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A Model for an Integrated Cellular Manufacturing System with Tools and Operators Assignment: Two tuned Meta-Heuristic Algorithms

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Abstract
This paper presents a mathematical model for cell formation, cell layout, and resources assignment problems simultaneously. This model focuses on the influence of the man-machine relationship aspect on the cellular manufacturing system (CMS) design. The main purpose of the model is to demonstrate how to design the CMS with the new aspect such that the costs associated with processing, layout, worker, and machine idle time, machine and tool are minimized. The proposed model is applied to a numerical example using Lingo software. Due to the complexity of the presented model, a genetic algorithm (GA) is employed to find satisfactory solutions. To verify the solutions, a harmony search (HS) algorithm is used. Additionally, the Taguchi method is utilized to adjust the parameters in two proposed algorithms. Finally, to validate the model, some numerical examples are presented. Results emanating from the research show that the proposed HS algorithm is a favorable method for the presented model.
Keywords: *Cell formation, Cell layout, Taguchi method, Genetic algorithm, Harmony search*

Introduction

Today's production systems work under stressful environments in a universal marketplace of heavy competition, unpredictable demand, and customized products, in which traditional production systems do not perform satisfactorily. One approach to enhancing productivity is group technology (GT), in which products are identified in terms of families (groups) with respect to similarities and attributes in the manufacturing process (Shabtay *et al.,* 2010).

A CMS is a production system implementing GT characteristics (Alhourani, 2013). The CMS possesses considerable benefits such as decreased material-handling cost, shorter setup time, reduced work-in-process inventories, and better lead times (Alhourani, 2013).

The CMS design is capable of solving problems consisting of (1) cell formation involving grouping part and corresponding machines in the cells for better flow of materials, (2) cell layout, which determines the physical placement of cells in the shop floor, and (4) resources assignment that assigns tools, operators and materials to the cells (Khaksar-Haghani *et al.* 2013). In this regard, Tavakkoli-Moghaddam *et al.* (2005) developed a nonlinear programming model for dynamic cell formation applying a meta-heuristic approach to find solutions. Safaei *et al.* (2008) considered a dynamic cell formation model using fuzzy conditions.

Deljoo *et al.* (2010) presented a mixed-integer programming (MIP) model for the dynamic cell formation solving the problems by the GA. Rafiei and Ghodsi (2013) presented

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a bi-objective mathematical model to dynamic cell formation. The objectives of their model were to minimize dynamic cell formation costs and to maximize labor utilization employing a hybrid ant colony optimization-genetic algorithm (ACO-GA) to solve the model. Paydar and Saidi-Mehrabad (2013) developed a GA and variable neighborhood search to maximize grouping efficacy in the cell formation problem. Majazi Dalfard (2013) presented a new model for larger quantities of material flow at a closer distance in a dynamic cell formation using simulated annealing (SA) to solve the model.

Ahi *et al.* (2009) used the TOPSIS method to cell formation and cell layout in CMS. Chang *et al.* (2013) proposed a model to cell formation problem and intra-cell layout and tabular search (TS) algorithm to solve it. Tavakkoli-Moghaddam *et al*. (2006) applied a SA algorithm to a nonlinear model for the group layout problem and cell formation problem with stochastic demands. Kia *et al*. (2011) developed a minimization model with stochastic demands in CMS designs for group layout problems and cell formation problem. Wu *et al.* (2007) presented a GA for cell formation and group layout problems in a two-stage procedure. Safaei and Tavakkoli-Moghaddam (2009) combined the cell formation and group cell transportation in a model using outsourcing production.

Jolai *et al.* (2012) combined the cell formation and group layout in a model and used the electromagnetism-like algorithm. Kia *et al*. (2012) aggregated cell formation and group layout decisions for multi-period planning in a model solved by a SA algorithm. Javadi *et al.* (2014) proposed an integrated mathematical formulation for cell formation and group layout using GA and electromagnetism-like algorithm to find solutions. Mahdavi *et al*. (2013) aggregated cell formation and inter-cell layout with forward and backward transportation for distances between cells were in a model. Kia *et al.* (2013) proposed a multi-objective model for group layout and cell formation with a variable number of cells. Kia *et al*. (2014) also introduced a model for the dynamic cellular manufacturing system (DCMS) design with the cell formation and multi-floor group layout decisions proposing an efficient GA to derive near-optimal solutions. Wirojanagud *et al.* (2007) proposed a model to worker planning about the capability of operator learning skills in the performance of different jobs, in which the objective function was to minimize the operator hiring/firing cost.

Rabbani *et al.* (2007) proposed a mathematical model for Parallel Machine Scheduling with Controllable Processing Time Considering Energy Cost and Machine Failure Prediction.

Solimanpur *et al.* (2009) presented a multi-objective model for the cell formation and labor assignment using fuzzy goal programming (FGP) for solutions. Aryanezhad *et al.* (2008) considered an operator skill level of dynamic cell formation in the model. Mahdavi *et al*. (2010) presented an MIP model considering cell formation, material transportation, operator assignment and inventory in. Hamedi *et al.* (2012) proposed a multi-objective programming model for a capability-based virtual CMS design with dual-resource constraint consisting of machine tools and workers solved this through a SA algorithm. Gen (2012) introduced a multi-objective hybrid GA for manufacturing scheduling in the fuzzy environment using different mathematical models.

Mahdavi *et al.* (2014) introduced a bi-objective model for the CMS design considering worker and the ε-constraint method to find solutions. Kim *et al.* (2012) developed an integer model for the loading problem in a flexible manufacturing system under tool constraints. AL-Ahmari and Alharbi (2009) combined cell formation, tool and operator assignments in a model. Bagheri and Bashiri (2014) used an LP-metric approach to a proposed model consisting of cell formation, layout, and operator assignment elements. Mehdizadeh and Rahimi (2016) aggregated the dynamic cell formation, group layout and operator assignment in an MIP model. Sun (2007) utilized the Taguchi method to set up four GA parameters in the job shop scheduling design.

Table 1.
A summary of the literature review.

Articles/ Authors	Type of problem					Solving method
	Cell Formation	Intra-cell layout	Inter-cell Layout	Operator Assignment	Tool Assignment	
Jolai et al. (2012)	*	*				EM-like algorithm
Tavakkoli-Moghaddam et al. (2006)	*	*	*			SA
Kia et al. (2014)	*	*	*			GA
Kia et al. (2013)	*	*	*			Multi-objective
Aryanezhad et al. (2008)	*			*		Lingo
Mahdavi et al. (2010)	*			*		Lingo
AL-Ahmari and Alharbi (2009)	*			*	*	Lingo
Bagheri and Bashiri (2014)	*		*	*		LP-metric
Mehdizadeh and Rahimi (2016)	*	*	*	*		MOSA and MOVDO
Current research	*		*	*	*	Lingo, GA, and HS

A summary of some recently published papers is presented in Table 1. As shown in this table, there is no research to date solving cell formation, cell layout, operator assignment and tool assignment problems simultaneously. The present paper attempts to fill the gap by proposing a new integrated mathematical model, in which an operator is a major component of industrial systems. In most of the research on the CMS design, the operator is assumed to be a working element, such as part, machine, and tool. Based on the literature review, the most frequently-used criteria for operator assignment are hiring, firing and salary costs. This paper focuses on developing a new aspect of the operator assignment. Assuming that nm represents the number of machines being operated by each worker, st is the worker servicing time per machine, mt is the machine working time and nt the walking time between two machines, where:

$$nm = \frac{st + mt}{st + nt}$$

The number of machines must be represented by the total number; otherwise, we have:

$$nm_{lower} < nm < nm_{upper}$$

The total expected cost (i.e., cost of production per cycle from one machine) for nm_{lower} machine is given by:

$$COP_{nm_{lower}} = \frac{wc.(st + mt) + nm_{lower}.mc.(st + mt)}{nm_{lower}}$$

where wc is the worker cost per unit time and mc is machine cost per unit time. The total expected cost for nm_{upper} machine is given by the following:

$$COP_{nm_{upper}} = ((st + nt))(wc + mc.nm_{upper}))$$

The number of machines assigned to workers represents the minimum total cost per piece. Among the advantages emanating through the implementation of the proposed subject and model, one can refer to a less material handling cost, less idleness of machines and operators, less work-in-process inventory, better work flexibility and better utilization of machines. This paper is organized as follows. In Section 2, the proposed mathematical model is presented. Solution algorithms are introduced in Section 3. Section 4 and 5 present a numerical example with computational results and Section 6 presents the conclusion.

Problem Definition and Formulation

The problem is formulated as a mixed-integer non-linear problem (MINLP) model based on cell formation, inter-cell layout, and resource assignment with a man-machine relationship aspect simultaneously. The objective is to minimize the sum of the process, material transportation, operator and machine idleness, machine purchase, and tool costs. Main constraints are cell size, operator and machine time capacity, number of machines, cell-position assignment, machine magazine capacity and idleness of the machines and operators.

The problem is formulated according to the following assumptions:

- Each part type has a number of operations that must be processed based the route sheet of parts.
- All machine types are supposed to be multi-functional.
- All machine types are supposed to be identical.
- Demand for each part type is known.
- Tool life for each tool type is known.
- Capability and time capacity of each machine are precise and constant over the planning horizon.
- Capability and available time of each operator type are known.
- Capability of each operator type for processing each part on each corresponding machine type and each tool type are known.
- Cost of idleness of each machine and each worker are known.
- Number of slots needed by each tool type and number of slots available at each machine type is given and fixed.
- Total servicing time (i.e., loading and unloading time) of a worker to each machine is given.
- Cost of each machine type for a unit of time is known.
- The rate of each operator type for a unit of time is known.
- Number of cell candidate positions is constant over the planning horizon.

The following notations are used in the mathematical model.

Indices

i	Part type (i = 1, ..., I)
o	Operation type (o = 1, ..., O)
m	Machine type (m = 1, ..., M)
k	Manufacturing cell (k = 1, ..., K)
p	Position (p = 1, ..., P)
h	Tool (h = 1, ..., H)
w	Worker (w = 1, ..., W)

Parameters

mt_{oimhw}	Working time of machine m to perform operation o on part i with tool h by worker w
a_{oimhw}	1, if machine m is used to process operation o for part i with tool h by worker w; and 0, otherwise
θ_i^{inter}	Cost of inter-cell movement for part i per unit of distance
θ_i^{intra}	Cost of intra-cell movement for part i per unit of distance
Q_i	Demand of part i
TC_m	Time capacity of machine m
TC_w	Time capacity of operator w
U_k	Upper bound of machines allowed in cell k
$A_{kk'}$	Average distance between cells k, k'
st_{oimhw}	Worker servicing time per machine m to perform operation o on part i with tool h by operator w

nt_{oimhw}	Walking time between machine *m* that used to process operation *o* for part *i* with tool *h* by worker *w* to the next machine
λ_{oimhw}	Operating cost on machine *m* to process operation *o* on part *i* with tool *h* by worker *w*
$\mu_{kk'}$	1, if $k \neq k'$; and 0, if $k = k'$
I_w	Idleness cost of worker *w* for time unit
I_m	Idleness cost of machine *m* for time unit
π_m	Purchase cost of machine *m*
Sl_h	Number of slots needed by tool *h*
SS_m	Capacity of tool magazine on machine *m*
mc_m	Cost of machine *m* for time unit
wc_w	Cost of worker *w* for time unit
δ_h	Cost of tool *h*
$Batch_i^{inter}$	Batch size of inter-cell movement for part *i*
$Batch_i^{intra}$	Batch size of intra-cell movement for part *i*
$TLife_h$	Tool life of tool *h*

Decision variables

x_{oimkhw}	1, if machine *m* is used to process operation *o* for part *i* with tool *h* by worker *w* in cell *k*; and 0, otherwise
v_{hm}	Number of tool copies of tool *h* on machine *m*
u_{oimk}	1, if machine *m* is used to process operation *o* for part *i* in cell *k*; and 0, otherwise
z_{oim}	1, if machine *m* is used to process operation *o* for part *i*; and 0, otherwise
zz_{mk}	1, if machine *m* assigned to cell *k*; and 0, otherwise
y_{kp}	1, if cell k assigned to position *p*; and 0, otherwise
$\varphi1_{mw}$	1, if machine (nm_{upper}) m assigned to operator *w*; and 0, otherwise
$\varphi2_{mw}$	1, if machine (nm_{lower}) m assigned to operator *w*; and 0, otherwise
nm_{mw}	Number of machine *m* assigned to operator *w*
${nm_{lower}}_{mw}$	Lower total number of machine *m* assigned to operator *w*
${nm_{upper}}_{mw}$	Upper total number of machine *m* assigned to operator *w*
COP_{nm}	Cost of production per cycle from one machine
$COP_{{nm_{lower}}_{mw}}$	Cost of production per cycle from one machine (nm_{lower}) m and worker w
$COP_{{nm_{upper}}_{mw}}$	Cost of production per cycle from one machine (nm_{lower}) m and worker w
nnm_{mwk}	Number of machine *m* assigned to operator *w* in cell *k*
$Id1_{mw}$	Idleness of machine *m* assigned to operator *w*
$Id2_{mw}$	Idleness of operator *w* assigned to machine *m*

$$in \sum_{o=1}^{O}\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{h=1}^{H}\sum_{w=1}^{W} Q_i\lambda_{oimhw}x_{oimkhw} \quad (1)$$

$$+ \sum_{o=1}^{O-1}\sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{k'=1}^{K}\sum_{p'=1}^{L}\left\lceil\frac{Q_i}{Batch_i^{inter}}\right\rceil\theta_i^{inter}\mu_{kk'}A_{kk'}\left(\sum_{m=1}^{M}u_{oimk}\right)\left(\sum_{m=1}^{M}u_{o+1,imk'}\right)y_{kp}y_{k'p'}$$

$$+$$

$$\sum_{o=1}^{O-1}\sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{k\prime=1}^{K}\left[\frac{Q_i}{Batch_i^{intra}}\right]\theta_i^{intra}(1-\mu_{kk'})A_{kk\prime}\left(\sum_{m=1}^{M}u_{oimk}\right)\left(\sum_{m=1}^{M}u_{o+1,imk'}\right)$$
$$+$$
$$\sum_{w}^{W}I_w\left(\sum_{m}^{M}Id2_{mw}\right)$$
$$+$$
$$\sum_{m}^{M}I_m\left(\sum_{w}^{W}Id1_{mw}\right)$$
$$+$$
$$\sum_{m}^{M}\sum_{w}^{W}\pi_m\times\left(nm_{lower_{mw}}\varphi2_{mw}+nm_{upper_{mw}}\varphi1_{mw}\right)$$
$$+$$
$$\sum_{h=1}^{H}\delta_h\sum_{m=1}^{M}v_{hm}$$

s.t.

$$\sum_{m}^{M}\sum_{k}^{K}\sum_{h}^{H}\sum_{w}^{W}a_{oimhw}x_{oimkhw}=1 \qquad \forall o,i \qquad (2)$$

$$x_{oimkhw}\le a_{oimhw} \qquad \forall o,i,m,k,h,w \qquad (3)$$

$$\sum_{m}^{M}\sum_{w}^{W}nnm_{mwk}\le U_k \qquad \forall k \qquad (4)$$

$$u_{oimk}=z_{oim}zz_{mk} \qquad \forall o,i,m,k \qquad (5)$$

$$nnm_{mwk}zz_{mk}=nm_{lower_{mw}}\varphi2_{mw}+nm_{upper_{mw}}\varphi1_{mw} \qquad \forall m,w,k \qquad (6)$$

$$\sum_{o}^{O}\sum_{i}^{I}\sum_{k}^{K}\sum_{h}^{H}Q_i(mt_{oimhw}+st_{oimhw})x_{oimkhw}\le TC_w+M\varphi1_{mw} \qquad \forall m,w \qquad (7)$$

$$\sum_{o}^{O}\sum_{i}^{I}\sum_{k}^{K}\sum_{h}^{H}Q_i mt_{oimhw}x_{oimkhw}nm_{upper_{mw}}\le TC_w+M\varphi2_{mw} \qquad \forall m,w \qquad (8)$$

$$\sum_{o}^{O}\sum_{i}^{I}\sum_{k}^{K}\sum_{h}^{H}Q_i(mt_{oimhw}+st_{oimhw})x_{oimkhw}\le TC_m+M\varphi1_{mw} \qquad \forall m,w \qquad (9)$$

$$\sum_{o}^{O}\sum_{i}^{I}\sum_{k}^{K}\sum_{h}^{H}Q_i mt_{oimhw}x_{oimkhw}nm_{upper_{mw}}\le TC_m+M\varphi2_{mw} \qquad \forall m,w \qquad (10)$$

$$\frac{(mt_{oimhw}+st_{oimhw}).x_{oimkhw}}{st_{oimhw}+nt_{oimhw}}\le nm_{upper_{mw}} \qquad \forall o,i,m,k,h,w \qquad (11)$$

$$nm_{upper_{mw}}=a_{oimhw}\left(nm_{lower_{mw}}+1\right) \qquad \forall o,i,m,k,h,w \qquad (12)$$

$$COP_{nm_{lower_{mw}}}=$$

$$\frac{a_{oimhw}\left((mt_{oimhw}+st_{oimhw})(wc_w+nm_{lower_{mw}}\times mc_m)\right)}{nm_{lower_{mw}}} \quad \forall\ o,i,m,h,w \quad (13)$$

$$COP_{nm_{upper_{mw}}} = a_{oimhw}\left((st_{oimhw}+nt_{oimhw}).\left(wc_w+mc_m\times nm_{upper_{mw}}\right)\right) \quad \forall\ o,i,m,h,w \quad (14)$$

$$COP_{nm_{lower_{mw}}} \le COP_{nm_{upper_{mw}}} + M\varphi1_{mw} \quad \forall m,w \quad (15)$$

$$COP_{nm_{upper_{mw}}} \le COP_{nm_{lower_{mw}}} + M\varphi2_{mw} \quad \forall m,w \quad (16)$$

$$\varphi1_{mw}+\varphi2_{mw}=1 \quad \forall m,w \quad (17)$$

$$\sum_{p=1}^{P} y_{kp}=1 \quad \forall k \quad (18)$$

$$\sum_{k=1}^{K} y_{kp}\le 1 \quad \forall p \quad (19)$$

$$\sum_{o}^{O}\sum_{i}^{I}\sum_{k}^{K}\sum_{w}^{W} mt_{oimhw}x_{oimkhw} \le TLife_h.v_{hm} \quad \forall h,m \quad (20)$$

$$\sum_{h}^{H} Sl_h\, v_{hm} \le SS_m \quad \forall h,m \quad (21)$$

$$\sum_{h}^{H}\sum_{w}^{W} x_{oimkhw}=u_{oimk} \quad \forall\ i,o,m,k \quad (22)$$

$$Id1_{mw}=\left(nm_{upper_{mw}}.st_{oimhw})-(mt_{oimhw}+st_{oimhw})\right)\varphi1_{mw} \quad \forall o,i,m,k,h,w \quad (23)$$

$$Id2_{mw}=\left((mt_{oimhw}+st_{oimhw})-(nm_{lower_{mw}}st_{oimhw})\right)\varphi2_{mw} \quad \forall o,i,m,k,h,w \quad (24)$$

$$x_{oimkhw}\,,u_{oimk}\,,y_{kp}\,,\varphi1_{mw}\,,\varphi2_{mw}\,,z_{oim}\,,zz_{mk}\in\{0,1\} \quad (25)$$

$$nm_{lower_{mw}}\,,nm_{upper_{mw}}\,,nnm_{mwk},v_{hm}\ge 0\,,integer \quad (26)$$

Mathematical model

The first term in the objective function (1) represents the total cost of the process. The second and third terms represent the total material transportation cost. The fourth term represents the total idleness cost of operators. The fifth term represents the total idleness cost of machines. The sixth term represents the total machine purchase cost. The seventh term represents the total tool cost. Equations (2) and (3) express the operation-part-machine-tool-worker combinations. Equation (4) limits the cell size. Equation (5) can be used to define the machine-cell combination. Equation (6) is used to ensure that the number of machine *m* is assigned to operator *w* in cell *k*. Equations (7) and (8) express the time capacity of operator *w*. Equations (9) and (10) express the time capacity of machine m. Equation (11) ensures that the upper total number of machine *m* is assigned to operator *w*.

Equation (12) ensures that the lower total number of machine *m* is assigned to operator *w*. Equations (13) and (14) express the cost of production per cycle from one machine in the lower and upper total numbers of machine *m* assigned to operator *w*. Equations (15) - (17) guarantee that the lowest COP is chosen. Equations (18) and (19) ensure that each cell should be assigned to only one candidate position and a position can be opened only for one cell. Constraints (20) determines the tool and machine assignment, the magazine capacity restriction is represented by Constraint (21). Equation (22) express the operation-part-machine-cell combinations. Equations (23) and (24) ensures that the idleness of the machines and operators. Equations (25) and (26) can be used to define the type of variable.

Linearization of the proposed model

The presented our mathematical model is an MINLP model because of second, third and sixth terms and Equations (5), (6), (8) and (10). A set of auxiliary variables are to be defined to linearize these Equations and terms. Three classic approaches from Majazi Dalfard (2013), Mahdavi *et al*. (2013) and Mahdavi *et al*. (2010) have been used in different steps. The following constraints should be added to the base model.

In second term, we have:

$$\gamma_{oikk'} \geq \left(\sum_{m=1}^{M} u_{oimk}\right) + \left(\sum_{m=1}^{M} u_{o+1,imk'}\right) - 1 \qquad \forall o,i,k,k' \qquad (27)$$

$$\gamma_{oikk'} \leq \frac{1}{2}\left(\sum_{m=1}^{M} u_{oimk} + \sum_{m=1}^{M} u_{o+1,imk'}\right) \qquad \forall o,i,k,k' \qquad (28)$$

$$yy_{kk'pp'} \geq y_{kp} + y_{k'p'} - 1 \qquad \forall k,k',p,p' \qquad (29)$$

$$yy_{kk'pp'} \leq \frac{1}{2}\left(y_{kp} + y_{k'p'}\right) \qquad \forall k,k',p,p' \qquad (30)$$

$$\gamma yy_{oikk'pp'} \geq \gamma_{oikk'} + yy_{kk'pp'} - 1 \qquad \forall o,i,k,k',p,p' \qquad (31)$$

$$\gamma yy_{oikk'pp'} \leq \frac{1}{2}\left(\gamma_{oikk'} + yy_{kk'pp'}\right) \qquad \forall o,i,k,k',p,p' \qquad (32)$$

In third term, we have:

$$\gamma_{oikk'} \geq \left(\sum_{m=1}^{M} u_{oimk}\right) + \left(\sum_{m=1}^{M} u_{o+1,imk'}\right) - 1 \qquad \forall o,i,k,k' \qquad (33)$$

$$\gamma_{oikk'} \leq \frac{1}{2}\left(\sum_{m=1}^{M} u_{oimk} + \sum_{m=1}^{M} u_{o+1,imk'}\right) \qquad \forall o,i,k,k' \qquad (34)$$

In sixth term, we have:

$$\varphi 2nm_{lower_{mw}} \leq nm_{lower_{mw}} \qquad \forall m,w \qquad (35)$$

$$\varphi 2nm_{lower_{mw}} \leq M\varphi 2_{mw} \qquad \forall m,w \qquad (36)$$

$$\varphi 2nm_{lower_{mw}} - nm_{lower_{mw}} \geq M(\varphi 2_{mw} - 1) \qquad \forall m,w \qquad (37)$$

$$\varphi 1nm_{upper_{mw}} \leq nm_{upper_{mw}} \qquad \forall m,w \qquad (38)$$

$$\varphi 1nm_{upper_{mw}} \leq M\varphi 1_{mw} \qquad \forall m,w \qquad (39)$$

$$\varphi 1nm_{upper_{mw}} - nm_{upper_{mw}} \geq M(\varphi 1_{mw} - 1) \qquad \forall m,w \qquad (40)$$

In Equation (5), we have:

$$zzz_{oimk} \geq z_{oim} + zz_{mk} - 1 \qquad \forall o,i,m,k \qquad (41)$$

$$zzz_{oimk} \leq \frac{1}{2}\left(z_{oim} + zz_{mk}\right) \qquad \forall o,i,m,k \qquad (42)$$

In Equation (6), we have:

$$zznnm_{mwk} \geq nnm_{mwk} - M(1 - zz_{mk}) \qquad \forall o, i, m, k \qquad (43)$$

$$zznnm_{mwk} \leq nnm_{mwk} + M(1 - zz_{mk}) \qquad \forall o, i, m, k \qquad (44)$$

In Equations (8) and (10), we have:

$$xnm_{upper_{oimkhw}} \leq nm_{upper_{mw}} \qquad \forall o, i, m, k, h, w \qquad (45)$$

$$xnm_{upper_{oimkhw}} \leq Mx_{oimkhw} \qquad \forall o, i, m, k, h, w \qquad (46)$$

$$xnm_{upper_{oimkhw}} - nm_{upper_{mw}} \geq M(x_{oimkhw} - 1) \qquad \forall o, i, m, k, h, w \qquad (47)$$

$$\gamma_{oikk'}, yy_{kk'pp'}, \gamma yy_{oikk'pp'}, zzz_{oimk} \in \{0,1\} \qquad (48)$$

$$xnm_{upper_{oimkhw}}, \varphi 2nm_{lower_{mw}}, \varphi 1nm_{upper_{mw}}, zznnm_{mwk} \geq 0, \quad integer \qquad (49)$$

Since the presented mathematical model is NP-hard, a meta-heuristic algorithm is proposed to solve large-sized problems.

Solution Algorithms

Arguably, the most noteworthy advantage of a meta-heuristic algorithm is to find a solution for NP-hard problems. A number of authors, such as Tavakkoli-Moghaddam *et al.* (2010), Molaei *et al.* (2014), Mohammadi and Ehtesham Rasi. (2022), Eram *et al.* (2021),Mahmoodi *et al.* (2023) and Mahdavgi *et al.* (2009), proposed meta-heuristics to solve real-sized problems. To validate the results, we presented an HS algorithm. Moreover, in order to obtain better solutions, the GA and HS parameters are adjusted and tuned. The details are given in the next sub-sections.

Genetic algorithm

The GA was developed by Holland (1975). It started coding to chromosome form. After producing the first random chromosomes, assessment of performance is performed using the fitness function. The remaining chromosomes and offspring make a generation through crossover and mutation. Finally, the elitism process introduces solutions. The GA utilized for our CMS framework is as follows:

Three elements are assumed in our CMS problem. The first element shows the assignment of cells to position type using [Ce_Lo]. The components of the *C*×*L* matrix are the number of assignment alternatives for each cell to each position taking a value in [0, 1]. This matrix is used to define Constraints (18) and (19). The next element shows the assignment of machines to operators using [Ma_Wo]. The components of the *M*×*W* matrix present the number of each machine type to be assigned to each operator. This matrix is used to define all the relative constraints. The third element shows operation-part-machine-cell-tool-operator [OP_Pa_N3], where N3 is equal to [Ma_Ce_To_Wo]. The parts of the *J*×*P*×*M*×*C*×*T*×*W* matrix present the assignment of part operations to each machine and each operator using each tool in each cell taking a value in [0, 1]. These matrices are used to define all the relative constraints.

Initial solution

In this step, numbers randomly chosen between zero and one are defined to present the matrices [Ce_Lo], [Ma_Wo] and [OP_Pa_Ma_Ce_To_Wo]. Fig. 1 shows the solution representation.

y_{11}	…	y_{1l}	…	y_{Cl}	$N1_{11}$	…	$N1_{mw}$	$N2_{11}$	…	$N2_{mw}$	x_{111111}	…	x_{11111w}	x_{21111w}	…	x_{JPMCTW}

Figure 1. *Solution representation*

Fitness value

To define the objective function of the CMS model, the fitness value is defined. The other name for the new chromosome is offspring, which is derived from the fitness function which is utilized to estimate and generate fresh chromosomes.

Pick out chromosomes

In this paper, a roulette wheel is used to pick out the chromosomes.

Crossover

New offspring for the future generation is produced using the crossover operation. By comparing the crossover probability and random numbers between zero and one, we choose the chromosome for the crossover operation.

Mutation

A mutation operation is created other opportunities for not choosing chromosomes through comparison of the mutation probability and random numbers between zero and one.

Elitism

In addition to the old operation, there exists another possibility in the elitism process for elite chromosomes having superior fitness value. Fig. 2 depicts the Pseudo code of the GA (Mousavi *et al.* 2014).

Harmony Search

Musical performance refers to the search for the lovely harmony in all harmonies. Geem *et al.* (2001) developed an optimization algorithm based on the musical performance, called HS. This algorithm searches for the best solution derived through the objective function. The algorithm is initiated by playing a new harmony and comparing this harmony with harmonies in harmony memory (HM) whose procedure leads to improvement in the quality of harmony in a step-by-step fashion. Then, HM updates and verifies the stop criterion.

```
                                              Procedure: GA
                     input: problem data, Pc; Pm; Pop; and NOG
                                  output: objective function value
begin
    define (Pc; Pm; Pop; and NOG )
       for k=1: NOG
            chromosomes=generate between [0,1] randomly
            objective function value for each chromosome=evaluate (chromosomes)
            R=Best chromosome with minimum objective function value
            selection process (based on roulette wheel method)
            generate r1 between (0,1) for each chromosome
          if Pc ≤r1
              do crossover operator on each chromosome
          else generate r2 between (0, 1)
            if Pm ≤r2
              do mutation operator on each chromosome
            end
        end
        elitism process
        updating (objective function value and R)
endfor
output objective function value
Return (R).
```

Figure 2. *Pseudo code of the GA*

All the decision variables (notes) saved in HM and the values for these notes in the new harmony are specified based on the following:

1) Precise selection of the value for the HM domain.

2) Random selection of the entire domain of values with a selection rate or harmony memory considering rate (HMCR) between zero and one.
3) Selection of some deal identical values for HM domain with a pitch adjustment rate (PAR) between zero and one and a free distance bandwidth (bw) (Askarzadeh and Zebarjadi, 2014).

The Pseudo code of the HS algorithm is shown in Fig. 3 (Askarzadeh and Zebarjadi, 2014).

```
Procedure: HS
input: problem data, HM size, HMCR, PARmax, PARmin, bwmax, bwmin and tmax
output: objective function value
begin
  generate a number of feasible harmonies for storing in HM
  compute the objective function value for each harmony
    for t=1, 2, ..., tmax
    update the time varying parameters
    for i=1, 2, ..., n
    if rand (0,1)>HMCR
      xnew (i)=A random value from the possible range
    else
     xnew (i)=corresponding value from a random harmony of HM
       if rand (0,1)<PAR(t)
     xnew(i)= xnew(i)+bw(t)*[rand(0,1) - rand(0,1)]
      end
    end
end
   compute the objective function value of the new harmony
     if Fnew<Fworst
   store the new harmony in HM
   remove the worst harmony from HM
end
output objective function value
end
```

Figure 3. *Pseudo code of the HS*

Numerical Example

The proposed CMS model is executed by a branch-and-bound algorithm using Lingo 9.0 software and a laptop involving five Intel (R) Core (TM) i5-3230 CPU @ 2.60 GHz and 6 GB RAM for a small example. This small example involved three cells, two machines, two parts, two tools, three locations and two operators. There are two operations to be performed on each part, consecutively. There are four options for machine-tools-operator assignments in each operation. Each operation is performed on four alternative machine-tool-operator assignments. Walking time to the next machine takes zero time. Maximum machine capacities for each cell are 2, 2 and 2, respectively. Table 2 shows data for the small example.

Some columns in Table 2 involve the machine data, such as available time (hours), machine idle cost, constant cost, number of tool slots available in machines, and variable cost. The quantity of demand and within cell movement costs and between cell movement costs for each part type are shown in this table. The machining time and machining costs required for each operation on a machine to part and with a tool by an operator combination are illustrated in Table 2.

Table 2.
Typical test problem

Tc_m	I_m	π_m	SS_m	mc_m	MACHINE	TOOL	WORKER	Part / OPERATION	i_1 o=1	i_1 o=2	i_2 o=1	i_2 o=2
					M_1	h_1	W_1		0.02,10	0.02,10	0.02,11	0.02,14
45	20	3000	7	2	M_1	h_1	W_2					
					M_1	h_2	W_1		0.02,9	0.02,11	0.02,12	0.02,12
					M_1	h_2	W_2					
					M_2	h_1	W_1					
45	0	4000	7	3	M_2	h_1	W_2		0.02,14	0.02,15	0.02,10	0.02,12
					M_2	h_2	W_1					
					M_2	h_2	W_2		0.02,14	0.02,16	0.02,12	0.02,13
						Q_i			300		100	
						θ_i^{inter}			50		75	
						θ_i^{intra}			10		10	

The value 0.02 in the first figure indicates operation time, and the second figure (10) indicates operation cost. The data sets related to worker information, such as time capacity (hours), idle cost of operators (unit of time), variable cost, total operator servicing (loading and unloading) time per machine, is shown in Tables 3. The related parameters for tools and distance between cells are given in Tables 4 and 5.

Table 3.
Typical test problem

Worker	Tc_w	I_w	wc_w	st_{oimhw}
W_1	45	10	2	0.03
W_2	45	10	1	0.03

Table 4.
Information relating to tools for a test problem

Tool	Sl_h	δ_h
h_1	3	50
h_2	3	60

Table 5.
Information related to the distance between cells for test problems

$A_{kk'}$	1	2	3
1	1	2	4
2	2	1	2
3	4	2	1

Tables 2 to 5 shows small example data, and Tables 6 and 7 show the results of the proposed MIP model for the small example.

Table 6.
Objective functions and components for example.

Total	Total Cost of process	Inter-cell material transportation cost	Intra-cell material transportation cost	Idleness Cost of operator	Idleness Cost of machine	total machine purchase cost	tool cost
18380.4610	7900	0	270	0.2	0.2	10000	210

Table 7.
Optimal selection of cells, locations, machines, operations, tools and operators for example

Cells	Locations	Machines	Tools	Operators	i_1		i_2		Number of tools	Number of machines	Number of Operators
					o_1	o_2	o_1	o_2			
k_3	p_3	M_1	h_1	W_1		0.02,10			1	2	1
		-	h_2		0.02,9				1	-	-
k_2	p_2	M_2	h_1	W_2			0.02,10	0.02,12	2	1	1
		-	h_2						-	-	-
k_1	p_1	-	-	-	-	-	-	-	-	-	-

Two machine types 1, one of tool types 1 and 2, and one operator 1 are selected in cell 3 in location 3 to process part types 1. One machine type 2, two tool types 1, and one operator 2 are selected in cell 2 in location 2 to process part type 2.

Computational Results

In order to validate and evaluate the execution of two meta-heuristic algorithms on the CMS design, an arrangement of random numerical examples is generated. In order to solve the presented model, MATLAB (R2013b) software is used to code the algorithms on a laptop with five Intel Core i5 CPU and 6 GB RAM. The Taguchi method is performed in Minitab software version 17.3.1 to tune the parameters and analyze the data.

Generating random data

In this section, 20 examples are constructed in different sizes through the generation of uniformly distributed random points for some of the provided parameters. The extent of each problem relies on the following components:

- The number of operations (*o*).
- The number of parts (*i*).
- The number of machines (*M*).
- The number of cells (*k*).
- The number of tools (*h*).
- The number of workers (*W*).
- The greatest number of machines in each cell (U_k).
- The number of locations (*p*).

The properties of the twenty planned examples are shown in Table 8. The details of the parameters required for the twenty problem instances are shown in Table 9.

Table 8.
Attributes of test examples.

Problem No.	*o*	*i*	*M*	*k*	*h*	*W*	U_k	*p*
1	3	3	3	2	3	3	3	2
2	4	3	3	2	3	3	3	2
3	4	3	4	2	3	4	4	2
4	4	4	4	2	3	4	4	2
5	5	4	4	2	3	4	4	2
6	5	5	4	3	4	4	4	3
7	5	5	5	3	4	5	4	3
8	6	5	5	3	4	5	4	3
9	6	6	5	3	4	5	4	3
10	6	6	6	3	4	6	5	3
11	7	6	6	3	4	6	5	3
12	7	7	6	4	4	6	5	4
13	7	7	7	4	5	7	6	4
14	8	7	7	4	5	7	6	4
15	8	8	7	4	5	7	6	4
16	8	8	8	5	5	8	7	5
17	9	8	8	5	5	8	7	5
18	9	9	8	5	5	8	7	5
19	9	9	9	5	5	9	7	5
20	9	9	10	5	6	10	7	5

Table 9.
Information relating to the random production of test problems

Parameter	Amount	Parameter	Amount	Parameter	Amount
mt_{oimhw}	0.02	t'_{jpmtw}	0.03	mc_m	$U(3-8)$
θ_i^{inter}	50	nt_{oimhw}	0	wc_w	$U(2-5)$
θ_i^{intra}	10	λ_{oimhw}	$U(5-15)$	δ_h	$U(50-100)$
Q_i	*U(10- 200)*	I_w	$U(5-20)$	$Batch_i^{inter}$	$U(10-15)$
Tc_m	50	I_m	$U(5-20)$	$Batch_i^{intra}$	$U(5-10)$
Tc_w	50	π_m	$U(4000-8000)$	$TLife_h$	$U(1-3)$
U_k	4	Sl_h	$U(3-5)$	SS_m	$U(10-20)$

Tuning Parameters

The Taguchi method is employed to tune the parameters of the GA and HS algorithms. In the Taguchi method, an orthogonal array is utilized for the design of experiences with control of *N* (Mousavi et al., 2014). The Taguchi method was not affected by a not manageable factor (*N*) and manageable factor (*S*). The *S/N* analysis aims at attaining a more suitable situation for optimization of *S/N*. Despite the availability of diverse classes for quality attributes of the *S/N*, in this review, the "smaller is better" is used.

$$S/N = -10 \times \text{Log}\left(\frac{S(y^2)}{n}\right) \quad (50)$$

where *n* and *y* are the quantity and the response of orthogonal arrays, respectively/individually. We utilize the L^9 design to actualize the Taguchi procedure, in where the values and levels of the GA and HS parameters are presented in Table 10.

Table 10.
GA and HS parameters and levels

	Algorithm Parameters	Low (1)	Medium (2)	High (3)
GA	POP (A)	30	40	50
	P_c (B)	0.5	0.6	0.7
	P_m (C)	0.01	0.05	0.1
	NOG (D)	100	200	300
HS	HMS (A)	5	10	20
	HMCR (B)	0.9	0.95	0.99
	PAR (C)	0.01	0.1	0.3
	bW (D)	0.1	0.5	0.9

Orthogonal arrays to the GA and HS using the Minitab software are shown in Tables 11 and 12, individually.

Table 11.
Tuning process of the GA

A	**B**	**C**	**D**	R_1	R_2	R_3	R_4	R_5	$S/N\ Ratio$	**Mean**
1	1	1	1	233750	226500	230210	229400	223690	-107.187	228710
1	2	2	2	202830	204920	219800	225360	211210	-106.568	212824
1	3	3	3	224250	206120	222420	226580	193420	-106.646	214558
2	1	2	3	229240	230140	211620	223430	209730	-106.888	220832
2	2	3	1	220470	210920	207390	233400	205110	-106.677	215458
2	3	1	2	209200	218570	212250	235670	232360	-106.922	221610
3	1	3	2	224260	214170	204560	200220	226550	-106.617	213952
3	2	1	3	233720	220060	227090	218650	203960	-106.885	220696
3	3	2	1	205800	197220	199120	209550	196460	-106.094	201630

Table 12.
Tuning process of the HS

A	B	C	D	R_1	R_2	R_3	R_4	R_5	$S/N\ Ratio$	Mean
1	1	1	1	239540	225220	227110	235720	206830	-107.127	226884
1	2	2	2	191660	205830	185850	212660	216200	-106.141	202440

1	3	3	3	181680	192330	201790	187220	220840	-105.900	196772
2	1	2	3	195490	193510	178970	194300	184310	-105.549	189316
2	2	3	1	206530	221320	225570	229970	223390	-106.907	221356
2	3	1	2	196720	203800	215090	207120	214710	-106.345	207488
3	1	3	2	191890	207670	204350	177840	195580	-105.834	195466
3	2	1	3	207290	228710	218880	222240	209770	-106.750	217378
3	3	2	1	216800	211200	212680	233300	209650	-106.725	216726

Tables 13 and 14 outlines the means of the *S/N* for the GA and HS, respectively.

Table 13.
S/N mean for the factor levels of the GA

	Factors			
Level	A	B	C	D
1	-106.8	-106.9	-107.0	-106.7
2	-106.8	-106.7	-106.5	-106.7
3	-106.5	-106.6	-106.6	-106.8
Delta	0.3	0.3	0.5	0.2
Rank	3	2	1	4

Table 14
The S/N mean for the factor levels of the HS

	Factors			
Level	A	B	C	D
1	-106.4	-106.2	-107.7	-106.9
2	-106.3	-106.6	-106.1	-106.1
3	-106.4	-106.3	-106.2	-106.1
Delta	0.2	0.4	0.6	0.9
Rank	4	3	2	1

Figs. 4 and 5 show the mean of the signal to noise ratio with its parameter levels of the GA and HS, respectively. In these figures, the highest means for the *S/N* values represent the best parameter levels.

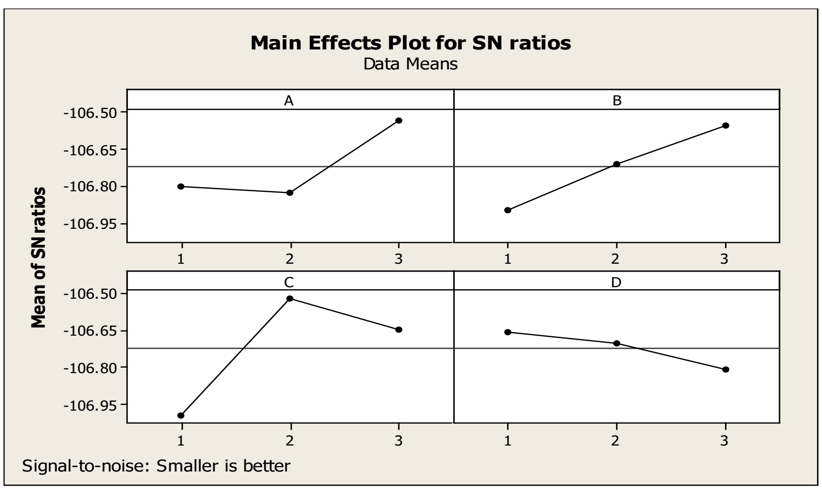

Figure 4. *Taguchi S/N ratio plot for the GA*

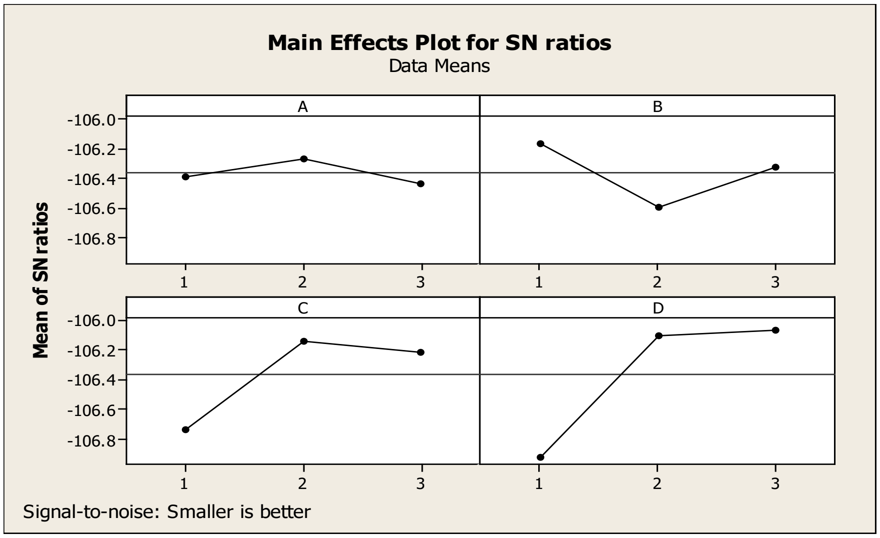

Figure 5. *Taguchi S/N ratio plot for the HS*

The best levels for the GA and HS parameters are presented in Table 15.

Table 15.
GA and HS parameters and levels

	Algorithm Parameters	Optimal value
GA	POP (A)	50
	P_c (B)	0.7
	P_m (C)	0.05
	NOG (D)	100
HS	HMS (A)	10
	HMCR (B)	0.9
	PAR (C)	0.1
	bW (D)	0.9

Analysis of the Results

In order to solve the proposed model, Matlab (R2013b) software is used to code the algorithms on the above laptop. 20 random generated problems are utilized to validate the GA results and execution of the solution quality and the CPU time of the GA and HS algorithms in Table 8. The objective function and CPU time values acquired by the GA and HS are presented in Table 16. The percentage differences of the objective function and the CPU time values of the GA and HS are shown in Table 16. The results in this table show that, on average, HS works more optimally than the GA, at 21.16% and 91.44% in terms of objective function value and CPU time, respectively.

Furthermore, as indicated by Figs. 6 and 7, HS demonstrated more optimal performance than GA in the objective function and CPU time in all cases.

Table 16.
Objective function and CPU time of the generated problems

	GA		HS			
No.	Objective	CPU (s)	Objective	CPU (s)	Objective function difference %	CPU time difference %
1	51426	60.32	38269	22.27	34.380307	170.857656
2	54783	59.09	41877	22.31	30.818827	164.858808
3	69298	59.86	46276	23.07	49.749330	159.471175
4	85560	60.23	77569	23.14	10.301796	160.285220
5	88015	60.78	78610	23.38	11.964127	159.965783
6	143200	64.82	94388	28.19	51.714201	129.939695

	GA		HS			
No.	Objective	CPU (s)	Objective	CPU (s)	Objective function difference %	CPU time difference %
7	169010	66.75	152320	31.25	10.957195	113.600000
8	144410	68.19	99229	31.12	45.532052	119.119537
9	189830	69.91	123450	33.03	53.770757	111.656070
10	189610	74.49	174840	38.01	8.447724	95.974743
11	208940	75.27	145960	40.69	43.148808	84.984026
12	286610	85.03	273510	52.44	4.789587	62.147216
13	370990	97.06	362150	61.85	2.440977	56.928052
14	332434	102.33	314540	70.89	5.688943	44.350402
15	370770	108.97	346290	76.29	7.069219	42.836545
16	436610	115.83	391920	88.49	11.402837	30..896146
17	521890	130.59	455220	98.01	14.645665	33.241506
18	554910	140.29	506390	105.21	9.581548	33.342838
19	542180	177.29	499980	141.85	8.440338	24.984138
20	564960	199.72	521325	154.33	8.370019	29.411002
Average	268771.8	93.841	237205.65	58.291	21.16071	91.44253

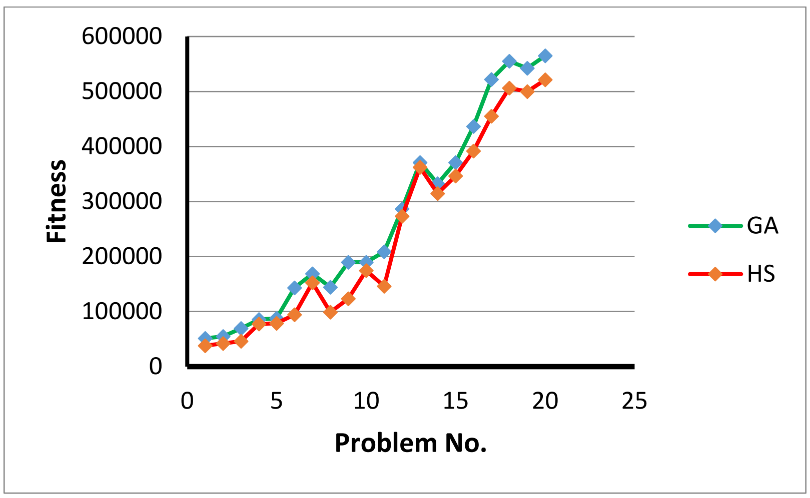

Figure 6. *Trend of objective function values of the generated problems for the proposed algorithms*

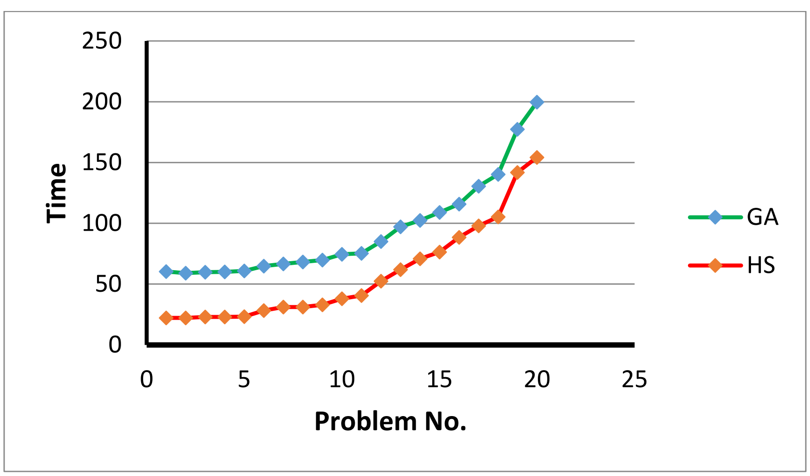

Figure 7. *The trend of CPU times of solving the generated problems by the proposed algorithms*

The one-way analysis of variance (ANOVA) was utilized to compare the performances of the GA and HS algorithm statistically. This process is performed in MINITAB software version 17.3.1. The ANOVA output outlined in Table 17 demonstrates that at a confidence level of 95% the two algorithms reveal no significant differences in the mean objective function. Performances of both algorithms can also be observed in Figs. 8 and 9.

Table 17.
ANOVA results to compare the algorithms in terms of the mean objective function value.

Source	DF	SS	MS	F	*P*-value
Solving methodologies	1	9964218258	9964218258	0.32	0.575
Error	38	1.18327E+12	31138589480		
Total	39	1.19323E+12			

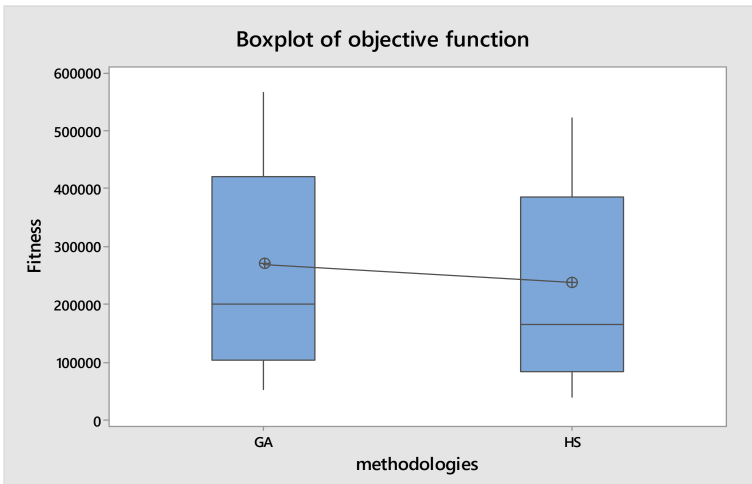

Figure 8. *Boxplot of the objective function values*

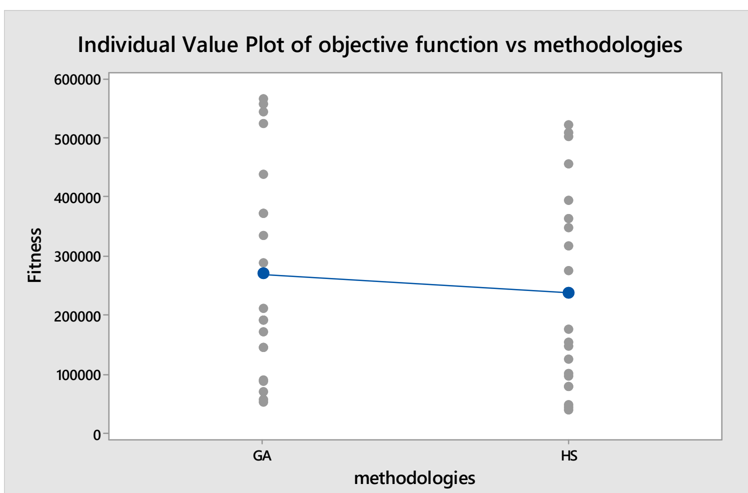

Figure 9. *Individual value plot of the objective function values*

The ANOVA output depicted in Table 18 demonstrates that GA and HS algorithms have significant differences in the average CPU time with 95% level of confidence. Performances of both algorithms can also be observed in Figs. 10 and 11. The Tukey test output is shown in Fig. 12 indicates that there are significant differences between the means of CPU time of methodologies.

The results show that HS functions more optimally than GA in terms of objective function value and CPU time, respectively.

Table 18.
ANOVA results to compare the algorithms in terms of CPU time

Source	DF	SS	MS	F	*P*-value
Solving methodologies	1	12638	12638	7.59	0.009
Error	38	63237	1664		
Total	39	75875			

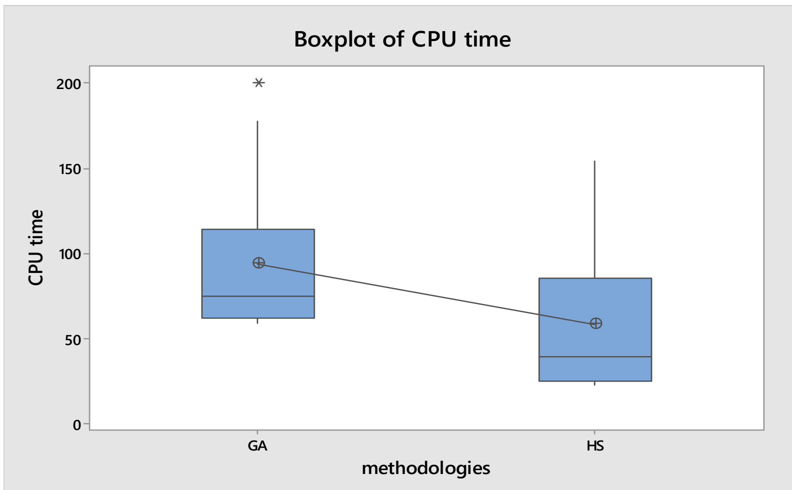

Figure 10. *Boxplot of the CPU time*

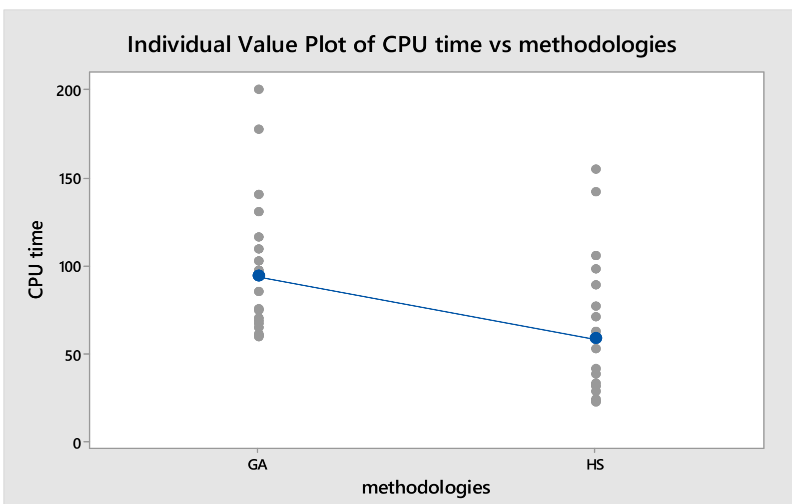

Figure 11. *Individual value plot of the CPU time*

Summary
S R-sq R-sq(adj) R-sq(pred)
40.7939 16.66% 14.46% 7.65%
Means

meth N Mean StDev ۹۵٪ CI
(۱۱۲/۳۱ ,۷۵/۳۷) ۴۰/۹۰ ۹۳/۸۴ ۲۰ ۱
(۷۶/۷۶ ,۳۹/۸۲) ۴۰/۶۸ ۵۸/۲۹ ۲۰ ۲
Pooled StDev=۴۰/۷۹۳۹

Tukey Pairwise Comparisons
Grouping Information Using the Tukey Method and ۹۵٪ Confidence
N meth Mean Grouping
A ۹۳/۸۴ ۲۰ ۱
B ۵۸/۲۹ ۲۰ ۲

Figure 12. *Tukey test output for the mean CPU time*

Conclusion

In this paper, a mathematical model was presented for the three important problems in the CMS with respect to man and machine relationship. The objective was to minimize the operation cost, layout cost, worker and machine idle cost, machine cost and tooling cost. The proposed model was solved using the branch and bound algorithm for a numerical example. Due to NP-hardness of the model, the two meta-heuristic algorithms GA and HS were used to solve the proposed model and the Taguchi method was utilized to tune the parameters. The tuned algorithms were then compared with reference to the objective function value and the CPU time in various different size problems. The ANOVA statistical test was used to compare the performance of the GA and HS algorithms. Based on the results, the HS was the favorable method for our model, statistically. Finally, we have three suggestions for future research:

1. Future research can focus on other meta-heuristic algorithms.
2. The model can be extended in a stochastic or fuzzy environment.
3. The response surface methodology (RSM) can be employed to tune the parameters.

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