Machine cell formation for dynamic part population considering part operation trade-off and worker assignment using simulated annealing-based genetic algorithm

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Abstract: In this study, an integrated mathematical model for the cell formation problem is proposed considering the dynamic production environment. The proposed model yields, manufacturing cells, part families and worker's assignment simultaneously by allowing a cubic search space of 'machine-part-worker' in the CMS. The resources are aggregated into manufacturing cells based on the optimal process route among the user specified multiple routes. The model interprets flexibility in the processing of subsets of a part operation sequence in the different production mode (internal production/subcontracting part operation). It is a tangible advantage during unavailability of worker and unexpected machine break down occurring in the real world. The proposed cell formation problem has been solved by using a simulated annealing-based genetic algorithm (SAGA). The algorithm imparts synergy effect to improve intensification, diversification in the cubic search space and increases the possibility of achieving near-optimum solutions. To evaluate the computational performance of the proposed approach the algorithm is tested on a number of randomly generated instances. The results substantiate the efficiency of the proposed approach by minimising overall cost. [Received: 17 August 2018; Accepted: 28 July 2019]

Keywords: dynamic cellular manufacturing systems; worker assignment; multiple process route; system reconfiguration; part operation trade-off; subcontracting part operation; simulated annealing-based genetic algorithm.

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1 Introduction

In modern manufacturing, worldwide product variety with low production cost and consistent quality level to cater the need of customer signify a capable production system. The traditional manufacturing systems such as job shops and flow shops do not satisfy such requisite. the job shop manufacturing system provides maximum production flexibility for a wide variety of jobs in small lots and more throughput time for high production volume (Stevenson et al., 2005) in a flow shop manufacturing system, machines are arranged according to the operation sequence of the product. Specialised machines are setup to perform limited operations, but inflexible to produce a product for which they are not designed. The system is suitable for high production volume.

The cellular manufacturing (CM) is based upon the principles of group technology. It takes advantage of the similarity among parts, through standardisation and common processing. The CM groups the machines into machine cells and the parts into part families (Hu and Yasuda, 2006). The CM suppresses the demerits of traditional manufacturing by increasing the flexibility and variety in production. The major advantage appears to be in terms of significant improvement of material flow, which reduces inventory level, the distance travelled by the material, and cumulative lead times (Fry et al., 1987; Chu and Hayya, 1991; Shafer et al., 1992; Collet and Spicer, 1995; Levasseur et al., 1995; Singh and Rajamaani, 1996).

The conventional cellular manufacturing systems (CMS) do not respond to the changes in part operation sequence while redesigning a part, the variation in product mix and the demand size over different production segments of planning span. Here the product mix and part demand are considered to be stable for the entire planning span. Thus, the CMS configuration designed for one period may not be efficient for the successive periods in a dynamic production environment. Hence the manufacturing cells need to be reconfigured during successive periods to maximise the effectiveness of production system. The reconfiguration involves machine relocation in the cells and modification in part process route in successive periods.

The effectiveness of production system in the CMS environment is paramount importance which is a function of productivity and worker availability. The involvement of workers in production is one of the significant factors in the cellular manufacturing environment, since ignoring this issue can considerably reduce the overall productivity of the organisation. The assignment of worker in manufacturing cell is a critical aspect for effective utilisation of manufacturing resources in the dynamic production environment.

In this study, multiple process route (internal production/subcontracting part operation) for each part type, and worker availability for each of them have been considered in the CFP. The resources are aggregated into manufacturing cells based on the optimal process route among the user specified alternative routes. The trade-off between duplicate machines and inter-cell movements of parts optimises the cellular configuration by the minimisation of vacillation in manufacturing cell and the maximisation of workload balancing.

The proposed model simultaneously considers several manufacturing aspects such as system reconfiguration, multiple part process route, production capacity, machine duplication, part operation trade-off, worker availability, internal production, and subcontracting part operation. A simulated annealing-based genetic algorithm (SAGA) is applied to the 3-dimensional/cubic search space for optimisation of the number of machines, parts, and workers in the cellular manufacturing system producing multiple product mix. The main constraints are the production capacity, worker availability and the maximum cell size.

2 Literature review

In this study, an integrated mathematical model for multi period cell formation problem considering flexibility in worker assignment is proposed. Extensive research has been devoted to the development of integrated cell formation (CF) model and solution techniques for identifying part families and machine cells in the dynamic production environment.

2.1 Dynamic and deterministic production requirements

The most of the research work reported on CMS design methods presume a stable part demand and product mix in multi period production. In reality, the performance of CMS gets adversely affected by variation in part demands and product mix.

Wicks and Reasor (1999) investigated the advantages of multi period approach over the existing single period CMS design using genetic algorithm. Mungwattana (2000) described the differences between robust design and adaptive design strategies for the CMS considering dynamic and stochastic production requirements, employing routing flexibility. Defersha and Chen (2006) illustrated the structural and operational issues of dynamic cellular manufacturing. The significance of several design aspects is demonstrated in an integrated manner for the CMS. The commercially available optimisation software is used to solve the instances. Pillai and Subbarao (2007) proposed the periodic average part demand to avoid cellular reconfiguration. A mixed integer formulation for the robust manufacturing cell design has been presented to minimise the machine duplication and inter-cell part movements. A genetic algorithm-based heuristic is applied to solve the problems. Safaei et al. (2008) developed a mixed integer programming model to design the cellular manufacturing system under dynamic production. A hybrid meta-heuristic based on mean field annealing (MFA) and simulated annealing (SA) so-called MFA-SA is used to solve the proposed model.

2.2 Worker assignment in cellular manufacturing system

The majority of the cell formation methods are confined to the incidence of machine cells-part families and production capacity that limits the production system design (Russell et al., 1991). A few authors have addressed the cell formation problem with the view point of worker's assignment as well to enhance the overall productivity in organisations.

Cesani and Steudel (2005) explored the 'labour flexibility' as operator movement between the cells and within the same cell. The influence of labour assignment strategies on the cell performance has been presented to indicate the workload balance. Yaakob and Watada (2009) evaluated the inter-relationship among multi-functional workers based on their social behaviour, mental factor and work performance. The results approve the viability of methodology for worker assignment to the cellular manufacturing system. Aryanezhad et al. (2009) incorporated the worker's assignment to enhance productivity and quality of traditional dynamic cellular manufacturing system. The computational performance of the proposed model has been validated on several numerical instances using Lingo software. Murali et al. (2009) illustrated the worker's assignment into virtual cell considering job criticality and varied worker efficiencies. The objective is to maximise the efficiency of workers to process critical jobs by minimising multi-cell assignment and cross training of workers. Mahdavi et al. (2010) considered cubic search space 'machine-part-worker' in dynamic cell formation problem. The model is capable of balancing the workload among workers and machines with respect to the cellular reconfiguration in successive period segments of production planning. Azadeh et al. (2015) assigned workers to manufacturing cells to minimise the inconsistency in decision making style, the material handling, and the cell establishment cost. The decision making style of operators based on personal attributes is used for clustering of machines, parts, and workers simultaneously. The mathematical model has been validated using general algebraic modelling system (GAMS23.5.2/CPLEX). Feng et al. (2017) determined the optimal allocation of machines, parts and workers for the integrated cell formation problem. The model includes the simultaneous consideration of production planning, coexistence of alternative process routings, lot splitting, workload balancing among cells and worker over-assignment to multiple cells. A hybrid approach combining combinatorial particle swarm optimisation and linear programming (CPSO-LP) is proposed to solve real-sized problems. Arghish et al. (2018) emphasised the effect of man-machine relationship using economic and environmental criteria for a type-2 fuzzy cell formation problem. The model is aimed to minimise the cost of processing, material movement, energy loss, and tooling. The performance of the model is evaluated by making results comparative among tuned meta-heuristics: genetic algorithm (GA), particle swarm optimisation (PSO), harmonic search (HS) and differential evaluation (DE). The emanated results reveal the PSO outperforms the GA, DE, and HS algorithm. Behnia et al. (2018) promoted the sense of interest among the workforces to enhance the synergy effect and growth of the organisation. A bi-level mathematical model is proposed to reduce the numbers of voids and exceptional elements based on the decentralised decision making style.

2.3 Worker's training to enhance production flexibility

The training process is recognised as a tool to develop the worker's proficiency in the dynamic production environment. The multi skilled workers play a significant role in improving the overall productivity of the organisation.

Min and Shin (1993) assumed availability of multi-skilled worker with different levels of job skills in the manufacturing system. A sequential heuristic is proposed to generate machine cells and worker's assignment to form the corresponding human cells assigning appropriate part-machine value to solve the CFP. Askin and Huang (2001) formulated worker's assignment and training model for the worker team formation in the CMS. The team synergy is generated by maximising the fitness between the workers ability/instinct and task requirement while minimising the training cost of workers. A Greedy heuristics have been developed to solve the large size problem due to computational complexity. Norman et al. (2002) considered human skill and permits a change in skill level of the workers by cross training to maximise the productivity in the CMS. Wirojanagud et al. (2007) measured individual skill differences to minimise the total worker cost and missed production cost over multiple period of time. The general cognitive level (GCA) of workers is focused to determine the amount of hiring, firing and cross training of workers. Suer and Tummaluri (2008) determined skill level of workers by the number of times a worker is allotted to a particular operation. The model generates alternative worker staffing level for each part type and determines the optimal number of workers by assigning parts to the manufacturing cells. Soolaki (2012) minimised variation in the total cell load and cost factors, by assigning workers on machines based on their skill level in the dynamic production environment. The model is aimed to develop a multi-objective DCMS integrating the multi-period production planning, the system reconfiguration, and the available time of workers, etc. The proposed model has been validated using elitist multi objective genetic algorithm. Mahdavi et al. (2012) demonstrated the three dimensional assignment (machine-part-worker) in cellular manufacturing system. The model interprets inter-cell movements for parts and workers for processing on corresponding machines. The test problems have been attempted using branch and bound methods through Lingo software. Saidi-Mehrabad et al. (2013) demonstrated the effects of worker training and reconfiguration in multi-period production planning. The model is capable to determine the system reconfiguration, backorder and inventory holding, training and salary of workers. The main constraints are the demand satisfaction, machine availability, production capacity, available time of worker and training. Mahdavi et al. (2014) investigated the interactional interest among workers and their work ability for the CFP. The objective is to minimise the voids in the task matrix and interest matrix, illustrating the worker's ability to deal with machine types and coordination among workers in the manufacturing cells.

2.4 Aggregate production planning

The aggregate production planning enhances the utilisation of human and equipment resources of a production system. It establishes optimal workforce levels, production, and inventory over a given finite planning horizon to meet the consumer demand.

Masud and Hwang (1980) proposed an aggregate production planning model to treat the explicitly conflicting multiple objectives for multiple products. The model optimises the workforce level, the production level, the inventory level, and the amount of over time production for multi period production. The results obtained validate the adaptability of multi objective decision-making strategies in different circumstances. Kamien and Li (1990) discussed the possible market and non-market subcontracting cost mechanisms as a production planning strategy. The linear decision rules are derived for part production, inventory, and subcontracting to minimise the variability in production and inventory. Bard (2004) specified the input data for a staffing model to optimise the permanent workforce for mail processing at distribution centres. The alteration in the workforce size and composition makes the problem complicated by wide fluctuations in weekly demand. A careful balance is interpolated among limits on overtime, part-time hours, and casual leaves. An engineering approach is proposed to estimate the productivity based on a single run of the optimisation model. Takey and Mesquita (2006) developed a linear programming model to determine the monthly production rates, inventory levels of finished products, and workforce requirements to accomplish the production plans. The effective usage of model with improvements in the demand forecasting processes achieves a global reduction of inventory levels of raw materials and final products. Leung and Chan (2009) proposed a goal programming model to deal with the aggregate production planning problem to optimise quarterly profit, repairing cost, and machine utilisation. The model provides better control on inventory levels, machine utilisation with a given workforce level, and shortages. The Results obtained substantiate the robustness of the proposed model with respect to objective value. Sillekens et al. (2011) integrated production capacity planning and workforce flexibility planning. The model considers discrete capacity adaptations originated from the technical characteristics of assembly lines, work regulations and shift planning. The solution framework contains different primal heuristics and pre-processing techniques embedded in a decision support system. The computational results with sufficient solution quality on different problem instances are solved by problem specific heuristics. Nah and Kim (2013) developed a framework combining workforce planning and operator deployment for a mixed call centre. The sensitivity analysis substantiates the effectiveness of methodology in an environment where the unit penalty cost of an abandoned call is relatively high among competitive hospitals.

The review of the research literature cited above reveals the application of several methodologies for cell formation problem and worker assignment in cellular manufacturing environment. These approaches presume, production volume is equal to demand size in each period segment of planning span. In reality, however, the production volume may not be equal to the demand size due to production capacity shortage and/or sudden machine breakdown. Thus demand size in each period segment of planning span can be satisfied by internal production and/or subcontracting part processing.

A few authors (Nsakanda et al., 2006; Defersha and Chen, 2006; Ahkioon et al., 2009) addressed subcontracting/outsourcing only as a subset of the part demand size. It may lead to a vacillation in manufacturing cells by increasing work load unbalancing, machine duplication, and reduction in the effectiveness of the manufacturing system. Deep and Singh (2015) avoided variability in the production capacity requirements of multi period production system using periodic average demand, multiple process routes, and trade-offs between inter-cell part movement and machine duplication to optimise the workload distribution among cells in the dynamic cellular manufacturing environment.

The proposed work presents an integrated mathematical model for the cell formation problem, considering part operation trade-off and worker assignments in dynamic production requirement. The model formulation is based on the realistic industrial manufacturing vision considering multiple process routes. The part operation processing can be switched into different production modes (internal production and/or subcontracting part operation) considering production capacity and worker availability to minimise the vacillation in manufacturing cells. A SAGA has been developed to cope up with the complexity of the combinatorial optimisation problem and to expedite the search process.

The next section presents a mathematical formulation of the CMS design problem. The proposed solution algorithm is presented in Section 4. Numerical illustration of the proposed approach has been presented in Section 5. The conclusion of the research and future scope has been presented in the last section.

3 Problem formulation

The proposed integrated CMS model is based on multi-period production and worker assignment in a dynamic production environment. There are different machine types in the cells with multiple operational capabilities and limited production capacity to process the part types with specific operations requirement and processing time. In the manufacturing cells a candidate part operation can be processed internally within the production capacity or through subcontracting part operation to satisfy the part demand.

The proposed approach offers flexibility in a part operation processing by permitting it to be switched to different production modes (internal production and/or subcontracting) considering worker availability, production capacity shortage and/or sudden machine breakdown. The flexibility in processing of the subsets of a part operation sequence in different production mode leads the minimisation of vacillation in manufacturing cells by reduction in machine duplication and the maximisation of effectiveness in manufacturing system by increasing workload balancing. The overall objective is to minimise the summation of the machine cost, the operating cost, the system reconfiguration cost, the internal manufacturing cost, the subcontracting part operation cost, the material handling cost, and the hiring, firing and salary cost of workers. A mixed- integer mathematical formulation of dynamic cellular manufacturing system design is presented under the following assumptions.

- The operation time for each part type on different machine type are known.
- The product mix and production volume for each part type in each period is known.
- The production capacity of each machine type is constant over time.
- Operating cost (per hour) of each machine type is known.
- The number of cells to be formed is specified in advance, and remains constant overproduction planning span.
- Each machine type can perform one or more operation. Likewise, each part operation can be performed on different machine types with different machine operating times.
- Inter-cell material handling cost is constant for all moves regardless of distance.
- The part demand in each period is deterministic, hence leading to dynamic deterministic production requirements.
- Lot splitting is not allowed during material handling.
- The available time of each worker type is known for each period.
- Only one worker is allotted for each part operation on each corresponding machine type.

3.1 Notations

3.1.1 Index sets

p	$\{p = 1, 2, 3, \dots, P\}$	Part types.
k	$\{k = 1, 2, 3, \dots, Op\}$	Operation k of part type p.
m	$\{m = 1, 2, 3, \dots, M\}$	Machine types.
c	$\{c = 1, 2,3, \dots, C\}$	Manufacturing cells.
t	$\{t = 1, 2, 3, \dots, T\}$	Time periods.
w	$\{w = 1, 2, 3, \dots, W\}$	Worker type.

3.1.2 Model parameters

$A_{mc}(t)$	Number of machine type m available in cell c at time period t.
$A_{wc}(t)$	Number of worker type w available in cell c at time period t.
$D_p(t)$	Demand for part type p at time period t.
t_{kpmw}	Time required to perform operation k of part type p on machine type m with worker type w.
IE_p	Intercellular material handling cost per part type p.
IA_p	Intracellular material handling cost per part type p.
B_U	Upper cell size limit.
B_L	Lower cell size limit.
α_m	Amortised cost of machine type m per period.
β_m	Operating cost per hour of machine type m.
δ_m	Relocation cost of machine type m including uninstalling, shifting, and installing.
T_m	Capacity of each machine type m in hours.
T_w	Capacity of each worker type w in hours.
μ_{kp}	Production cost of operation k of part type p.
o_{kp}	Subcontracting cost of operations k of part type p.
S_w	Salary cost of worker type w.
H_w	Hiring cost of worker type w.
F_w	Firing cost of worker type w.

3.1.3 Decision variables

$N^+_{mc}(t)$	Number of machines of type m added in cell c in period t.
$N^-_{mc}(t)$	Number of machines of type m removed from cell c in period t.
$L^+_{wc}(t)$	Number of workers of type w added in cell c in period t.
$L^-_{wc}(t)$	Number of workers of type w removed from cell c in period t.
$OP_{kp}(t)$	Number of parts of type p processed for operation k through subcontracting in period t.
$XP_{kpmwc}(t)$	Number of parts of type p processed for operation k on machine m with worker type w in cell c in period t.
a_{kpm}	$\begin{cases} 1, & \text{if operation } k \text{ of the part type } p \text{ carried out on machine type } m. \\ 0, & \text{otherwise.} \end{cases}$

$$X_{kpmwc}(t) \quad \begin{cases} 1, & \text{if operation } k \text{ of part type } p \text{ carried out on machine } m \text{ with worker } w \\ & \text{in cell } c \text{ during period } t. \\ 0, & \text{otherwise} \end{cases}$$

3.2 Mathematical model

Using the above notations and model parameters, the mathematical model of dynamic CMS is presented below:

$$Z_{\min} = Z_1 + Z_2 + Z_3 + Z_4 + Z_5 + Z_6 + Z_7 + Z_8 + Z_9 + Z_{10} \tag{1}$$

$$Z_1 = \sum_{t=1}^{T}\sum_{m=1}^{M}\sum_{c=1}^{C} A_{mc}(t)\alpha_m$$

$$Z_2 = \sum_{t=1}^{T}\sum_{w=1}^{W}\sum_{c=1}^{C} A_{wc}(t)S_w(t)$$

$$Z_3 = \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{k=1}^{Op}\sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{c=1}^{C} XP_{kpmwc}(t)t_{kpmw}\beta_m$$

$$Z_4 = \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{k=1}^{Op}\sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{c=1}^{C} XP_{kpmwc}(t)\cdot \mu_{kp}$$

$$Z_5 = \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{k=1}^{Op} OP_{kp}(t)o_{kp}$$

$$Z_6 = \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{c=1}^{C} IE_p \cdot XP_{kpmwc}(t)\sum_{k=1}^{o_p-1}\left(1 - X_{k+1,pmwc}(t)\cdot X_{kpmwc}(t)\right)$$

$$Z_7 = \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{c=1}^{C} IA_p \cdot XP_{kpmwc}(t)\cdot \sum_{k=1}^{o_p-1} X_{k+1,pmwc}(t)\cdot X_{kpmwc}(t)$$

$$Z_8 = \frac{1}{2}\sum_{t=1}^{T}\sum_{m=1}^{M}\sum_{c=1}^{C}\left(N_{mc}^{+}(t) + N_{mc}^{-}(t)\right)\delta_m$$

$$Z_9 = \sum_{t=1}^{T}\sum_{w=1}^{W}\sum_{c=1}^{C} L_{wc}^{+}(t)\cdot H_w(t)$$

$$Z_{10} = \sum_{t=1}^{T}\sum_{w=1}^{W}\sum_{c=1}^{C} L_{wc}^{-}(t)\cdot F_w(t)$$

The model objective function consists of ten cost components (equation set 1). The cost components are detailed below in terms of decision variables.

Z_1 The constant cost of all machines required in manufacturing cells over the planning span. This cost is obtained by the product of the number of machine type *m* allocated to cell *c* in period *t* and their associated costs.

Z_2 The salary paid to workers assigned to manufacturing cells over the planning span. It is the product of the number of worker type *w* allocated to cell *c* during period *t* and their associated costs.

Z_3 Machine operating cost; the cost of operating machines for part production. This cost depends on the cost of operating each machine type per hour and the number of hours required for each machine type.

Z_4 The production cost of part operation; the labour cost incurred for part production. It is the summation of the product of the number of part operations allocated to each machine type and the labour cost.

Z_5 Subcontracting cost of part operation; the cost sustains for part operation being subcontracted due to limited production capacity, sudden machine breakdown, and unavailability of worker.

Z_6 Inter-cellular material handling cost; the cost upholds for the successive operations of the same part type, carried out in different cells. The cost is directly proportional to part volume moved between interdependent cells.

Z_7 Intracellular material handling cost; the cost incurs for the consecutive operations of a candidate part being processed on different machines in the same cell.

Z_8 Manufacturing cells reconfiguration cost; this cost upholds the number of machine type relocated/added and/or removed in successive period segments of planning span.

Z_9 Hiring cost of worker; this cost is incurred when workers type *w* are hired and assigned to manufacturing cells lacking workforce.

Z_{10} Firing cost of worker; the cost sustained in the firing of worker types *w* from manufacturing cells in successive periods, as no more workers are required.

The optimal CMS design problem is subjected to several constraints-expressed in equations (2)–(9).

$$\sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{k=1}^{Op}\sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{c=1}^{C} a_{kpm} X_{kpmwc}(t) = 1 \tag{2}$$

Constraint (2) ensures the assignment of each part operation to one machine with a worker type in one cell at time period *t*.

$$\sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{k=1}^{Op}\sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{c=1}^{C} XP_{kpmwc}(t) + OP_{kp}(t) \le D_p(t) \tag{3}$$

Constraint (3) determines each part demand can be satisfied in time period *t* objectively through internal production or subcontracting part operation. More specifically the term '$XP_{kpmwc}(t)$' represents an internal processing of part operations assigned to manufacturing cells. Since limiting machine capacity or sudden machine breakdown results subcontracting of part operation.

$$\sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{k=1}^{Op}\sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{c=1}^{C} t_{kpmw}\cdot XP_{kpmwc}(t) \le T_m A_{mc}(t) \tag{4}$$

$$\sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{k=1}^{Op}\sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{c=1}^{C} t_{kpmw}\cdot XP_{kpmwc}(t) \le T_w A_{wc}(t) \tag{5}$$

Constraints (4) and (5) ensure the internal part operation processing to be limited to production capacity and worker availability.

$$\sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{k=1}^{Op}\sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{c=1}^{C}\left(XP_{k+1,pmwc}(t)+OP_{k+1p}(t)=XP_{kpmwc}(t)+OP_{kp}(t)\right) \tag{6}$$

Constraint (6) maintains the material flow conservation – a part operation can be internally processed or subcontracted to satisfy the part demand. The consecutive operations in an operation sequence set of part type p carries equal production volume.

$$\sum_{t=1}^{T}\sum_{m=1}^{M}\sum_{c=1}^{C} A_{mc}(t-1)+N_{mc}^{+}(t)-N_{mc}^{-}(t)=A_{mc}(t) \tag{7}$$

Constraint (7) ensures the number of machines in the current period is equal to the number of machines in the previous period, adding the number of machines being moved in, and subtracting the number of machines being moved out from the cells.

$$B_U \le \sum_{t=1}^{T}\sum_{m=1}^{M}\sum_{c=1}^{C} A_{mc}(t) \le B_L \tag{8}$$

Constraints (8) preserve the cell size within the upper and lower bounds.

$$\sum_{t=1}^{T}\sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{c=1}^{C} A_{wc}(t-1)+L_{wc}^{+}(t)-L_{wc}^{-}(t)=A_{wc}(t) \tag{9}$$

Constraint (9) ensures the total number of workers of each type assigned to different cells in each period will not exceed the total available number of worker type.

$$a_{kpm} \in \{0,1\} \tag{10}$$

$$X_{kpmwc}(t) \in \{0,1\} \tag{11}$$

$$XP_{kpmwc}(t) \ge 0 \tag{12}$$

$$XP_{kpmwc}(t) \in \mathbb{Z} \tag{13}$$

$$OP_{kp}(t) \ge 0 \tag{14}$$

$$OP_{kp}(t) \in \mathbb{Z} \tag{15}$$

$$N_{mc}^{+}(t) \ge 0,\ N_{mc}^{-}(t) \ge 0 \tag{16}$$

$$N^{+}_{mc}(t) \in \mathbb{Z},\ N^{-}_{mc}(t) \in \mathbb{Z} \tag{17}$$

$$L^{+}_{wc}(t) \geq 0,\ L^{-}_{wc}(t) \geq 0 \tag{18}$$

$$L^{+}_{wc}(t) \in \mathbb{Z},\ L^{-}_{wc}(t) \in \mathbb{Z} \tag{19}$$

In addition to these constraints, restrictions represented by equations (10)–(19) denote the logical binary and a non-negative integer requirement on decision variables.

4 Simulated annealing-based genetic algorithm

The traditional genetic algorithm works on multiple points in the search space, hence suffer from premature convergence and affects the quality of solution. The conventional mechanism of genetic algorithm set off the pattern of effective solutions higher than the average in successive generations. It strict the hunting zone and rapidly converge the population, does not necessarily achieve a global optimum solution.

In order to explore the solution region efficiently and to expedite the solution search space, the simulated annealing strategy is combined in the genetic algorithm. The SAGA incorporates the best features of genetic algorithm (searching larger regions of solution spaces) and simulated annealing (refining exhaustive solution of local region).

The basic idea is to use the genetic operators of genetic algorithm to quickly converge the search to near-global minima/maxima, which will further be refined to a near optimal solution by using a simulated annealing process. Recent work on genetic algorithm-oriented hybrids is the simulated annealing genetic algorithm (SAGA) proposed by Brown et al. (1989).

The proposed algorithm imparts synergy effect between the SA and GA by presenting a hybrid algorithm. In this algorithm, the initial solution of SA comes from the evolution of the GA. The solution obtained by sampling of SA serves as the initial individual of GA so that a hybrid search is made possible. The proposed hybrid SAGA algorithm is applied to the considered CMS problem with a matrix schema and the novel operators are presented in the following sections.

4.1 Solution representation schema

In the solution representation schema, three matrices $[PM_{pk}]$, $[PW_{pk}]$ and $[PC_{pk}]$ are employed in each period segment of the planning horizon, denoting allocation of part-operation to machine type m, worker type w, and cell type c. By combining the three matrices described above, the solution representation schema is shown in Figure 1.

PM_{pk} machine performing operation k on part type p, where $PM_{pk} \in \varphi_{kp}$ and $\varphi_{kp} = \{m \mid a_{kpm} = 1\}$

PW_{pk} worker carrying out operation k on part type p, where $PW_{pk} \in \psi_{kp}$ and $\psi_{kp} = \{w \mid X_{kpmwc} = 1\}$

PC_{pk} cells allocated with operation k of part type p, where $1 \leq PC_{pk} \leq C$.

Figure 1 Solution representation schema

$$\begin{bmatrix} PM_{11} & PM_{12} & \dots & PM_{1k} \\ PM_{21} & PM_{22} & \dots & PM_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ PM_{p1} & PM_{p2} & \dots & PM_{pk} \end{bmatrix} \begin{bmatrix} PW_{11} & PW_{12} & \dots & PW_{1k} \\ PW_{21} & PW_{22} & \dots & PW_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ PW_{p1} & PW_{p2} & \dots & PW_{pk} \end{bmatrix} \begin{bmatrix} PC_{11} & PC_{12} & \dots & PC_{1k} \\ PC_{21} & PC_{22} & \dots & PC_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ PC_{p1} & PC_{p2} & \dots & PC_{pk} \end{bmatrix}$$

4.2 Initialisation of population

The initial population of preferred volume is generated randomly in steps. In the first step, the segments [PM_{pk}] [PW_{pk}] of the chromosome are generated randomly considering feasibility of performing part operation on machines with the availability of workers. In the second step segment [PC_{pk}] of the chromosome is filled randomly. Solution for a given problem is represented by the embedded segments known as a chromosome.

A strategy is applied with objective to minimise the number of inter-cell moves of parts. The part operations associated with each part type are assigned to machines existing in the cells. This process is repeated until all the parts are assigned to machines. Given a candidate part-machine assignment solution, the heuristic computes the number of inter-cell part transfer that would yield a minimum number of inter-cell transfer (if a part operation is assigned to cell C_1, each operation of part is assigned to cell C_1).

Occasionally, cells may have parts that contravene the specified lower or upper bounds on cell size as per subjected constraints [equation (8)]. To ensure the cell size within the specified lower and upper bounds, parts family is to be adjusted by moving parts from cell having maximum number of parts for cell having less than the minimum number of specified parts.

4.3 Fitness assessment

The fitness value is a decisive factor to measure the quality of a candidate solution or chromosome with reference to the designed objective function (1) subjected to constraints (2)–(9) and restrictions (10)–(19). The fitness values are used to select the parent solutions to obtain the next generation of solutions. The descendants or new solutions are selected with the higher fitness value obtained by playing binary tournament between parent solutions.

4.4 Genetic operators

4.4.1 Parent selection

After evaluating the fitness of the parent solutions in the population, better performing solutions are selected to produce the descendants. Parent solutions with higher fitness value have a higher chance of being selected more often. The selection is made by playing binary tournament between solution sets according to their fitness value.

4.4.2 Crossover or recombination

Crossover is performed between two selected parent solutions which create two new descendant solutions by exchanging segments of the parent solutions, thus descendant solutions retain partial properties of the parent solutions. Figure 2 depicts the solution sets of parents 1 and 2 selected for crossover. For crossover, the selection of segments can be row-wise or column-wise following the matrix limits and the crossover probabilities.

Figure 2 Crossover or recombination, (a) row wise crossover (b) column wise crossover (see online version for colours)

Parent 1	5	6	8	4	3	2	1	1	1	Child 1	5	6	8	4	3	2	1	1	1
	4	7	8	2	2	4	2	2	2		4	7	8	2	2	4	2	2	2
	3	4	1	1	2	4	3	3	3		3	4	1	1	2	4	3	3	3
	3	2	5	2	2	3	1	1	1		2	4	6	2	4	4	2	2	2
Parent 2	3	2	1	3	1	3	3	3	3	Child 2	3	2	1	3	1	3	3	3	3
	2	1	5	2	3	2	1	1	1		2	1	5	2	3	2	1	1	1
	3	1	5	1	1	4	2	2	2		3	1	5	1	1	4	2	2	2
	2	4	6	2	4	4	2	2	2		3	2	5	2	2	3	1	1	1

(a)

Parent 1	5	6	8	4	3	2	1	1	1	Child 1	5	6	8	3	1	3	3	3	3
	4	7	8	2	2	4	2	2	2		4	7	8	2	3	2	1	1	1
	3	4	1	1	2	4	3	3	3		3	4	1	1	1	4	2	2	2
	3	2	5	2	2	3	1	1	1		3	2	5	2	4	4	2	2	2
Parent 2	3	2	1	3	1	3	3	3	3	Child 2	3	2	1	4	3	2	1	1	1
	2	1	5	2	3	2	1	1	1		2	1	5	2	2	4	2	2	2
	3	1	5	1	1	4	2	2	2		3	1	5	1	2	4	3	3	3
	2	4	6	2	4	4	2	2	2		2	4	6	2	2	3	1	1	1

(b)

4.4.3 Mutation

The mutation is performed to maintain the diversity in the solutions. The mutation operator is carried out on parent solutions with a low probability of occurrence. The operator can be implemented by inverting the segment of a solution schema and place the mutated content in the reverse order, as shown in Figure 3.

Figure 3 Mutation (see online version for colours)

Parent 1	3	2	1	3	1	3	3	3	3	Child 2	3	2	1	3	1	3	1	1	1
	2	1	5	2	3	2	1	1	1		2	1	5	2	3	2	3	3	3
	3	1	5	1	1	4	2	2	2		3	1	5	1	1	4	2	2	2
	2	4	6	2	4	4	2	2	2		2	4	6	2	4	4	2	2	2

4.5 Emendation operation

The crossover and mutation operations may distort solution set by violating the cell size constraint, i.e., a few cells may have less than the minimum number of machine type while a few others may have specified more than maximum number of machine type. The emendation operation is performed on the distorted solution schema to preserve the cell size within the specified lower and upper bounds by moving parts from cell having maximum number of parts to cell having less than the minimum number of parts specified as per equation (8).

4.6 Elimination of duplicate machine

The initial solution obtained in the form of independent manufacturing cells may lead to machine duplication in the cells. The duplication of machine needs to be minimised to drive down the investment. Although, the reduction in machine duplication results in increment in inter-cell material handling cost, however, it is more economical to have inter-cell moves instead of having extra machines. In this segment, trade-off of having duplicate machines versus having inter-cell move is considered. If eliminating duplicate machines in lieu of inter-cell movement results in reduction of total cost, the machine will be eliminated. Following algorithm is used for the purpose.

- Select a machine type to be considered. Calculate the total number of machines allocated in different cells to meet the production requirements.
- To eliminate duplicate machines of the machine type selected, and the workload (which the machine type performs in each cell) is noted. The work load is defined as the quantity of the part type to be produced. If the cost saved by eliminating a unit of the machine type is greater than the inter-cell material handling cost, eliminate the unit of machine in the cell which has the minimum work load.
- If all the machine types have been considered, terminate. Otherwise, go to step 1.

4.7 Simulated annealing-based search

In simulated annealing phase, the algorithm effectively regulates the search direction by avoiding solution being trapped in local optima during the evolutionary process. The initial temperature 't_z' is set in such a way that the non-improving solutions are accepted with a probability of about 95% in the primary iterations by using the following equation: $t_z = -\left|Z_i\ (PM_iPW_iPC_i) - Z_j(PM_jPW_jPC_j)\right| / \ln(0.95)$, where, Z_i and Z_j are the two objective values of the solutions *i* and *j*, respectively, generated at random to determine the initial temperature t_z. The algorithm attempts to perform a metropolis random walk that samples the objective function from close solutions in current population. The search starts with an objective function value at a feasible solution $f(z)$ and moves from solutions to neighbouring solution to improve the objective function value. If the objective function value of the neighbour solution $f(n)$ is less than the current feasible solution $f(z)$, it is accepted as a current solution. Otherwise to escape from local optima the Metropolis algorithm accepts the move with a probability value to escape from local optima. The pseudo code for the SA-based search is shown in Figure 4.

Figure 4 Pseudo code for the SA-based search

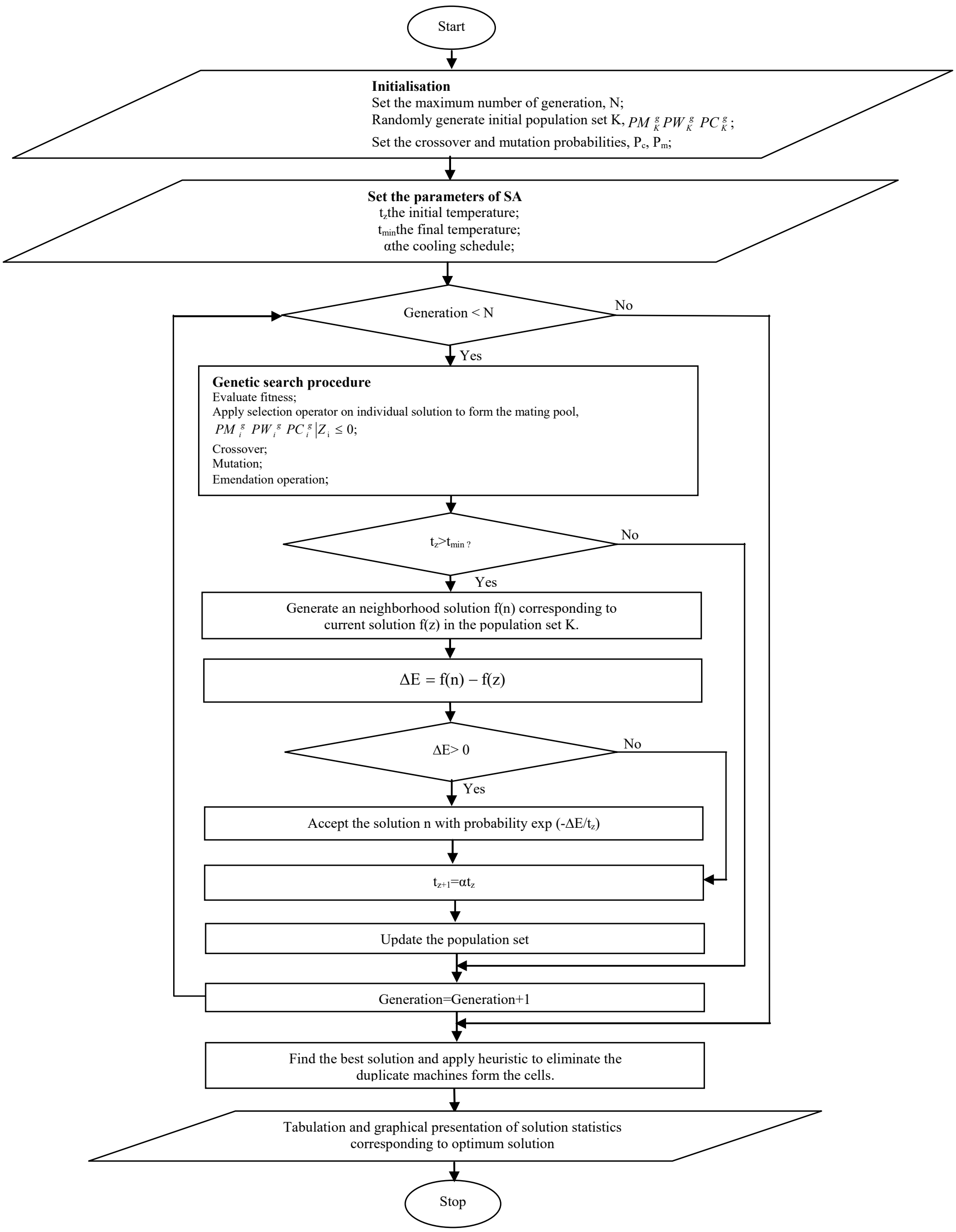
- Generate solution *n* in the neighbourhood of *z*
- Select $n \in N$ with probability $U(0, 1)$;
- if $f(n) \leq f(z)$ then
- return *n*;
- else, return *n*; with probability $\exp\left(\frac{-(f(n)-f(z))}{t_z}\right)$
- else return *z*;

4.8 Termination of algorithm

The algorithm continues to generate the solution sets of descendants until a criterion for termination is met. A single criterion or a set of criteria for termination can be adopted.

In this case the termination criterion is the maximum number of iterations, i.e., the algorithm stops functioning when a specified number of iterations is reached (Figure 5).

Figure 5 Scheme of optimisation using SAGA



5 Numerical illustration

The multi period approach to the preliminary design of a cellular manufacturing system is unique in its treatment of the dynamic production environment by simultaneous formation of machine cells, part family and worker's assignment to the manufacturing system. The need for the multi period production in cellular manufacturing environment arises due to variability in part population of product mix and worker's capability to handle distinct machine type. The cellular manufacturing system design obtained with the assumption of constant demand size and product mix would require cellular reconfiguration of manufacturing system and shuffling of workers in machine cells as the part population changes in successive period segments of the planning horizon. The objective of this section is to numerically illustrate the effectiveness of production system by maximisation of productivity and worker availability to the manufacturing system in the dynamic production environment. To evaluate the computational performance and the validity of the proposed model, a set of fifteen distinct random problem scenarios is generated based on the distributed parameters presented in Table 1.

Table 1 Parameter setting

Parameter	*Value*	*Parameter*	*Value*
Dp	U(100, 1,000)	μ_{kp}	\$U(1, 10)
t_{kpmw}	U(0, 1) hour	O_{kp}	\$U(1, 20)
T_w	U(0, 100) hours	IE_p	\$U(0.1, 2)
T_m	U(0, 1,000) hours	IA_p	\$U(0.1, 2)
$\sum \mathrm{w}\cdot\mathrm{X}_{\mathrm{kpmwc}}$	$2\forall k\cdot p$	S_w	\$U(100, 1,000)
α_m	\$U(1,000, 2,000)	H_w	\$U(100, 500)
β_m	\$U(1, 20)	F_w	\$U(100, 500)
δ_m	\$U(100, 1,000)		

The term 'U' implicates the uniform distribution of the parameters. The parameter '$\sum w \cdot X_{kpmwc}$' stands for the number of alternative workers to process operation k of part type p on the machine m in the cell c. It is obvious that by increasing the parameter '$\sum w \cdot X_{kpmwc}$' the solution space increases progressively because the number of alternative worker for each part operation increases.

5.1 Parameter calibration and analysis of results

The proposed combinatorial cell formation problem is attempted by using meta-heuristics (GA, SA, and SAGA). The quality of the solution is influenced by parameters of the algorithms, calibrated by using the Taguchi method (TM) of optimisation. The TM is performed by selecting the response on 'smaller is better' as S/N ratio should be minimised (Mousavi et al., 2014). The functional values of parameters under different level for the algorithms are calibrated by employing L^9 design of Taguchi method, depicted in Table 2.

Table 2 Parameters and levels of algorithms (GA, SA, and SAGA)

Algorithm	*Parameters*	*(1)*	*(2)*	*(3)*
GA	Pop	80	100	120
	Pc	0.6	0.7	0.75
	Pm	0.01	0.015	0.02
SA	t_z	80	100	120
	Pm	0.1	0.15	0.2
	α	0.98	0.95	0.9
SAGA	t_z	80	100	120
	Pc	0.6	0.7	0.75
	Pm	0.1	0.15	0.25
	α	0.98	0.95	0.9

The optimum functional values of input parameters of the three algorithms (GA, SA, and SAGA) for each of the ten distinct problem scenarios are derived using L^9 design of Taguchi Method, presented in Table 3. The population size (Pop), the probability of crossover (Pc), and the probability of mutation (Pm) are the parameters of Genetic algorithm. The initial temperature (t_z), the cooling schedule (α) and the probability of mutation (Pm) are the three parameters of the Simulated Annealing algorithm. For the SAGA, four parameters, the initial temperature (t_z), the probability of crossover (Pc), the probability of mutation (Pm), and the cooling schedule (α) are calibrated for the distinct problem scenarios.

Table 3 Input parameters of GA, SA, and SAGA algorithms for the generated problems

Prob. no.	*GA*			*SA*			*SAGA*			
	Pop	*Pc*	*Pm*	t_z	α	*Pm*	t_z	*Pc*	*Pm*	α
1	100	0.75	0.1	100	0.9	0.1	100	0.75	0.1	0.95
2	100	0.7	0.02	100	0.95	0.2	100	0.7	0.25	0.98
3	100	0.6	0.15	120	0.9	0.15	120	0.6	0.25	0.95
4	120	0.6	0.02	100	0.95	0.2	100	0.7	0.25	0.98
5	100	0.7	0.02	120	0.98	0.2	100	0.6	0.15	0.9
6	120	0.6	0.2	100	0.9	0.1	120	0.7	0.1	0.9
7	80	0.7	0.015	100	0.98	0.15	120	0.7	0.1	0.9
8	100	0.7	0.02	100	0.95	0.2	100	0.7	0.25	0.98
9	100	0.75	0.01	100	0.95	0.2	100	0.75	0.1	0.95
10	100	0.75	0.1	120	0.9	0.15	120	0.75	0.15	0.98
11	100	0.6	0.015	100	0.95	0.2	100	0.75	0.1	0.95
12	100	0.75	0.1	100	0.9	0.1	120	0.6	0.25	0.95
13	120	0.7	0.1	120	0.98	0.2	120	0.6	0.25	0.95
14	120	0.7	0.01	120	0.98	0.2	80	0.75	0.25	0.9
15	80	0.6	0.1	100	0.95	0.2	100	0.7	0.25	0.98

Table 4 Summary of computational datasets

Problem number	*Part × machine, cell, period, worker*	*Number of variables, and constraints*	*GA*		*SA*		*SAGA*	
			Objective	*CPU time (seconds)*	*Objective*	*CPU time (seconds)*	*Objective*	*CPU time (seconds)*
1	2×3, C = 2, T = 2, W = 3	394, 738	54,476	0.00	54,476	0.00	54,476	0.00
2	3×3, C = 2, T = 2, W = 3	555, 1,079	29,786	0.03	29,786	0.03	29,337	0.03
3	4×3, C = 2, T = 2, W = 3	716, 1,420	65,474	4.25	65,644	6.25	65,474	8.25
4	5×3, C = 2, T = 2, W = 3	877, 1,761	44,323	10.987	50,344	13.321	50,344	17.631
5	6×3, C = 2, T = 2, W = 3	1,038, 2,102	43,558	19.454	43,373	24.765	48,944	28.987
6	4×3, C = 2, T = 3, W = 3	1,056, 2,112	117,667	162.197	117,632	172.197	117,632	182.197
7	3×4, C = 2, T = 2, W = 4	1,134, 2,262	71,000	213.321	67,348	243.321	65,768	263.321
8	4×4, C = 2, T = 2, W = 4	1,136, 2,264	76,358	251.328	68,997	261.534	76,358	272.447
9	6×4, C = 2, T = 2, W = 4	1,134, 3,510	172,684	256.543	167,364	271.671	162,678	280.492
10	4×4, C = 2, T = 2, W = 4	1,480, 2,992	67,659	311.124	65,443	341.124	65,428	361.124
11	5×4, C = 2, T = 2, W = 4	1,826, 3,772	111,914	360.764	129,936	375.192	129,936	390.765
12	6×4, C = 2, T = 3, W = 4	3,210, 6,630	123,517	418.662	123,517	458.662	123,517	486.324
13	10×8, C = 2, T = 3, W = 8	35,758, 74,074	184,809	550.732	184,359	580.732	184,325	613.732
14	10×8, C = 3, T = 3, W = 8	53,182, 110,656	214,760	623.789	226,935	663.789	212,735	683.789
15	12×8, C = 3, T = 3, W = 8	63,732, 132,726	343,348	728.232	341,465	854.745	341,050	915.345

It is evident that the required computational time of the algorithm increases with the problem size in terms of number of variables, constraints and periods. All of the small size problems (problems 1–3) were successfully solved in less than 15 seconds with the highest number of variables and constraints encountered being 716 and 14,20 respectively. The medium size problems (problems 4–12) were solved in 486.324 seconds with the highest number of variables and constraints 3,210 and 6,630 respectively. The problem 15, the largest size in the set, having 63,732 and 132,726 numbers of variables and constraints respectively, solved in 915.345 seconds. In fact, even larger size problems than the problem 15 can be attempted, but these would take accordingly more computational time (Table 4).

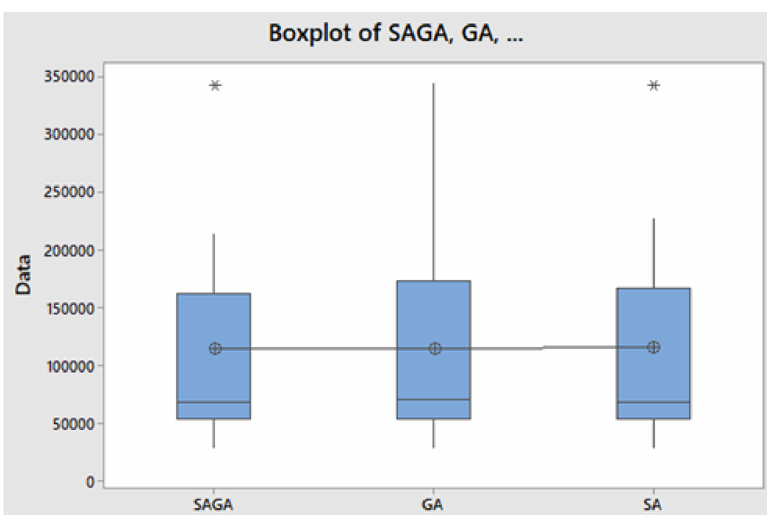
To evaluate the computational performance of the algorithms (GA, SA, and SAGA) and elicit the best solution approach for the three dimensional cell formation problem, each of the ten problem scenarios is attempted using 1.86 GHz Pentium-IV workstation with Window 8 using MATLAB-2009.

Table 5 Analysis of variance

Source	*DF*	*Adj SS*	*Adj MS*	*F-value*	*P-value*
Factor	2	15,967,026	7,983,513	0.00	0.999
Error	42	2.98231E+11	7,100,733,787		
Total	44	2.982247E+11			

The performances of the algorithms are statistically evaluated by the analysis of variance (ANOVA) method on the results obtained for each of the fifteen problems using MINITAB-17. The executed results of the ANOVA test reveal no significant difference in the mean objective function value at a confidence level of 95% (Table 5). The box plots of total cost value substantiate the effective performance of SAGA in comparison of GA and SA (Figure 6). The ANOVA test is conducted using MINITAB-17 software.

Figure 6 Box plot of total cost value (see online version for colours)



5.2 Numerical example

To illustrate the validity of the proposed model for the three dimensional design of CMS, the datasets for problem no. 15 are presented in Tables 6–7. Using this numerical instance, an optimal solution has been obtained making use of SAGA. The problem contains 12 parts types to be produced in three period segments using eight machine types, eight worker types, and three manufacturing cells. Each part type is assumed to have three operations to be performed on alternative machine types and workers. Table 6 presents information for machine and worker attributes. The dataset related to machine-part-worker incidence, production volume at each period, material handling cost, and processing time for each operation of part types on distinct machine with worker flexibility is presented in Table 7. The production cost parameters such as internal production cost (μ_{kp}) and subcontracting cost (o_{kp}) for each part operation are generated by a normal distribution with parameters (\$1–\$10).

Table 6 Dataset for machine and worker information of problem 15

Machine info					*Worker info*				
Machine type	T_m	α_m	β_m	δ_m	*Worker type*	T_w	S_w	H_w	F_w
M_1	700	1,900	6	700	W_1	50	150	75	75
M_2	700	1,300	8	600	W_2	50	450	40	85
M_3	700	1,400	7	600	W_3	50	475	25	55
M_4	700	1,800	6	800	W_4	50	315	14	40
M_5	700	1,500	6	750	W_5	50	160	28	50
M_6	700	1,400	7	350	W_6	50	440	12	60
M_7	700	1,300	8	680	W_7	50	450	26	70
M_8	700	1,500	9	700	W_8	50	210	18	60

The 3D cell configurations (machine-part-worker) for three periods corresponding to the optimal solution of the proposed model for problem 15 are shown in Table 8. The multiple process route for each part type and objective function value are depicted in Table 9 and 10 respectively.

Part families, machine groups, worker availability for processing each part operation on machine type, and machine replication are also depicted in the 3D cell configurations presented in Table 8. For instance, one unit each of machine type 7 and 8 are assigned to cell 1 in the period 2. The worker assignment to part operations within the cell is represented by the incidence matrix in rectangular shape. For instance operation 1 of part type 12 in period 2 must be performed by 9 workers of type 4 ($9W_4$) on machine type 7 in cell 1. Similarly, operation 2 performed by worker type 5 on the machine type 8 in cell 1, and operation 3 performed by worker type 1 on machine 6 in cell 2. Thus, the processing of part 12 in period 2 requires one intra-cell movement and one inter-cell movement.

One unit of machine type 6 is added into the cell 1, and also one unit of machine type 7 is removed from cell 1 at the beginning of period 3. A total of 3 workers of type 7 are fired and a total of 3 workers of types 3 are hired at the beginning of period 2.

Table 7 Dataset for part demand and machining requirements of part type for problem 15

Part type	*Part demand (Dp)*			IE_p	IA_p	*Data type*	*Operation j*					
							1		*2*		*3*	
	t = 1	*t = 2*	*t = 3*				*1*	*2*	*1*	*2*	*1*	*2*
P_1	450	650	0	0.62	0.83	M/C, worker, time	M1, W7 0.5	M1, W6 0.5	M2, W5 0.94	M3, W7 0.24	M4, W8 0.45	M2, W8 0.45
P_2	650	300	400	0.75	1	M/C, worker, time	M3, W3 0.86	M3, W2 0.86	M5, W5 0.76	M4, W5 0.56	M7, W4 0.47	M6, W4 0.37
P_3	0	450	0	1.25	1.5	M/C, worker, time	M5, W2 0.19	M4, W5 0.74	M6, W4 0.49	M5, W6 0.45	M8, W5 0.65	M7, W7 0.59
P_4	750	550	600	0.62	0.83	M/C, worker, time	M6, W2 0.44	M3, W8 0.44	M4, W4 0.36	M1, W4 0.49	M7, W1 0.67	M6, W7 0.51
P_5	550	0	750	0.87	1.16	M/C, worker, time	M4, W1 0.48	M1, W4 0.77	M6, W3 0.57	M4, W6 0.48	M8, W2 0.67	M5, W7 0.24
P_6	0	450	450	0.62	0.83	M/C, worker, time	M1, W6 0.61	M1, W3 0.61	M2, W2 0.68	M3, W5 0.55	M5, W3 0.88	M4, W4 0.63
P_7	450	0	300	0.75	1	M/C, worker, time	M6, W1 0.89	M5, W4 0.24	M7, W4 0.81	M6,W6 0.34	M8, W2 0.51	M7, W3 0.71
P_8	650	0	350	0.62	0.83	M/C, worker, time	M2, W2 0.58	M3, W6 0.96	M6, W5 0.13	M5, W7 0.36	M8, W3 0.19	M7, W8 0.89
P_9	750	350	200	0.87	1.16	M/C, worker, time	M4, W7 0.45	M3, W8 0.67	M5, W3 0.76	M4, W6 0.61	M7, W4 0.35	M6, W5 0.78
P_{10}	900	450	500	1	1.33	M/C, worker, time	M2, W7 0.81	M1, W1 0.78	M3, W6 0.12	M2, W3 0.47	M5, W2 0.48	M3, W2 0.57
P_{11}	0	0	700	0.87	1.16	M/C, worker, time	M2, W8 0.44	M1, W6 0.39	M4, W2 0.72	M3, W7 0.48	M6, W5 0.66	M5, W3 0.36
P_{12}	450	600	0	0.75	1	M/C, worker, time	M6, W1 0.49	M4, W7 0.67	M7, W4 0.72	M6, W4 0.59	M8, W5 0.33	M7, W8 0.48

Table 8a Optimal cubic cell configuration (machine-part-worker) obtained for numerical problem 15, $t = 1$ (see online version for colours)

Cell no.	*Machine type*	*Qty*	*Part type* 1	5	7	8	12	2	4	9	10
C1	1	1	$5W_6$								
	4	1	$0W_8$	$6,0W_{1,6}$			$0W_7$	$0W_5$	$6W_4$	$0W_6$	
C2	5	1		$3W_7$	$3W_4$						
	6	1			$4W_6$	$2W_5$	$6W_4$	$0W_4$	$0W_7$	$0W_5$	
	8	1			$5W_2$	$3W_3$	$3W_5$				
C3	2	1	$5W_8$								$0W_7$
	3	1				$0W_6$		$12W_2$	$0W_8$	$0W_8$	$3,0W_{6,2}$

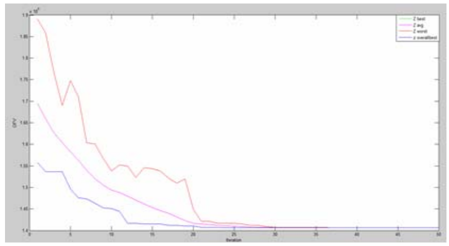
Table 8b Optimal cubic cell configuration (machine-part-worker) obtained for numerical problem 15, $t = 2$ (see online version for colours)

Cell no	*Machine type*	*Qty*	*Part type* 12	2	3	4	9	1	6	10
C1	7	1	$9W_4$		$0W_7$					
	8	1	$4W_5$							
C2	4	1		$0W_5$	$7W_5$	$4W_4$	$0W_6$		$0W_4$	
	6	1	$6W_1$	$0W_4$	$5W_4$	$0,0W_{2,7}$	$0W_5$			
C3	1	1						$7W_6$	$6W_3$	$0W_1$
	2	1						$0W_5$		
	3	1		$6W_2$			$5W_8$	$0W_7$	$0W_5$	$2,0W_{6,2}$

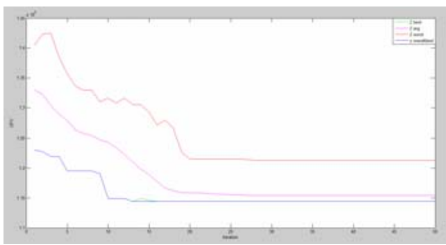
Table 8c Optimal cubic cell configuration (machine-part-worker) obtained for numerical problem 15, $t = 3$ (see online version for colours)

Cell no	*Machine type*	*Qty*	*Part type* 7	8	4	5	6	2	9	10	11
C1	6	1	$6,3W_{1,6}$	$1W_5$	$0W_7$			$3W_4$	$0W_5$		
	8	1	$4W_2$	$2W_3$							
C2	1	1			$6W_4$		$6W_6$			$0W_1$	
	4	1				$8,0W_{1,6}$	$0W_4$	$5W_5$	$0W_6$		
C3	2	1		$5W_2$							$7W_8$
	3	1			$0W_3$		$0W_5$	$7W_2$	$3W_8$	$2,0W_{6,2}$	$0W_7$
	5	1				$4W_7$					$6W_3$

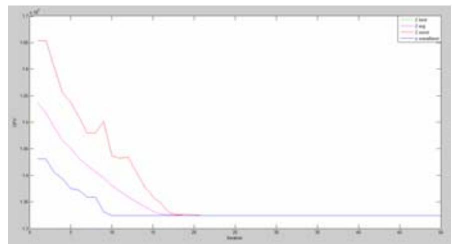
Figure 7 Progress of SAGA for search of optimal solution corresponding to the objective function value (OFV) for numerical instance 15, (a) period 1 (b) period 2 (c) period 3 (see online version for colours)



(a)



(b)



(c)

Table 9 Multiple process route for each part type in each period obtained by the proposed model for problem 15

a				*b*				*c*			
Part no.	*Period 1*			*Part no.*	*Period 2*			*Part no.*	*Period 3*		
	1	*2*	*3*		*1*	*2*	*3*		*1*	*2*	*3*
1	M1	M2	M4*	1	M1	M2*	M3*	2	M3	M4	M6
2	M3	M4*	M6*	2	M3	M4*	M6*	4	M1	M3*	M6*
4	M4	M3*	M6*	3	M4	M6	M7*	5	M4	M4*	M5
5	M4	M4*	M5	4	M4	M6*	M6*	6	M1	M3*	M4*
7	M5	M6	M8	6	M1	M3*	M4*	7	M6	M6	M8
8	M3*	M6	M8	9	M3	M4*	M6*	8	M2	M6	M8
9	M3*	M4*	M6*	10	M1*	M3	M3*	9	M3	M4*	M6*
10	M2*	M3	M3*	12	M6	M7	M8	10	M1*	M3	M3*
12	M4*	M6	M8					11	M2	M3*	M5

Note: *Subcontracted part operation.

Table 10 Optimal objective function value and its components for problem 15

Total cost	*Amortised cost (α_m)*	*Operating cost (β_m)*	*Relocation cost (δ_m)*	*Inter-cell movement cost (IE_p)*	*Intra-cell movement cost (IA_p)*
341,050	32,200	63,040	5,030	10,417	14,553

Internal production cost (μ_{kp})	*Subcontracting part operation cost (o_{kp})*	*Salary cost (S_w)*	*Hiring cost (H_w)*	*Firing cost (F_w)*
52,750	90,000	67,705	3,420	1,935

The solution obtained in terms of multiple part process route and part operation trade-off in different production modes considering production capacity shortage and worker availability for each part operation in each period are depicted in Table 9. For instance, the part 5 undergoes three different operations at the period 1 to complete the production process. The first operation of part 5 is performed on the machine M4 by six workers of type 1 (6, $0W_{1,6}$) in cell 1 (Tables 8–9), and the third operation processed on machine M5 by 3 workers of type 7 ($3W_7$) in cell 2, whereas the second operation of part type 5 cannot be performed due to limited production capacity of 700 hrs of the machine M4 in cell 1. Since the machine M4 in cell 1 is assigned to process first operation of part type 5 of cell 1 and inter-cell operation of part 4 from cell 3. The production volume of 550 units for first operation of part type 5 with the processing times of 0.48 ($6W_1$) hrs per unit, exploits total of 264 hrs of machine type 4. The production volume of 750 units for part type 4 with the processing time of 0.36 ($6W_4$) hrs per unit, exploits 270 hrs of machine type 4 in cell 1. Hence the second operation of part type 5 with processing time of 0.48 ($0W_6$) hrs per unit cannot be processed on the machine M4 in cell 1 as it requires 264 hrs for required production volume of 550 units. Hence the second operation of part type 5 for production volume 550 units is subcontracted from cell 1 at period 1.

In the proposed work the trade-off is made among intracellular, intercellular part movement and machine duplication to minimise all the three cost components (IE_p, IA_p, and α_m) considering worker availability. This is essential since, high intracellular movement cost for successive part operations implies large cell size, reducing the effectiveness of the manufacturing system. On the other side, minimum inter-cell movements may lead to increase machine duplication in cells, adversely affecting the benefits of a CMS by inappropriate workload distribution among cells.

6 Conclusions and future scopes

The proposed research work is aimed to find optimal 3D/cubic configuration ‘part-machine-worker’ to deal with dynamic production in CMS. In this study, an application of SAGA is presented in the cell formation problem. The followings are the significant remarks:

- A relatively comprehensive mathematical programming model for dynamic CFP brings many production parameters into the formulation. This would make the problem more practical and realistic.
- The algorithm aggregates resources into three dimensional manufacturing cells based on the selected optimal process route among the user specified multiple routes.
- The model offers flexibility in the part production (internal production/ subcontracting) achieved by processing the subsets of a part operation sequence within the given production capacity limit. It is a tangible advantage during worker unavailability and unexpected machine breakdown occurring in the real world.
- The model is computable with single part routing as well as multiple part routings. The proposed approach can also be readily used where limits are imposed on the cell sizes and/or number of cells.

- The trade-off between duplicate machines and inter-cell movements of part operations optimise the cellular configuration by the minimisation of vacillation in manufacturing cell and the maximisation of workload balancing.
- The proposed hybrid algorithm SAGA proves to be an effective approach, prevents premature convergence, and imparts synergy effect between the SA and GA.

The research work is extendable for incorporating more realistic features for future work. A few guidelines for future research work are outlined as follows:

- The mathematical model can be developed with production capacity constraints to delineate if an operation can be assigned to a machine or not. Data required for formulation can be the specified machine adjacency requirement, similar cohabitation and separation constraints. These constraints permit handling of different machine that must remain grouped for different reasons.
- Multiple process plans (internal production/subcontracting) for each part type can be employed for lot splitting, selecting the optimum alternative route of the process plans within the productive capacity limit.
- The algorithm can be extended to plant layout problem considering dynamic production.
- The study for comparison of the benchmark results obtained using other techniques is very important research assignment, and shall be taken up in due course.

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