APEM journal

Advances in Production Engineering & Management
Volume 13 | Number 1 | March 2018 | pp 5–17
https://doi.org/10.14743/apem2018.1.269

ISSN 1854-6250
Journal home: apem-journal.org
Original scientific paper

Comparison among four calibrated meta-heuristic algorithms for solving a type-2 fuzzy cell formation problem considering economic and environmental criteria

Arghish, O.[a], Tavakkoli-Moghaddam, R.[b,c,*], Shahandeh-Nookabadi, A.[d], Rezaeian, J.[e]

[a]Department of Industrial Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran
[b]School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran
[c]LCFC, Arts et Métiers Paris Tech, Metz, France
[d]Department of Industrial and Systems Engineering, Isfahan University of Technology, Isfahan, Iran
[e]Department of Industrial Engineering, Mazandaran University of Science and Technology, Babol, Iran

A B S T R A C T

In this paper, a mathematical model is proposed using economic and environmental criteria for a type-2 fuzzy (T2F) cell formation (CF) problem emphasizing the effect of the man-machine relationship aspect. This model aims to show the use of this aspect in CF to minimize the costs of processing, material movement, energy loss, and tooling. For this purpose, a two-stage defuzzification procedure is used to convert the T2F variable into a crisp value. Due to NP-hardness of the model and problem, a genetic algorithm (GA) is used to derive the appropriate solutions. Furthermore, because there is no any existing benchmark to validate the performance of the proposed model, three tuned meta-heuristic algorithms, namely, differential evolution (DE), harmony search (HS) and particle swarm optimization (PSO), are proposed and used. The present research uses the Taguchi method to adjust the parameters in the four proposed algorithms. Furthermore, 15 examples are used to validate the presented model. The results show that PSO is the most appropriate algorithm for solving the model.

A R T I C L E I N F O

Keywords:
Cell formation;
Environmental factor;
Genetic algorithm;
Particle swarm optimization;
Harmony search;
Differential evolution

**Corresponding author:*
tavakoli@ut.ac.ir
(Tavakkoli-Moghaddam, R.)

Article history:
Received 29 June 2017
Revised 22 January 2018
Accepted 20 February 2018

1. Introduction

Nowadays, the competitive environment throughout the world has led the involved manufacturing industries to supply the highest quality, affordable products such that recent approaches focus more on the ever-growing manufacturing costs including those associated with location, energy, and transportation system. Group technology (GT) as one of the most efficient approaches tries to group parts and machines in terms of their similarities in production processes, functionalities, and geometries [1]. Cellular manufacturing (CM) as an application of GT in a manufacturing system is utilized to classify similar parts into families assigning different machines to cells [2]. The CMS design involves four principal stages, in which each of them can be considered as an individual problem, namely CF, layout, scheduling and resource assignment (RA) [3]. As the CF problem comes up as the first stage in the CMS design, investigators have attempted to optimally solve the problem.

For instance, Majazi-Delfard [4] introduced a non-linear model for the dynamic cell formation (DCF) in terms of the quantity and length of intra- and inter-cell travels. Deljoo *et al.* [5] provided a GA-based solution to the DCF problem identifying errors in the models recommended in the literature, declining their helpful perspective and presenting a novel formulation for the DCF problem. Bagheri and Bashiri [6] utilized a LP-metric approach to a proposed model comprising of CF, layout and worker assignment components. Xu *et al*. [7] provided a bat algorithm (BA) to the dual flexible job-shop scheduling problem considering the process sequence and machine selection flexibility. Zupan *et al*. [8] presented a method based on a combination of schmigalla modified triangular method, the schwerdfeger circular process, and a simulation model to the layout optimization of a production cell considering the intensity of the material flow. Nie *et al*. [9] utilized a simulation model for a Token-oriented Petri net-based flexible manufacturing cell.

Mahdavi *et al*. [10] presented a two-stage approach to a CF problem considering interval T2F interactional interests among workers. In the first stage, a multi-depot multiple traveling salesman problem model is used to assign workers to cells. In the second stage, a mathematical model is applied to assign machines to cells. With respect to the historical perspective, sustainability was conceptualized in the late 1960's and early 1970's stressing the environmental effect of industrial projects [11]. Sustainability was represented by Lozano [12] in three dimensions, in which themes in economic, environmental, and social aspects interact in the temporal respective. The literature review also reveals the fact that while the CMS design has received considerable attention, social and environmental aspects have been underexplored with the majority of the criteria investigated in the associated literature devoted to economic rather than social and environmental issues [13].

Niakan *et al*. [14] proposed a mathematical model of the problem comprising of two objectives to investigate the trade-off between the total cost minimization and social issue maximization attempting to solve the problem using a non-dominated sorting genetic algorithm (NSGA-II). In addition, Niakan *et al*. [15] proposed a model for the cost minimization and the machine energy loss minimization incorporating a social constraint developing an NSGA-II solve the problem. Furthermore, Niakan *et al*. [16] introduced a model possessing two objectives for the DCF problem minimizing production and worker costs and total production waste including energy, chemical material, raw material, CO_2 emissions. Proposing the social criteria as constraints, the researchers utilized the NSGA-II and multi-objective simulated annealing (MOSA) algorithms to provide a solution for the bi-objective model.

The literature mostly considers input parameters in the CF to be deterministic. However, in practice, there are a large number of uncertain and imprecise parameters involved. As the quantity of data may not always be sufficient for the uncertain parameters prediction, fuzzy logic is utilized as a robust instrument to gauge this uncertainty through the medium of the personal knowledge [17]. To describe type-2 fuzziness, a T2F variable represents a map extending from the fuzzy possibility space to the real number space [18]. Miller and John [19] assert that further uncertainty degrees supplied through the interval type-2 fuzzy sets (IT-2FS) logic makes it possible to more optimally show the uncertainty and vagueness of resource planning models. Qin *et al*. [18] presented three categories of critical values (CVs) for a regular fuzzy variable (RFV) and three reduction methods for a T2F variable.

Research conducted by Kundu *et al*. [20] examines transportation problems using T2F parameters wherein the first values of the T2F parameters were defuzzified using CV-based reduction methods to type-1 fuzzy variables, and the centroid method was employed for total defuzzification.

The review of the related literature reveals the most commonly used criteria in CF to be the associated costs. Therefore, to bridge this gap, a mathematical model was developed using economic and environmental criteria and a T2F parameter for CF and RA problems simultaneously. The novelty of the present research partly lies in the consideration of worker-machine relationship for worker allocation where the worker can be considered as a significant industrial system component. The present paper consists of the problem statement and mathematical model (Section 2), solution methodologies (Section 3), computational results (Section 4), and conclusion (Section 5).

2. Problem statement and definition of objective function

This section discusses a T2F model for the CF considering economic, environmental and man-machine relationship aspects.

2.1 Worker-machine relationship

Nowadays, numerous machine tools are either totally or partially automatically operated with the worker being usually idle for a portion of the cycle. The potential use of this idle time can enhance worker earnings and the efficiency of a manufacture. The man-machine process chart evidently depicts the respective idle machine time and worker time areas, which normally represent desirable locations to initiate effective improvements. Although this chart is generally implemented to specify the number of machines assigned to a worker, the application of a mathematical model can substantially lessen the time needed to do so. Such ideal situations are generally referred to as synchronous servicing with the number of machines assigned computed as shown in Eq. 1.

$$m = \frac{s + r}{s + w} \tag{1}$$

where m represents the number of machines being operated by each worker, s worker servicing time per machine, r machine working time and w walking time between two machines, the number of machines must be represented by a whole number; otherwise, we have the following equation.

$$ml \leq m < mu \tag{2}$$

If the number of machines does not represent a whole number, the minimum total cost per piece criteria can be used for the optimum operation. The total cost per piece for ml and mu machines are given in Eqs. 3 and 4.

$$T\mathrm{C}_{ml} \; = \; (C_1.(s + r) + ml.C_2.(s + r))/ml \tag{3}$$

$$T\mathrm{C}_{mu} \; = (s + w)(C_1 + C_2.mu) \tag{4}$$

where C_1 and C_2 are the worker and machine costs, respectively. The number of machines assigned to workers represents the minimum total cost per piece [21].

2.2 Environmental criteria

With the passage of time, humans have damaged the environment through the waste production and uncontrolled use of natural resources to satisfy the ever-increasing unprecedented use level, which was far beyond the nature's capacity to restore and/or regenerate itself. The fear of an uncertain future for the world made it necessary to grasp how individuals, organizations, and governments have cooperated to discover approaches to prevent a global collapse [22]. One of the objective function terms is to minimize the total system energy loss cost. The relationship between man and the machine in the CF model leads to the far better use of both workers and machine time, and more optimal balance in the work cycle. The man and machine relationship tools depict the areas, in which machine and worker idle times take place. Thus, the use of these idle times can enhance worker earnings enhancing the production efficiency [21]. In the researchers' proposed model, all the machines are considered as a multi-functional task. The machines require highly skilled workers thus providing workers with the opportunity to acquire numerous skills expanding their potential.

2.3 T2F set

A T2F set was proposed as an extension of an ordinary fuzzy set. Let Γ be the universe, Pos: $\mathcal{A} \rightarrow [0,1]$ be a set function on the ample field $\mathcal{A}$ and Pos is a possibility criterion. If $(\Gamma, \mathcal{A}, Pos)$ is a possibility space, then an m-ary regular fuzzy vector $\xi = (\xi_1, \xi_2, \ldots, \xi_m)$ is a map $\Gamma \rightarrow [0,1]^m$ for any $t = (t_1, t_2, \ldots, t_m) \in [0,1]^m$, one has the following equation:

$$\{\gamma \in \Gamma \mid \xi(\gamma) \leq t\} = \{\gamma \in \Gamma \mid \xi_1(\gamma) \leq t_1, \xi_2(\gamma) \leq t_2, \ldots, \xi_m(\gamma) \leq t_m\} \in \mathcal{A} \tag{5}$$

as m=1, ξ is a RFV. Let $\widetilde{Pos}$: $\mathcal{A}\rightarrow$ [0,1] be a set function on $\mathcal{A}$ such that $\{\widetilde{Pos}$ (A) | $A\epsilon$ $\mathcal{A}\}$ is an RFVs and $\widetilde{Pos}$ is a fuzzy possibility criteria. If $\mu_{\widetilde{Pos(\Gamma)}}(1) = 1$, then $\widetilde{Pos}$ is a regular fuzzy possibility criteria. If $(\Gamma, \mathcal{A}, \widetilde{Pos})$ is a fuzzy possibility space (FPS), then an m-ary T2F vector $\tilde{\xi} = (\tilde{\xi}_1, \tilde{\xi}_2, ..., \tilde{\xi}_m)$ is a map $\Gamma \rightarrow$□m for any $r = (r_1, r_2, \ldots, r_m) \in \Re^m$, as shown in Eq. 6.

$$\{\gamma \in \Gamma |\, \tilde{\xi}(\gamma) \leq r\} = \{\gamma \in \Gamma |\, \tilde{\xi}_1(\gamma)\ \leq r_1,\, \widetilde{\xi_2}(\gamma) \leq r_2, \ldots,\, \widetilde{\xi_m}(\gamma) \leq r_m\} \in A \tag{6}$$

as $m = 1$, $\tilde{\xi}$ is a T2F variable [18].

Critical value

Let $\xi = (r_1, r_2, r_3, r_4)$ and $\xi = (r_1, r_2, r_3)$ be a trapezoidal and triangular RFV, respectively. Then, we have the following items in Table 1 [18].

Table 1 Component of RFVs

	trapezoidal	triangular
optimistic CV of $\tilde{\xi}$	$r_4/(1 + r_4 - r_3)$	$r_3/(1 + r_3 - r_2)$
pessimistic CV of $\tilde{\xi}$	$r_2/(1 + r_2 - r_1)$	$r_2/(1 + r_2 - r_1)$
The CV of $\tilde{\xi}$	$\begin{cases} \dfrac{2r_2 - r_1}{1 + 2(r_2 - r_1)} & r_2 > \dfrac{1}{2} \\ \dfrac{1}{2} & r_2 \leq \dfrac{1}{2} \leq r_3 \\ \dfrac{r_4}{1 + 2(r_4 - r_3)} & r_3 \leq \dfrac{1}{2} \end{cases}$	$\begin{cases} \dfrac{2r_2 - r_1}{1 + 2(r_2 - r_1)} & r_2 > \dfrac{1}{2} \\ \dfrac{r_3}{1 + 2(r_3 - r_2)} & r_2 \leq \dfrac{1}{2} \end{cases}$

Centroid method

The centroid method is the most commonly used method for transforming the type-1 fuzzy into crisp values. The centroid method can be defined by the Eq. 7 for the discrete case [23].

$$z^* = \frac{\sum_z z.\, \mu_{\tilde{A}}(z)}{\sum_z \mu_{\tilde{A}}(z)} \tag{7}$$

Defuzzification

In the present research, a two-stage defuzzification procedure is employed to transform the T2F variable to crisp value. Initially, the CV is utilized for RFVs for transforming the T2F into type-1 fuzzy. Then, the centroid method is employed in order to transform the type-1 fuzzy into crisp values.

2.4 Assumptions

For the CF considered in this paper, every single operation on each part classification can be executed on multi-functional and identical machines. Each part type demand, each tool type's tool life, maximum cell number and worker-part-machine-tool-worker combination compatibility are given. The average quantity of energy wasted by each machine type in a unit of time and energy price in a unit of time is also known as is the total servicing time of a worker for each machine.

2.5 Notations and parameters

r_{opmhg}	Machine m working time for performing operation o on part p with tool h by worker g
a_{opmhg}	1, if machine m is employed to operation o for part p with tool h by worker g; and 0, otherwise
α_p^{inter}	Cost related to inter-cell movement for part p in a distance unit
α_p^{intra}	Cost related to intra-cell movement for part p in a distance unit
Q_p	Demand for part p
T_m	Time capacity for machine m

T_g	Time capacity for worker g
U_k	Upper bound of machines allowed in cell k
$d_{kk\prime}$	Average distance among cells k and k'
s_{opmhg}	Worker servicing time per machine m to perform operation o on part p using tool h by worker g
w_{opmhg}	Walking time between machine m taken to process operation o for part p using tool h by worker g to the next machine
C_{opmhg}	Operating cost on machine m to process operation o on part p using tool h by worker g
$E_{kk'}$	1, if $k \neq k'$; and 0, if $k = k'$
C_{2_m}	Machine (m) cost for a time unit
C_{1_g}	Worker (g) cost for a time unit
γ_h	Cost of tool h
$Batch_p^{inter}$	Inter-cell batch size motion for part p
$Batch_p^{intra}$	Intra-cell batch size motion for part p
$ToolLife_h$	Tool life of tool h
φ_m	Average quantity of energy wasted by each machine m in unit time
$\widetilde{EC}$	Price of energy in unit time

2.6 Decision variables

x_{opmkhg}	1, if machine m is used for operation o of part p using tool h by worker g in cell k; and 0, otherwise
u_{hm}	Number of tool copies for tool h on machine m
y_{opmk}	1, if operation o of part p is performed on machine m in cell k; and 0, otherwise
l_{opm}	1, if operation o of part p is performed on machine m; and 0, otherwise
ll_{mk}	1, if machine m is assigned to cell k; and 0, otherwise
$V1_{mg}$	1, if (mu) machine m is allocated to worker g; and 0, otherwise
$V2_{mg}$	1, if (ml) machine m is allocated to worker g; and 0, otherwise
ml_{mg}	Lower whole quantity of machine m allocated to worker g
mu_{mg}	Upper whole quantity of machine m allocated to worker g
$TC_{ml\ mg}$	Total cost per piece from one machine (ml) m and worker g
$TC_{mu\ mg}$	Total cost per piece from one machine (mu) m and worker g
mm_{mgk}	Number of machine m assigned to worker g in cell k

2.7 Objective function

The objective function of the considered model is to minimize the costs of processing, material movement, energy loss, and tooling.

$$\begin{aligned}
\text{Min} = {} & \sum_{o=1}^{O}\sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{h=1}^{H}\sum_{g=1}^{G} Q_p C_{opmhg} x_{opmkhg} \\
& + \sum_{o=1}^{O-1}\sum_{p=1}^{P}\sum_{k=1}^{K}\sum_{k'=1}^{K} \left\lceil \frac{Q_p}{Batch_p^{inter}} \right\rceil \alpha_p^{inter} E_{kk'} d_{kk\prime} \left(\sum_{m=1}^{M} y_{opmk}\right)\left(\sum_{m=1}^{M} y_{o+1,pmk\prime}\right) \\
& + \sum_{o=1}^{O-1}\sum_{p=1}^{P}\sum_{k=1}^{K}\sum_{k'=1}^{K} \left\lceil \frac{Q_p}{Batch_p^{intra}} \right\rceil \alpha_p^{intra} (1 - E_{kk'}) d_{kk'} \left(\sum_{m=1}^{M} y_{opmk}\right)\left(\sum_{m=1}^{M} y_{o+1,pmk'}\right) \\
& + \sum_{m}^{M}\sum_{g}^{G} \left(ml_{mg} V2_{mg} + mu_{mg} V1_{mg}\right) \times \varphi_m \times \widetilde{EC} + \sum_{h=1}^{H} \gamma_h \sum_{m=1}^{M} u_{hm}
\end{aligned} \tag{8}$$

$$\text{s.t.}: \sum_{m}^{M}\sum_{k}^{K}\sum_{h}^{H}\sum_{g}^{G} x_{opmkhg}.\, a_{opmhg} = 1\,, \qquad \forall\, o,p \tag{9}$$

$$x_{opmkhg} \leq a_{opmhg}\,, \qquad \forall\, o,p,m,k,h,g \tag{10}$$

$$\sum_{m}^{M}\sum_{g}^{G} mm_{mgk} \leq U_k\,, \qquad \forall\, k \tag{11}$$

$$y_{opmk} = l_{opm} ll_{mk}\,, \qquad \forall\;\, o,p,m,k \tag{12}$$

$$mm_{mgk} ll_{mk} = ml_{mg} V2_{mg} + mu_{mg} V1_{mg}\,, \qquad \forall\, m,g,k \tag{13}$$

$$\sum_{o}^{O}\sum_{p}^{P}\sum_{k}^{K}\sum_{h}^{H} Q_p.\, x_{opmkhg}\left(r_{opmhg} + s_{opmhg}\right) \leq T_g + MV1_{mg}\,, \quad \forall\, m,g \tag{14}$$

$$\sum_{o}^{O}\sum_{p}^{P}\sum_{k}^{K}\sum_{h}^{H} Q_p.\, x_{opmkhg}.\, mu_{mg.} r_{opmhg} \leq T_g + MV2_{mg}\,, \quad \forall\, m,g \tag{15}$$

$$\sum_{o}^{O}\sum_{p}^{P}\sum_{k}^{K}\sum_{h}^{H} Q_p.\, x_{opmkhg}\left(r_{opmhg} + s_{opmhg}\right) \leq T_m + MV1_{mg}\,, \quad \forall\, m,g \tag{16}$$

$$\sum_{o}^{O}\sum_{p}^{P}\sum_{k}^{K}\sum_{h}^{H} Q_p.\, x_{opmkhg}.\, mu_{mg.} r_{opmhg} \leq T_m + MV2_{mg}\,, \quad \forall\, m,g \tag{17}$$

$$\frac{\left(r_{opmhg} + s_{opmhg}\right).\, x_{opmkhg}}{s_{opmhg} + w_{opmhg}} \leq\; mu_{mg}\,, \qquad \forall\;\, o,p,m,k,h,g \tag{18}$$

$$mu_{mg.} = a_{opmhg}\left(ml_{mg} + 1\right), \qquad \forall\;\, o,p,m,h,g \tag{19}$$

$$TC_{ml\;mg} = \frac{a_{opmhg}\left(\left(r_{opmhg} + s_{opmhg}\right)\left(C_{1_g} + ml_{mg} \times C_{2_m}\right)\right)}{ml_{mg}}\,, \forall\, o,p,m,h,g \tag{20}$$

$$TC_{mu\;mg} = a_{opmhg}\left(\left(s_{opmhg} + w_{opmhg}\right)\left(C_{1_g} + C_{2_m} \times\; mu_{mg.}\right)\right), \forall\, o,p,m,h,g \tag{21}$$

$$TC_{ml\;mg} \;\leq TC_{mu\;mg} + MV1_{mg}\,, \;\; \forall\, m,g \tag{22}$$

$$TC_{mu\;mg} \;\leq TC_{ml\;mg} + MV2_{mg}\,, \;\; \forall\, m,g \tag{23}$$

$$V1_{mg} + V2_{mg} = 1\,, \qquad \forall\, m,g \tag{24}$$

$$\sum_{o}^{O}\sum_{p}^{P}\sum_{k}^{K}\sum_{g}^{G} x_{opmkhg}.\, r_{opmhg} \;\leq ToolLife_h.\, u_{hm}\,, \qquad \forall\, m,h \tag{25}$$

$$\sum_{h}^{H}\sum_{g}^{G} x_{opmkhg} = y_{opmk}\,, \qquad \forall\, o,p,m,k \tag{26}$$

$$x_{opmkhg}\,, y_{opmk}\,, V1_{mg}\,, V2_{mg}\,, l_{opm}, ll_{mk} \in \{0,1\} \tag{27}$$

$$ml_{mg}, mu_{mg}, mm_{mgk} ll_{mk}, u_{hm} \;\geq 0\,, integer \tag{28}$$

The first sentence in the objective function (Eq. 8) represents the total cost of the process. The second and third terms represent the total material transportation cost. The fourth term is the cost of energy loss in the system at a time unit. The fifth term represents the total tool cost. Eq. 9 and Eq. 10 express the operation-part-machine-tool-worker combinations. Eq. 11 limits the cell size. Eq. 12 can be used to define the machine-cell combination. Eq. 13 is used to ensure that the quantity of machine m is assigned to worker g in cell k. Eq. 14 and Eq. 15 express the time capacity of the worker. Eq. 16 and Eq. 17 express the time capacity of the machine. Eq. 18 ensures that the upper whole number of machine m is assigned to worker g. Eq. 19 ensures that a lower whole number of machine m is assigned to worker g. Eq. 20 and Eq. 21 express the cost of a production per cycle from one machine in the lower and upper whole numbers of machine m assigned to worker g. Eq. 22 to Eq. 24 guarantee that the lowest TC is chosen. Eq. 25 represents the tool-machine combinations. Eq. 26 expresses the operation-part-machine-cell combinations. Eq. 27 and Eq. 28 can be used to define the type of variables.

3. Used methods

In the present paper, in order to solve the presented CF model, a GA is implemented and three DE, PSO and HS algorithms are employed to the obtained accredit outcome.

3.1 Genetic algorithm

Holland [24] was the first to develop the GA, which represented coding to a chromosome form. Subsequent to the production of the first random chromosomes, evaluation of performance was undertaken using the fitness function. The remaining chromosomes and offspring produce a generation through the medium of crossover and mutation. In the end, the elitism process is used to produce solutions [25]. The GA used for the CF framework is as follows. Two elements are given in the CF problem. The first element represents the assignment of machines to workers using [Ma_Wo]. This matrix is utilized to define the entirety of the relative constraints. The second element represents an operation-part-machine-cell-tool-worker [OP_Pa_N3], where N3 equals [Ma_Ce_To_Wo]. These matrices are employed to define the entirety of the relative constraints.

3.2 Differential evolution

The DE algorithm represents a recent evolutionary optimization technique for continuous nonlinear functions introduced by Noktehdan *et al.* [26] and Storn and Price [27]. The principal stages involved in the DE algorithm are defined as follows. Initially, a random population generation is formed and the objective function is evaluated. For each individual solution in the population, a mutated solution $\widehat{x_i}$ is produced as follows in Eq. 29.

$$\widehat{x_i} = x_{r1} + F(x_{r3} - x_{r2}) \tag{29}$$

where F represents a scalar ($F \in [0, 1]$), and x_{r1}, x_{r3}, x_{r2} represent randomly-selected subjects in the population i ($\widehat{x_i} \neq x_{r1} \neq x_{r3} \neq x_{r2}$). The crossover operation is employed to establish a trial vector through shuffling the information incorporated in the mutated vector and the current solution in Eq. 30.

$$y_i^j = \hat{x}_i^j \text{ for } R_j \leq CR \text{ and } y_i^j = x_i^j \text{ for } R_j > CR \tag{30}$$

where CR represents the crossover rate ∈ [0, 1], which needs to be specified by the user, and R_j represents a random real number ∈ [0,1] and j is the j-th parameter. A comparison is made between each trial vector ($\overrightarrow{y_i}$) and its parent ($\overrightarrow{x_i}$), and the more desirable one remains in the population in the selection stage [28].

3.3 Particle swarm optimization

The PSO algorithm represents a population-based stochastic optimization algorithm extended by Kennedy and Eberhart [29] composed of a population (i.e., swarm) of candidate solutions, referred to as particles, which are in inward motion towards search space with a designated velocity in search of an optimum solution. Each particle maintains a memory assisting it in preserving the path taken by its previous best location. The particle positions are identified as personal best and global best. The principal iterative process to arrive at the solution is executed by:

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{31}$$

$$v_i^{k+1} = wv_i^k + C_1 rand_1 \left(PBest_i - x_i^k\right) + C_2 rand_2 \left(P_{gi} - x_i^k\right) \tag{32}$$

Eq. 31 is used to calculate the i-th particle movement in the k-th replication, where v_i^k, x_i^k represent the velocity and the current location of the i-th particle in the k-th replication, respectively. Eq. 32 is employed to calculate the latest velocity vector of the i-th particle in the k-th iteration, $PBest_i$ represents the best location of the i-th particle, w represents the inertia factor controlling the magnitude of the old velocity, C_1 and C_2 represent acceleration constants (i.e., cognitive and social) based on the kind of search, local and global P_{gi} are denoted $lBest$ and $gBest$, respectively [30].

3.4 Harmony search

Musical performance can be defined as the quest for the lovely harmony among all harmonies. Geem *et al.* [31] introduced an optimization algorithm on the basis of musical performance, known as HS, searching for the best solution emanating from the objective function. The algorithm starts by playing a new harmony and comparing this harmony with those in harmony memory (HM), which results in the improvement in the harmony quality in a step-by-step manner. Subsequently, the HM updates and verifies the stop criterion. The entirety of the decision variables (notes) in HM together with the values for these notes in the new harmony are determined in the following manner: first, precise choice of the HM domain value. Second, random selection of the full value domain using a selection rate or the harmony memory considering rate (HMCR) between zero and one. Third, selection of ideal identical values for the HM domain with the pitch adjustment rate (PAR) between zero and one and a free distance bandwidth (Bw) [32].

4. Results and discussion

To investigate and evaluate the performance of the four meta-heuristic algorithms on the CF, some randomly-selected numerical examples are produced. To solve the proposed model, MATLAB (R2016b) software is utilized to provide the code the algorithms on a laptop having five Intel Core i5 CPU and 2 GB RAM. The TM is run in MINITAB software version 17.3.1 to calibrate the parameters for a subsequent data analysis.

4.1 Defuzzification of T2F variable

The energy price coefficient in the fourth sentence of the objective function ranges between 4 to 8. The coefficient is represented by the following discrete T2F variable.

$$\widetilde{EC} = \begin{cases} 3 & \text{with } \tilde{\mu}\widetilde{EC}\ (3) = (0.1, 0.4, 0.7) \\ 4 & \text{with } \tilde{\mu}\widetilde{EC}\ (4) = (0.9, 1, 1) \\ 5 & \text{with } \tilde{\mu}\widetilde{EC}\ (5) = (0.1, 0.3, 0.4, 0.6) \end{cases} \qquad \widetilde{EC} = \begin{cases} 7 & \text{with } \tilde{\mu}\widetilde{EC}\ (7) = (0.4, 0.5, 0.7, 0.8) \\ 8 & \text{with } \tilde{\mu}\widetilde{EC}\ (8) = (0.6, 0.8, 0.9) \\ 10 & \text{with } \tilde{\mu}\widetilde{EC}\ (10) = (0.4, 0.6, 0.7) \end{cases}$$

To solve the CF model under consideration in the initial step, a CV reduction method is employed to convert the energy price T2F variable in unit time to the corresponding type-1 fuzzy variable. During the second step, a centroid method is performed to reduce the type-1 fuzzy variable to the crisp value. The energy price crisp value is obtained using $EC = (3.99, 8.35)$.

4.2 Generating random data

15 random examples are produced in various sizes through the generation of uniformly distributed random points for a number of parameters given. The attributes of 15 designed test examples are shown in Table 2. Also, Table 3 shows the components of the model input parameters required for 15 problem instances.

Table 2 Attribute of test examples

Problem	Part	Operation	Machine	Cell	Tool	Worker	Problem	Part	Operation	Machine	Cell	Tool	Worker	Problem	Part	Operation	Machine	Cell	Tool	Worker
1	2	2	4	2	2	4	6	5	5	3	2	3	3	11	7	2	5	2	3	5
2	2	4	5	2	2	5	7	6	3	4	3	3	4	12	7	5	3	4	3	3
3	4	4	2	3	3	2	8	6	5	3	4	4	3	13	8	2	3	2	3	3
4	4	5	4	3	3	4	9	6	3	5	3	3	5	14	8	5	4	2	2	4
5	5	5	2	3	2	2	10	7	3	4	3	2	4	15	8	5	4	3	3	4

Table 3 Data identifying with random test problems

Parameter	Amount	Parameter	Amount	Parameter	Amount	Parameter	Amount
Q_p	$U(100-500)$	$\widetilde{EC}$	$U(3.99-8.35)$	T_g, T_m	55	C_{opmhg}	$U(9-20)$
$Batch_p^{intra}$	$U(5-10)$	α_p^{intra}	$U(10-30)$	r_{opmhg}	0.02	s_{opmhg}	0.01
$Batch_p^{inter}$	$U(10-15)$	α_p^{inter}	$U(50-75)$	w_{opmhg}	0	C_{1g}	$U(1-2)$
φ_m	$U(0.5-0.7)$	γ_h	$U(50-80)$	C_{2m}	$U(2-3)$	$ToolLife_h$	1

4.3 Parameter calibration

The TM is used to calibrate the parameters in the GA, DE, PSO and HS algorithms, as the values of meta-heuristic algorithm parameters influence the solution quality. Nevertheless, the present study, the "smaller is better" response is chosen as S/N should be minimized [25]. To perform the Taguchi procedure, the L^9 design is employed with the values and levels of the GA, DE, PSO and HS algorithm parameters outlined in Table 4 and the values derived after multiple tests on the examples of the classes using the frequent algorithm runs.

Table 4 GA, DE, PSO and HS parameters, and levels

Algorithm	Parameters	(1)	(2)	(3)	Algorithm	Parameters	(1)	(2)	(3)
	POP	30	40	50		NOP	30	40	50
GA	P_c	0.5	0.6	0.7	PSO	C_1	1.5	2	2.5
	P_m	0.01	0.05	0.1		C_2	1.5	2	2.5
	NOG	100	200	300		NOG	100	150	200
	NOP	20	30	50		HMS	5	10	20
DE	NOG	30	50	100	HS	HMCR	0.9	0.95	0.99
	P_c	0.1	0.5	0.9		PAR	0.01	0.1	0.3
	-	-	-	-		BW	0.1	0.5	0.9

4.4 Analysis of results and comparisons

To compare the results emanating from four algorithms and elicit the best methodology to solve the CF having the T2F variable, each of 15 examples, is solved using MATLAB (R2016b) software. In this paper, the GA, PSO, HS and DE algorithms are used, in which the probability of crossover (Pc), the generations number (NOG), the probability of mutation (Pm) and the size of population (POP) are the GA parameters. The generations number (NOG), the acceleration coefficients (C1, C2) and the size of population (NOP) are the PSO parameters. The harmony memory considering rate (HMCR), the Bandwidth (BW), the harmony memory size (HMS) and the pitch adjusting rate (PAR) are the HS parameters. The size of population (NOP), the probability of crossover (Pc) and the generations number (NOG) are the DE parameters.

Tables 5 and 6 incorporates the input parameter and the objective values of four algorithms in each example, in which the optimal values of the parameters are derived using L^9 design and the TM. To compare the performance of the GA, PSO, HS, and DE with reference to the objective function, a number of approaches are utilized in the present research. Initially, the average and the standard deviation of each of the 15 examples were obtained as shown in the last two rows in Table 6. The results from average and standard deviation of the 15 examples show that PSO has outperformed GA, HS, and DE. The graphical approach depicted in Fig. 1 is also applied twice to compare the algorithm performance in 15 produced examples. Moreover, this figure shows that the PSO appears to represent a better performance than the GA, HS, and DE in the objective function in the entirety of the examples.

Table 5 Input parameters of the PSO, FA and DE algorithms for the generated problems

	HS				PSO				GA				DE		
Prob. No.	*HMS*	*HMCR*	*PAR*	*BW*	*NOP*	C_1	C_2	*NOG*	*POP*	P_C	P_m	*NOG*	*NOP*	*NOG*	P_C
1	20	0.99	0.3	0.9	30	2	2	100	50	0.6	0.01	200	50	100	0.9
2	20	0.99	0.3	0.5	50	25	2	200	50	0.5	0.05	100	30	30	0.9
3	10	0.95	0.01	0.9	50	1.5	2	100	50	0.6	0.05	300	50	100	0.9
4	10	0.95	0.01	0.9	40	1.5	2.5	200	30	0.7	0.1	300	30	30	0.9
5	10	0.99	0.3	0.9	40	1.5	1.5	100	40	0.7	0.05	200	50	50	0.1
6	20	0.95	0.1	0.5	30	2	2	200	30	0.5	0.01	200	30	100	0.1
7	5	0.99	0.01	0.1	30	2	2.5	150	50	0.7	0.1	300	30	100	0.1
8	20	0.95	0.01	0.5	40	1.5	1.5	200	50	0.7	0.1	300	30	50	0.1
9	20	0.9	0.01	0.1	30	1.5	2.5	150	30	0.6	0.01	200	50	100	0.1
10	20	0.99	0.01	0.9	40	2	2.5	200	40	0.6	0.05	200	20	100	0.1
11	20	0.95	0.3	0.9	50	2	1.5	200	30	0.6	0.1	100	30	30	0.1
12	20	0.95	0.01	0.1	50	1.5	2	200	50	0.6	0.01	200	50	100	0.9
13	20	0.95	0.3	0.9	50	2	1.5	200	50	0.7	0.05	300	50	50	0.1
14	10	0.9	0.1	0.5	30	2	2	150	30	0.6	0.05	300	20	30	0.1
15	5	0.99	0.1	0.5	40	1.5	1.5	100	30	0.6	0.1	300	30	100	0.9

Table 6 Objective function of the PSO, FA and DE algorithms for the generated problems

Problem No.	HS Objective function	PSO Objective function	GA Objective function	DE Objective function
1	11579	11449	17874	12530
2	49371	34946	55498	53765
3	61232	59110	64833	63498
4	112440	89216	123982	119870
5	134230	100420	143563	139110
6	114140	101930	129390	128765
7	99366	71208	101550	99875
8	127030	126750	148510	144170
9	106320	105770	110289	107540
10	112430	109290	115410	113980
11	41477	37906	61187	49405
12	215630	214010	265670	231720
13	78911	70402	86832	84695
14	221480	175750	240290	238730
15	221080	220720	247720	225775
Average	113781	101925	127507	120895
St. Dev	64446	61827	73328	68000

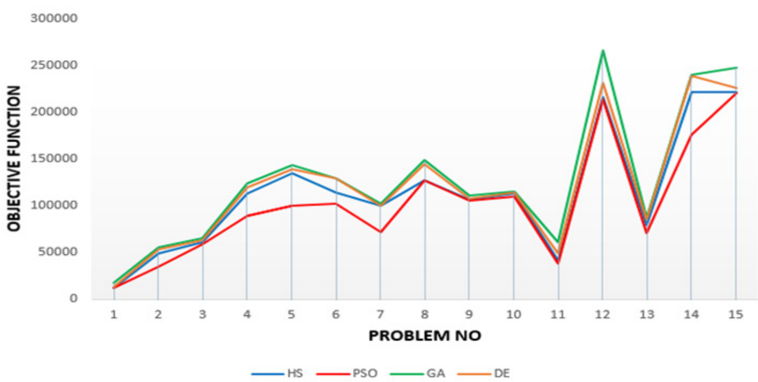

Fig. 1 Trend of the objective function values of the generated problems for the proposed algorithms

Table 7 Analysis of variance results to compare the algorithms in terms of mean objective function value

Source	DF	Adj. SS	Adj. MS	F-Value	P-value
Algorithms	3	5390788752	1796929584	0.40	0.754
Error	56	2.51675E+11	4494189326		
Total	59	2.57065E+11			

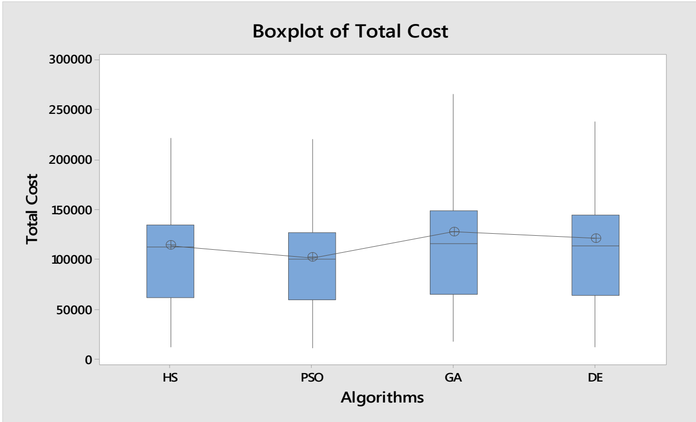

Fig. 2 Boxplot of the total cost values

In the end, the one-way analysis of variance (ANOVA) method is employed to statistically evaluate the performance of the GA, PSO, HS, and DE. This procedure was executed in MINITAB software version 17.3.1. The ANOVA method output outlined in Table 7 demonstrates that at a confidence level of 95 %, four algorithms reveal no significant differences in the mean objective function. Fig. 2 outlines the respective performance of the four algorithms.

5. Conclusion

In this paper, a T2F CF problem was examined with economic and environmental criteria. In the proposed model, the costs associated with processing, material movement, energy loss, and tooling were minimized. The most salient benefits of the mathematical model are as follows: CF using economic and environmental criteria at desirable cost defined by T2F and worker assignment through the man-machine relationship aspect. To solve the presented CF model, a GA was utilized, in which the PSO, HS, and DE algorithms were employed to evaluate the outputs of the proposed algorithm. Another remarkable advantage of the present research is the solution of the 15 random problems produced as the optimal rates of the algorithm parameters using TM for each problem. The results emanating from the algorithms reveal that the PSO algorithm outperforms the GA, DE, and HS algorithms in terms of the objective function on 15 random produced problems. The ANOVA method was also conducted to compare the performance of the GA, PSO, HS and DE algorithms statistically. Moreover, the trend pattern demonstrated that PSO outperformed GA, DE, and HS in the majority of the problems, in which a statistically significant difference was not observed showing that valid results were derived using the PSO. In the end, the following recommendations for further research are made:

- The application of the model can be extended to a stochastic environment.
- The proposed model can be considered with reference to other criteria for sustainability.
- The proposed model may be considered in the multi-period planning horizon.
- The Response Surface Methodology (RSM) may be implemented to set the parameters.
- Future research can concentrate on other meta-heuristic algorithms.
- The model can be extended to other T2F parameters.

References

[1] Rafiei, H., Ghodsi, R. (2013). A bi-objective mathematical model toward dynamic cell formation considering labor utilization, *Applied Mathematical Modelling*, Vol. 37, No. 4, 2308-2316, doi: 10.1016/j.apm.2012.05.015.

[2] Greene, T.J., Sadowski, R.P. (1984). A review of cellular manufacturing assumptions, advantages and design techniques, *Journal of Operations Management*, Vol. 4, No. 2, 85-97, doi: 10.1016/0272-6963(84)90025-1.

[**3**] Mehdizadeh, E., Rahimi, V. (2016). An integrated mathematical model for solving dynamic cell formation problem considering operator assignment and inter/intra cell layouts, *Applied Soft Computing*, Vol. 42, 325-341, doi: 10.1016/j.asoc.2016.01.012.

[4] Majazi Dalfard, V. (2013). New mathematical model for problem of dynamic cell formation based on number and average length of intra and intercellular movements, *Applied Mathematical Modelling,* Vol. 37, No. 4, 1884-1896, doi: 10.1016/j.apm.2012.04.034.

[5] Deljoo, V., Mirzapour Al-e-hashem, S.M.J., Deljoo, F., Aryanezhad, M.B. (2010). Using genetic algorithm to solve dynamic cell formation problem, *Applied Mathematical Modelling,* Vol. 34, No. 4, 1078-1092, doi: 10.1016/j.apm.2009.07.019.

[6] Bagheri, M., Bashiri, M. (2014)**.** A new mathematical model towards the integration of cell formation with operator assignment and inter-cell layout problems in a dynamic environment, *Applied Mathematical Modelling*, Vol. 38, No. 4, 1237-1254, doi:10.1016/j.apm.2013.08.026.

[7] Xu, H., Bao, Z.R.**,** Zhang, T. (2017). Solving dual flexible job-shop scheduling problem using a Bat Algorithm, *Advances in Production Engineering & Management*, Vol. 12, No. 1, 5-16, doi: 10.14743/apem2017.1.235.

[8] Zupan, H., Herakovic, N., Zerovnik, J., Berlec, T. (2017). Layout optimization of a production cell, *International Journal of Simulation Modelling*, Vol. 16, No. 4, 603-616, doi: 10.2507/IJSIMM16(4)4.396.

[9] Nie, X.D., Chen, X.D., Chen, X. (2016). Simulation study of flexible manufacturing cell based on token-oriented Petri net model, *International Journal of Simulation Modelling*, Vol. 15, No. 3, 566-576, doi: 10.2507/IJSIMM15(3)CO14.

[10] Mahdavi, I., Mahdavi-Amiri, N., Naderi, F., Paydar, M.M. (2017). Cell formation configuration using interval type-2 fuzzy interactional interests among workers, *International Journal of Operational Research*, Vol. 30, No. 2, doi: 10.1504/IJOR.2017.10007273.

[11] Stocchetti, A. (2012). The sustainable firm: From principles to practice, *International Journal of Business and Management*, Vol. 7, No. 21, 34-47, doi: /10.5539/ijbm.v7n21p34.

[12] Lozano, R. (2008). Envisioning sustainability three-dimensionally, *Journal of Cleaner Production*, Vol. 16, No. 17, 1838-1846, doi: 10.1016/j.jclepro.2008.02.008.

[13] Niakan, F., Baboli, A., Moyaux, T., Botta-Genoulaz, V. (2016). A bi-objective model in sustainable dynamic cell formation problem with skill-based worker assignment, *Journal of Manufacturing Systems*, Vol. 38, 46-62, doi: 10.1016/j.jmsy.2015.11.001.

[14] Niakan, F., Baboli, A., Moyaux, T., Botta-Genoulaz, V.A. (2015). A new multi-objective mathematical model for dynamic cell formation under demand and cost uncertainty considering social criteria, *Applied Mathematical Modelling,* Vol. 40, No. 4, 2674-2691, doi: 10.1016/j.apm.2015.09.047.

[15] Niakan, F., Baboli, A., Moyaux, T., Botta-Genoulaz, V. (2014). A new bi-objective mathematical model for sustainable dynamic cellular manufacturing systems, In: *Proceedings of the IEEE International Conference on Industrial Engineering and Engineering Management,* Selangor, Malaysia, 938-942, doi: 10.1109/IEEM.2014.7058776.

[16] Niakan, F., Baboli, A., Moyaux, T., Botta-Genoulaz, V. (2016). A bi-objective model in sustainable dynamic cell formation problem with skill-based worker assignment, *Journal of Manufacturing Systems*, Vol. 38, 46-62, doi: 10.1016/j.jmsy.2015.11.001.

[17] Safaei, N., Saidi-Mehrabad, M., Tavakkoli-Moghaddam, R., Sassani, F. (2008). A fuzzy programming approach for a cell formation problem with dynamic and uncertain conditions, *Fuzzy Sets and Systems*, Vol. 159, No. 2, 215-236, doi: 10.1016/j.fss.2007.06.014.

[18] Qin, R., Liu, Y.K., Liu, Z.Q. (2011). Methods of critical value reduction for type-2 fuzzy variables and their applications, *Journal of Computational and Applied Mathematics*, Vol. 235, No. 5, 1454-1481, doi: 10.1016/j.cam.2010.08.031.

[19] Miller, S., John, R. (2010). An interval type-2 fuzzy multiple echelon supply chain model, *Knowledge-Based Systems*, Vol. 23, No. 4, 363-368, doi: 10.1016/j.knosys.2009.11.016.

[20] Kundu, P., Kar, S., Maiti, M. (2014). Fixed charge transportation problem with type-2 fuzzy variables, *Information Sciences*, Vol. 255, 170-186, doi: 10.1016/j.ins.2013.08.005.

[21] Niebel, B.W. (1982). *Motion and time study*, Homewood, Irwin, USA.

[22] de Castro Hilsdorf, W., de Mattos, C.A.**,** de Campos Maciel, L.O. (2017). Principles of sustainability and practices in the heavy-duty vehicle industry: A study of multiple cases, *Journal of Cleaner Production*, Vol. 141, 1231-1239, doi: 10.1016/ j.jclepro.2016.09.186.

[23] Wang, L.X. (1996). *A course in fuzzy systems and control*, Prentice-Hall International, Inc., U.S.A.

[24] Holland, J.H. (1975). *Adaptation in natural and artificial systems: An introductory analysis with applications to biology, control and artificial intelligence*, MIT Press Cambridge, MA, USA.

[25] Mousavi, S.M., Hajipour, V., Niaki, S.T.A., Aalikar, N. (2014). A multi-product multi-period inventory control problem under inflation and discount: A parameter-tuned particle swarm optimization algorithm, *The International Journal of Advanced Manufacturing Technology*, Vol. 70, No. 9-12, 1739-1756, doi: 10.1007/s00170-013-5378-y.

[26] Noktehdan, A., Karimi, B., Husseinzadeh Kashan, A. (2010). A differential evolution algorithm for the manufacturing cell formation problem using group-based operators, *Expert Systems with Applications,* Vol. 37, No. 7, 4822-4829, doi: 10.1016/j.eswa.2009.12.033.
[27] Storn, R., Price, K. (1997). Differential evolution – A simple and efficient heuristic for global optimization over continuous spaces, *Journal of Global Optimization*, Vol. 11, No. 4, 341-359, doi: 10.1023/A:1008202821328.
[28] Sahin, O., Akay, B. (2016). Comparisons of metaheuristic algorithms and fitness functions on software test data generation, *Applied Soft Computing*, Vol. 49, 1202-1214, doi: 10.1016/j.asoc.2016.09.045.
[29] Kennedy, J., Eberhart, R. (1995). Particle swarm optimization, In: *Proceedings of the IEEE International Conference on Neural Networks*, Perth, WA, Australia, 1942-1948.
[30] Pant, M., Thangaraj, R., Abraham, A. (2009). Particle swarm optimization: Performance tuning and empirical analysis, *Foundations of Computational Intelligence*, Vol. 3, 101-128, doi: 10.1007/978-3-642-01085-9_5.
[31] Geem, Z.W., Kim, J.H., Loganathan, G.V. (2001). A new heuristic optimization algorithm: Harmony search, *Simulation*, Vol. 76, No. 2, 60-68, doi: 10.1177/003754970107600201.
[32] Askarzadeh, A., Zebarjadi, M. (2014). Wind power modeling using harmony search with a novel parameter setting approach, *Journal of Wind Engineering and Industrial Aerodynamics*, Vol. 135, 70-75, doi: 10.1016/j.jweia.2014.10.012.