the proposed model with fuzzy parameters is transformed into a certain auxiliary model by a method proposed by Khimens et al. [48]. In the second stage, we solve the multi-objective certain model by using the Torabi-Hosseini method [49], which was obtained in the first stage. Khimens et al. [48] presented a method for ranking fuzzy numbers. In this method, defining the fuzzy parameters of the objective functions is calculated based on the concepts of the expected distance and the expected value for triangular fuzzy numbers $\tilde{C} = (C^p, C^m, C^o)$ based on the following relations.

$$EI(\tilde{C}) = [E_1^c, E_1^c] = \left[\int_0^1 f_c^{-1}(x)d_x, \int_0^1 g_c^{-1}(x)d_x\right] = \left[\int_0^1 (x(c^m - c^p) + c^p)d_x\right]$$
$$= \left[\int_0^1 (x(c^o - c^m) + c^o)d_x\right] = \left[\frac{1}{2}(c^p + c^m), \frac{1}{2}(c^m + c^o)\right] \tag{16}$$

$$EV(\tilde{C}) = \frac{E_1^c + E_1^c}{2} = \frac{c^p + 2c^m + c^o}{4} \tag{17}$$

Based on Khaminz's method, we consider Equation (19) for Constraint $(\tilde{a}_i X \geq \tilde{b}_i; i = 1, 2, \ldots, l)$.

$$\left(\alpha \frac{a_i^o + a_i^m}{2} + (1-\alpha).\frac{a_i^p + a_i^m}{2}\right) X \geq \left(\alpha \frac{b_i^o + b_i^m}{2} + (1-\alpha).\frac{b_i^p + b_i^m}{2}\right) \tag{18}$$

For equal constraints $(\tilde{a}_i X = \tilde{b}_i; i = 1, 2, \ldots, l)$, we convert into the certain equivalent constraints as represented by:

$$\left(\frac{\alpha}{2}.\frac{a_i^o + a_i^m}{2} + \left(1 - \frac{\alpha}{2}\right).\frac{a_i^p + a_i^m}{2}\right) X \geq \left(\frac{\alpha}{2}.\frac{b_i^o + b_i^m}{2} + \left(1 - \frac{\alpha}{2}\right).\frac{b_i^p + b_i^m}{2}\right) \tag{19}$$

$$\left(\left(1 - \frac{\alpha}{2}\right).\frac{a_i^o + a_i^m}{2} + \frac{\alpha}{2}.\frac{a_i^p + a_i^m}{2}\right) X \geq \left(\left(1 - \frac{\alpha}{2}\right).\frac{b_i^o + b_i^m}{2} + \frac{\alpha}{2}.\frac{b_i^p + b_i^m}{2}\right) \tag{20}$$

After defuzzifying by the help of Equation (17), the membership function for the minimization objective function is obtained using Torabi-Hessian's method of Equation (21).

$$\mu_F = \begin{cases} 1 \; if \; Z < Z^{\alpha-PIS} \\ \dfrac{Z^{\alpha-NIS} - Z}{Z^{\alpha-NIS} - Z^{\alpha-PIS}} \; if \; Z^{\alpha-PIS} < Z < Z^{\alpha-NIS} \\ 0 \; if \; Z > Z^{\alpha-NIS} \end{cases} \tag{21}$$

Then, the membership function for the maximization objective function is obtained by:

$$\mu_F = \begin{cases} 1 \; if \; Z > Z^{\alpha-PIS} \\ \dfrac{Z^{\alpha-NIS} - Z}{Z^{\alpha-PIS} - Z^{\alpha-NIS}} \; if \; Z^{\alpha-NIS} \le Z \le Z^{\alpha-PIS} \\ 0 \; if \; Z > Z^{\alpha-NIS} \end{cases} \tag{22}$$

where the positive ideal solution $(\alpha - PIS)$ and the negative ideal solution $(\alpha - NIS)$ for each objective function and at the level of feasibility (α). In the following section, we aim to present the proposed solution algorithms for solving the developed model.

3. Proposed Solution Algorithm

As stated in [36], the CMS scheduling models are non-polynomial time hard (NP-hard) problems that are difficult to solve using different types of exact methods. In addition to its natural complexity, considering dynamic conditions increase its difficulty and combinatorial nature. Hence, meta-heuristic approaches should be employed to obtain a satisfying solution in a reasonable time. Several algorithms have been applied in the context of the DCMS design. One of the most popular algorithms is the Genetic Algorithm (GA). This motivates us to use the GA in this study based on the previous studies in the literature [50–55]. Due to a No Free Lunch theory, this chance for a new meta-heuristic algorithm always exists to reveal a better output in comparison with other existing algorithms [23]. In regards to this theory, this study employs two recent nature-inspired meta-heuristics including Keshtel Algorithm (KA) and Red Deer Algorithm (RDA) [56, 57]. At last but not least, the main innovation of this study is to propose a novel hybrid metaheuristic based on the advantages of the aforementioned algorithms. Here, first of all, due to the proposed multi-objective model, the structure of multi-objective optimization to be used in all algorithms is described. The next is the encoding plan of meta-heuristics and after that, the procedures of the proposed hybrid meta-heuristic algorithm are addressed in the following sub-sections. Note that since there is no innovation in the procedures of the GA, KA and RDA, individually, more explanation and details about these three algorithms are referred to their main papers [53–55,58–61].

3.1. Multi-objective Optimization

The proposed problem requires a trade-off between the objectives. In this case, the answer is a set of solutions, called Pareto-optimal solutions set. This set includes Pareto-optimal solutions, which explains the best trade-offs between the objectives. A solution dominates the other solution when it had better than in all objective functions [59–65]. Furthermore, the selection of the best solution in the first front of solutions is considered by calculating

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

Figure 1. General view of the solution representation.

$\begin{matrix} z_{11} & z_{12} & \cdots & z_{1M} \\ \vdots & \vdots & & \vdots \\ z_{h1} & z_{h2} & \cdots & z_{hM} \end{matrix}$	$\begin{matrix} x_{11} & x_{12} & \cdots & x_{1M} \\ \vdots & \vdots & & \vdots \\ x_{h1} & x_{h2} & \cdots & x_{hM} \end{matrix}$	$\begin{matrix} y_{11} & y_{12} & \cdots & y_{1M} \\ \vdots & \vdots & & \vdots \\ y_{h1} & y_{h2} & \cdots & y_{hM} \end{matrix}$
This part assigns machines to cells	This part represents the x components of machines	This part represents the y components of machines

Figure 2. Detailed view of solution representation in the first step.

the crowding distance between solutions. To get the Pareto-optimal solutions, we set a normal constraint method presented by [21].

3.2. Solution Representation

To show that how the constraints of the model will be handled by the presented solution algorithms, an encoding procedure is used to consider the solution representation in the format of a string-based presentation [64–66]. The solution can be a set of binary and integer numbers, matrices, or the combination of characters [67–69]. These ways are viewed to determine how a problem is formulated in the form of an algorithm and what operators of meta-heuristics are applied.

The first step of the proposed encoding procedure includes a matrix with H rows and M columns, which can be divided into the following sub-matrices.

- Sub-matrix of Z is related to the assignment of machines for manufacturing cells. This sub-matrix consists of H (i.e. the number of periods) rows and M (i.e. the number of machines) columns. Each element of this matrix is a number between 1 and C (i.e. the number of cells) and element Z_{ih} represents the number of cells including machine type i in period h.
- Sub-matrix X is related to the horizontal component of the 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 represent per horizontal and vertical components of the machines. Each element of this matrix is a number between 1 and E (i.e. the length of the job shop) and element x_{ih} represents the horizontal component of location involving machine i in period h.
- Sub-matrix Y is related to the vertical component of the 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. the width of the job shop) and element y_{ih}represents the vertical component of location involving machine i in period h.

Figures 1 and 2 illustrate the general and detailed views of the solution presentation of the algorithms related to the machines alignment for the manufacturing cells, respectively.

$$\begin{bmatrix} Z'_{11} Z'_{12} & & Z'_{1N} \\ \vdots \quad \vdots & \cdots & \vdots \\ Z'_{h1} Z'_{h1} & & Z'_{HN} \end{bmatrix}$$

Figure 3. Detailed view of the solution representation in the second step

The considered solution for the second step 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 Figure 3.

3.3. Proposed Novel Hybrid Meta-heuristic Algorithm (H-RDKGA)

As indicated from literature, the KA is very good at doing the exploitation action [56,70]. It seems that the swirling process can be done instead of two processes including roaring and fighting in RDA. Accordingly, for each male, the closest neighbor is specified and the swirling action is done. Due to the mating process, the GA mechanism is considered in this regard. Having a brief illustration, the KA is chosen as the intensification properties as well as the GA is measured the diversification phase. This opinion is employed to examine the proposed method with their individual methods and also other feasible alternatives for combinations. Given more details of proposed H-RDKGA, a pseudo-code is provided as seen in Figure 4.

4. Computational Results

A comparative study is presented in this section. First of all, to enhance the performance of employed metaheuristics and having a fair comparison, a full factorial design method is applied to tune the algorithms' parameters properly. After that, an extensive comparison among meta-heuristics based on different criteria is presented in the following sub-sections.

4.1. Tuning the Meta-heuristics

For tuning the parameters of the meta-heuristics, we use the Design of Experiment (DOE) method discussed in Montgomery [46]. The reason why we use this method compared to more efficient calibration techniques is that the method is simple and coarse [51–55,58,59] and hence, the direct impact of the algorithms on the problem solutions can be understood without the presence of a good calibration technique.

As given in the solution algorithm, the main parameters under consideration for the GA are the population size, maximum number of iterations, mutation and crossover rates. In the proposed KA, the population size, maximum number of iterations, the percentage of $N1$ and $N2$, maximum number of swirling are the key parameters. As such, the main parameters of the RDA are the population size, maximum number of iterations, number of males, and the rate of alpha, beta and gamma. At the last, the proposed parameters of the H-RDKGA are only the population size, maximum number of iterations, the number of males and the maximum number of swirling. We use the full factorial design to evaluate the different sets

```
Initialize the Red Deer population.
Calculate the fitness and sort them and form the hinds (N_hind) and male RDs (N_male).
Set the Pareto optimal frontier.
while (t< maximum number of iterations)
   for each male RD
     Calculate the distance between this male and all males.
     Select the closest neighbor.
     S=0;
     while (S< maximum number of swirling)
       Do the swirling.
       if the fitness of this new position is better than prior
         Update this lucky male.
           break
       endif
       S=S+1
     endwhile
   endfor
   Sort the males and also form the stags and the commanders.
   for each male commander
     Select a hind by roulette wheel selection.
     Mate (crossover) male commander with the selected hind.
    end for
   for each stag
     Select a hind randomly.
     Mate (crossover) stag with the selected hind.
   end for
   Select the next generation via roulette wheel selection.
   Update the Pareto optimal frontier
   t=t+1;
end while
Return the best non-dominated solutions
```

Figure 4. Pseudo-code of the H-RDKGA.

of values considered for conducting the DOE (given in Table 1). These ranges of values are decided based on the parameter settings provided in the literature [59–69].

4.2. Comparison among Employed Metaheuristics

This sub-section aims to probe the effectiveness and efficiency of the presented algorithms. Due to it, each meta-heuristic algorithm is performed in all the test problems for 30 times runs. In this case, the behavior of the algorithms in the two objective functions during 30 run times is considered. The behavior of the algorithms in terms of computational time is presented in Figure 5. As shown in this figure, the behavior of the algorithms is as the same overall. The proposed hybrid algorithm and KA show competitive results in this item. In general, the best algorithm in this criterion is KA. However, the worst behavior can be concluded from the RDA in most of the testes.

Finally, the average of outputs is saved and utilized to be evaluated by the assessment metrics of Prato-based algorithms. In this regard, Diversification Metric (DM), Spread of Non-dominance Solutions (SNS), Data Evolvement Analysis (DEA) and Percentage of Dominance (POD) are utilized. In all of them, a higher value brings a better capability of algorithms. The details about the evaluation metrics can be referred to some recent studies such as [65–69] Based on the calculation of these metrics, the outputs of the algorithms for test problems in medium and large sizes are noted in Table 2.

Table 1. Tuning the meta-heuristics.

Meta-heuristics	Parameters	Levels			Tuned value
GA	Population size	100	150	200	200
	Maximum No. of iterations	300	500	700	500
	Rate of mutation	0.05	0.15	0.25	0.15
	Rate of crossover	0.6	0.7	0.8	0.8
KA	Population size	100	150	200	100
	Maximum No. of iterations	300	500	700	300
	Percentage of *N*1	0.1	0.2	0.3	0.1
	Percentage of *N*2	0.4	0.5	0.6	0.6
	Maximum No. of swirling	5	10	15	10
RDA	Population size	100	150	200	150
	Maximum No. of iterations	300	500	700	700
	No. of males	15	25	30	25
	Alpha	0.5	0.6	0.7	0.6
	Beta	0.7	0.8	0.9	0.7
	Gamma	0.8	0.9	1	0.8
H-RDKGA	Population size	100	150	200	150
	Maximum number of iterations	300	500	700	500
	Number of males	15	25	30	30
	Maximum number of swirling	5	10	15	15

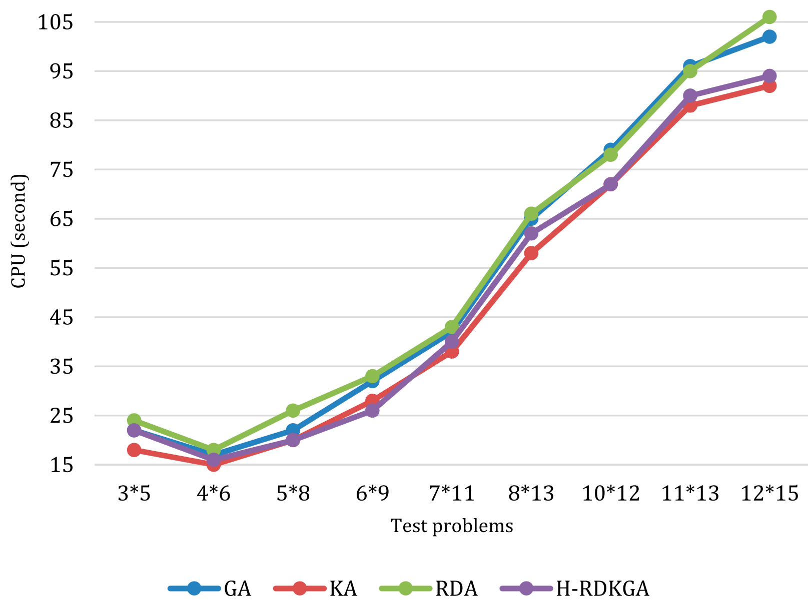

Figure 5. Behavior of algorithms in terms of computational time.

Later, the obtained results for each problem are converted to the Relative Percentage Deviation (*RPD*) computed by:

$$RPD = \frac{|Alg_{sol} - Best_{sol}|}{Best_{sol}} \tag{23}$$

where Alg_{sol} is the output of algorithm and $Best_{sol}$ is the best value ever found in the problem size. It should be noted that the lower value for the *RPD* is preferred.

Table 2. Evaluation metrics (i.e. DM, SNS, DEA and POD) to the performance of the algorithms.

	DM				SNS				DEA				POD			
Instances	GA	KA	RDA	H-RDKGA	GA	KA	RDA	H-RDKGA	GA	KA	RDA	H-RDKGA	GA	KA	RDA	H-RDKGA
3*5	14,962	14,389	16,452	16,765	2498	2267	1748	2699	0.18	0.16	0.12	0.15	0.16	0.22	0.14	0.22
4*6	17,641	17,275	19,743	18,746	6122	7210	5426	7495	0.20	0.12	0.18	0.12	0.18	0.18	0.19	0.21
5*8	8124	6833	7491	8945	7445	7296	6948	8155	0.24	0.22	0.26	0.18	0.22	0.20	0.10	0.18
6*9	34,685	29,164	34,112	35,647	3485	3105	2915	4039	0.28	0.14	0.22	0.14	0.15	0.14	0.11	0.16
7*11	13,418	12,742	13,671	14,289	2143	1834	7501	2867	0.16	0.26	0.18	0.16	0.17	0.18	0.16	0.12
8*13	24,914	25,199	23,749	28,763	1077	1282	675	2049	0.24	0.12	0.12	0.19	0.19	0.14	0.12	0.18
10*12	26,493	22,102	25,761	26,714	5482	4912	4466	4288	0.18	0.14	0.20	0.22	0.22	0.16	0.14	0.12
11*13	31,749	31,054	32,144	33,849	6388	5187	5514	6382	0.26	0.18	0.14	0.18	0.22	0.18	0.14	0.16
12*15	4784	7401	6195	7225	6237	5853	6432	7528	0.14	0.22	0.20	0.35	0.20	0.16	0.08	0.22

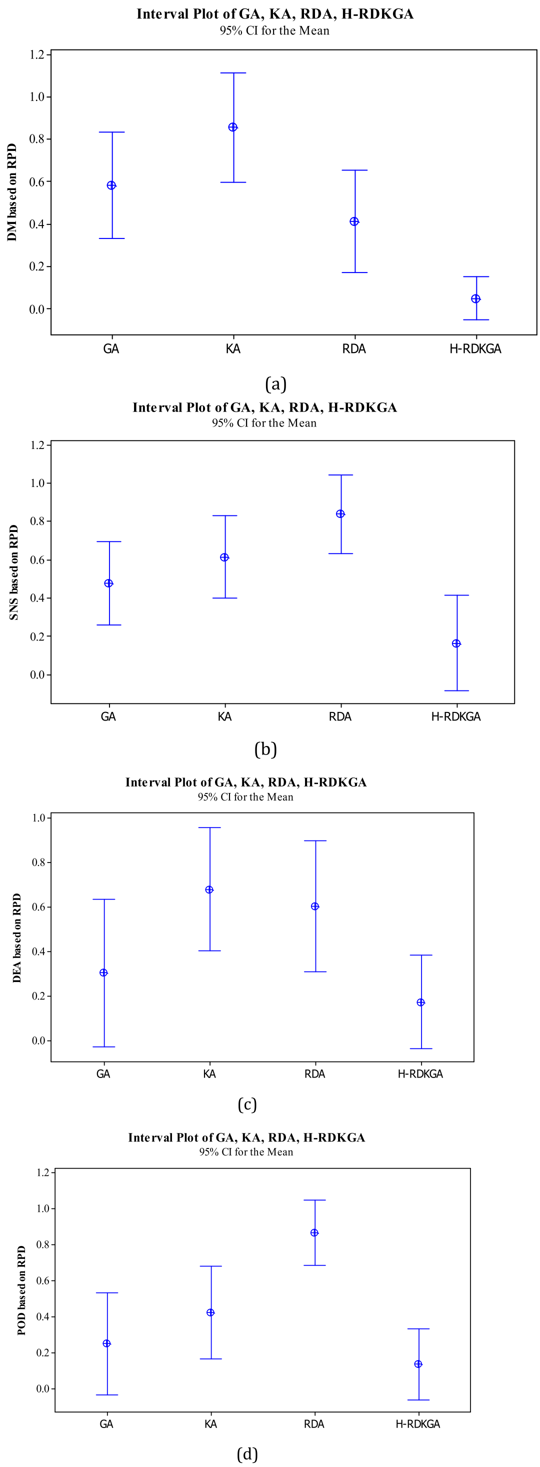

Figure 6. Means plot and LSD intervals to specify the RPD for the evaluation metrics (i.e. DM(a), SNS(b), DEA(c) and POD(d)).to compare the algorithms.

In the end, to verify the statistical validity of the results, we perform an analysis of variance (ANOVA) method to accurately analyze the results (as seen in Table 2 based on the *RPD*). The results demonstrate that there is a clear statistically significant difference between the performances of the algorithms. The means plot and LSD intervals (at the 95% confidence level) for all methods are shown in Figure 6. The results show the superiority of the proposed hybrid algorithm in all assessment metrics in this study.

5. Conclusion

The dynamic cell formation decision-making seeks to optimize the layouts of machines and the right allocations of products flow using a simplified objective function to formulate the manufacturing system. In many contexts, however, and perhaps most especially in developing countries such as Iran where the management of manufacturing system is of particular concern, such a simplified approach to dynamic cell formation is failing to deliver satisfactory all outcomes under the recent advances of the supply chain and manufacturing technologies. To this end, a practical cell formation decision-making model in a fuzzy environment was introduced by this study. More practicality and efficiency need capable algorithms for this complicated optimization problem, which are robust and computationally manageable. Hence, a novel hybrid meta-heuristic algorithm based on the advantages of GA, KA and RDA simultaneously, is proposed to compare with the general ones.

In this paper, a new bi-objective mixed-integer non-linear programming model was presented to consider the dynamic cell formation and inter/intra-cell layouts in the continuous space simultaneously. The purpose of the model was to determine concurrently the formation of cells and the intra- and inter-cellular layouts in a way that the total transportation cost of parts, the reconfiguration cost of cells, and the number of exceptional elements (EEs) were minimized. One of the main contributions of the presented model was the fuzzy conditions related to some parameters. In this regard, a Khimens' method was utilized to de-fuzzify the uncertain parameters. As a complicated optimization problem with several real-life constraints and operational decisions that should be taken in less time, four different meta-heuristics were employed to tackle the problem. Another innovation of this study was to propose a novel hybrid meta-heuristic algorithm based on the advantages of GA, KA and RDA simultaneously. The results showed that the proposed hybrid algorithm, called H-RDKGA, showed a better performance in comparison with its main individual algorithms. There are several recommendations for future directions of this study. For example, it is interesting to integrate the proposed model with a scheduling problem. The other approach is to use a two-stage or multi-stage stochastic programming method to tackle the uncertainty. From the aspect of the novel proposed hybrid algorithm, more in-depth analyses by other large-scale optimization problems may be considered. At last but not least, new meta-heuristics can be suggested to compare the results of the proposed algorithms.

Disclosure statement

The authors of this research certify that there is no any affiliation with or involvement in any organization or entity with financial and non-financial interests in the subject matter or materials discussed in this paper.

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