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Cell formation in a cellular manufacturing system using simulation integrated hybrid genetic algorithm

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ABSTRACT

Work-in-process (WIP) is an important performance measure of contemporary manufacturing systems such as cellular manufacturing system (CMS). The term value added WIP (VAWIP) is used because; the value of WIP increased at each stage of production due to the application of resources in the form of machines, time and energy. This research is an attempt of cell formation (CF) in CMS that would minimize the value added work in process. To achieve this objective a mathematical model is formulated and solved using discrete event simulation (DES) integrated hybrid genetic algorithm (SHGA) in which simulation and the genetic algorithm have been integrated to form an approach called SHGA and it has the advantages of using both. The proposed approach has been applied on local automobile part supply industry for cell formation. While solving problem with SHGA each population has been evaluated using the discrete event simulation (DES). The solution was found in the form of assigning machines to cells in a way that resulted in minimum value added work in process. A 8.55% reduction of value added work in process occurred using SHGA. The reduction of value added work in process VAWIP in the system resulted in the reduced waiting and throughput times, whereas increased throughput rate and machine utilization.

1. Introduction

A cellular manufacturing system (CMS) is an application of the group technology and it is used to design the layouts of production systems. A CMS is a system where collection of parts with a similar geometry, design or process can be processed together in cells. Cell formation is fundamental step in group technology (GT) and CMS. It has the advantages of flow line production as well as job shop. Cells in manufacturing systems are either product or process type. In product layouts similar products based on their shape, design and other attributes are processed in same cell while in process layout parts having different attributes but same manufacturing process are manufactured in same cell (Goldberg & Holland, 1988). Product type cellular layout is good for low variety production but for the high variety of products, process type cellular layout is recommended because of its flexibility to different part type with similar manufacturing processes.

Cell formation considers performance measures such as, intercellular movements or distance, intracellular movements, void and exceptional elements, throughput, grouping efficiency, tardiness, flow time and total manufacturing cost (Arkat, Hosseini, & Farahani, 2011; Jayaswal & Adil, 2004; Mutlu, Polat, & Supciller, 2013; Onwubolu & Mutingi, 2001; Saxena & Jain, 2011; Zeb et al., 2016). Another important performance measure of manufacturing system is work in process which greatly affects the other performance measures such as flow time, throughput rate, cycle time and it also creates the problems of blockage and bottlenecks. To improve the performance of manufacturing system WIP should be kept as low as possible. Very few authors considered average work in process as a cell formation objective in cellular manufacturing system such as, Saraswat, Venkatadri, and Castillo (2015) considered average work in process minimization objective for facility layout problems neglecting the machines assignments in cells and cell formation. Rafiei, Rabbani, Nazaridoust, and Ramiyani (2014a) used average work in process indirectly in cell formation objectives and in their case work in process was measured in terms of batch size of products because work in process of any product type at any machine and at any time of production process cannot be measured directly using analytical methods. However queuing theory and simulation can be used to measure work in process directly.

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In previous literature of scheduling and cell formation problem average work in process is considered as performance measure of the system (Amar, Camus, & Korbaa, 2011; Braglia, Frosolini, Gabbrielli, & Zammori, 2011; Rafiei, Rabbani, Nazaridoust, & Ramiyani, 2015; Zhou & Rose, 2013). This research considers value added work in process minimization objective which has not been paid due attention in previous literature of cell formation problems. The term value added is used because the value of the WIP increased at each stage of production due to application of resources in the form of machines, time and energy, therefore, it is very important to minimize the value added work in process because it affects the other performance measures such as flow time, throughput rate, cycle time, production cost and energy. Considering value added work in process as cell formation objective has advantage of achieving other objectives of cell formation such as throughput time, throughput rate and cycle time because, according to little's law work in process, throughput and cycle time are related to each other. (McKenna, 1989). Throughput time is related to inter and intracellular movements because it consists of move time, wait time and process time. Value added work in process objective function includes the cost of production and energy consumed by machines.

In this paper, a mathematical model is formulated to minimize the value added work-in-process (VAWIP) for cell formation problem. Discrete event simulation (DES) and genetic algorithm (GA) have been integrated to solve this model. In simulation integrated hybrid genetic algorithm (SHGA) approach each chromosome in each population is evaluated using discrete event simulation (DES) and remaining steps are similar to GA. A case study of cell formation problem in automobile spare parts industry is also presented as numerical example and solution is achieved by forming cells and assigning machines to them. It is observed that substantial amount of cost reduction occurs after cell formation. This paper has been organized as follows; an overview of previous research is presented in Section 2. A mathematical model formulated is in Section 3. (SHGA) and cell formation case study is in Section 4, followed by Section 5 which is about computational results and conclusions of the proposed research are in Section 6.

2. Literature review

Cell formation (CF) is one of the important tools in GT. In contemporary manufacturing systems CF is being carried out with specific objectives and their associated constraints to resolve various production issues using artificial intelligence techniques. Various researchers have formed cells in CMS on the basis of different objectives; a few of them are discussed in this section. Deljoo, Mirzapour Al-e-hashem, Deljoo, and Aryanezhad (2010) designed cells in CMS which minimized the cost of machine, operating cost, material handling and machine relocation cost using GA, However the effect of these objectives does not provide the information regarding the waiting time of parts within cells or on machines. The analysis of cellular manufacturing system should also consider the dynamic behavior of the system. Kia et al. (2012) used an integrated simulated annealing algorithm with nonlinear programming to minimize intercellular and intracellular movements along with the reduction in reconfiguration cost of cells, purchase cost of new machines, overhead cost of all machines utilized and operating cost of all machines in dynamic CMS and designed layout.

The grouping efficiency is primitive objective of cell formation and it highly cited by many researchers in cell formation problems such as, Ünler and Güngör (2009) used K-harmonic means algorithm to design cells in CMS and maximized grouping efficiency of CMS. Ahi, Aryanezhad, Ashtiani, and Makui (2009) used multiple attribute decision making and TOPSIS to design cells and maximized grouping efficiency. Li, Baki, and Aneja (2010) maximized grouping efficiency using ant colonial metaheuristics to form cells. Zeb et al. (2016) addressed cell formation problem to maximize cell efficiency by integrating simulated annealing with genetic algorithm in this method best individuals achieved in generations were further optimized by simulated annealing but in proposed methodology, GA and discrete event simulation are integrated in such way that each individual in each generation is evaluated using discrete event simulation (DES). The performance measure of grouping efficiency is most suitable for product layout. For process layout grouping efficiency will be effective only when it will consider the sequence of process routing along with queues at machines in cells.

The cellular manufacturing systems greatly reduce the movements of parts which results in the higher productivity with least manufacturing cost. Nouri and Hong (2013) minimized cell load variations using a newly developed algorithm called bacteria foraging algorithm. Bajestani, Rabbani, Rahimi-Vahed, and Baharian Khoshkhou (2009) used CF dynamic CMSs and formed cells to minimize machine depreciation cost, material handling and machine relocation costs using a scatter search algorithm. The machine relocation is a function of nature of part and sequence of process routing thus any change in the sequence of process routing will require again relocation of machine. Karoum, Elbenani, and El Imrani (2016) studied cell formation problem using clonal selection algorithm to minimize intercellular movements and maximize cell utilization. Mehdizadeh and Rahimi (2016) studied a simultaneous problem of cell formation and job assignment to minimize intercellular, intracellular, machine relocation, forward flow ratio, and operator related costs and solved problem using multi-objective simulated annealing and multi-objective vibration damping optimization. Paydar, Saidi-Mehrabad, and Teimoury (2014) presented an integrated model for supplier selection and cell formation problem to minimize material handling cost, intercellular and intracellular movements. Noktehdan, Seyedhosseini, and Saidi-Mehrabad (2016) introduced a new algorithm called league championship algorithm to minimize intercellular movements in cellular manufacturing system.

The performance of manufacturing system is largely influenced by the performance of labor and this factor is very difficult to control however some researcher attempted to model human resources in cellular manufacturing systems. Süer, Arikan, and Babayiğit (2009) minimized the number of tardy jobs and minimized total manpower needed for assignment in manufacturing cells. Mahdavi, Aalaei, Paydar, and Solimanpur (2010) modeled a dynamic CMS using linear programming to minimize holding cost, backorder cost, and intercellular material handling, machine cost, machine relocation cost, salary cost, hiring cost and firing cost. Zohrevand, Rafiei, and Zohrevand (2016) focused cell formation problem with objectives of total cost of machine procurements, overtime utilization, and worker hiring firing, workers moves in cells, worker overtime cost, and labor utilization. Bagheri and Bashiri (2014) focused cell formation problem by integrating workers assignment model with CF to minimize intercellular and intracellular movements. In CMS performance of labor can be improved by designing a system with minimum movements and absenteeism.

Another important issue in the cellular manufacturing system is machine breakdown or failure of machines due to known or unknown causes which must be addressed for achieving the highest throughput rate with reduced cycle time. Jouzdani, Barzinpour, Shafia, and Fathian (2014) formed cells in CMS using simulated annealing to minimize cost of machine breakdown, setup cost, cost of inter and intracellular movements. The time between failure and time to repairs are the most important components for analyzing

Table 1
Comparison with previous literature.

No	Features of CMS							Performance Measures												
	Authors	Alternating Routing[a]	Data Type[b]	Production Demand	Environment type[c]	Cell Size limit	Machine capacity	Machine layout	Labor issues	Cell load variation	Cell efficiency	Machine relocation	Exceptional elements	Material Handling	Machine Reliability	Machine Investment	Processing Time cost	Average WIP	Value Added WIP	Solution Method
1	Noktehdan et al. (2016)	SM	B		C	✓	✓							✓						Table 2[a]
2	Mohammadi and Forghani (2016)	SR	B	✓	C	✓	✓	✓	✓					✓						
3	Renna and Ambrico (2015)	SR	B	✓	U	✓	✓					✓		✓		✓				
4	Niakan, Baboli, Moyaux, and Botta-Genoulaz (2016)	SR	B		U									✓			✓			
5	Sadeghi, Seidi, and Shahbazi (2016)	SR	S		U	✓			✓		✓			✓						
6	Liu, Wang, Leung, and Li (2016)	SR	B		C	✓	✓			✓				✓		✓	✓			
7	Soto et al. (2016)	SM	B	✓	C	✓								✓						
8	Zeb et al. (2016)	SM	B		C	✓					✓									
9	Bootaki, Mahdavi, and Paydar (2015)	SM	B	✓	U		✓			✓		✓		✓						
10	Yadollahi et al. (2014)	SM	S		C	✓								✓	✓		✓			
11	Zohrevand et al. (2016)	SM	S		U	✓	✓			✓		✓			✓					
12	Paydar et al. (2014)	SM	S	✓	U	✓	✓		✓					✓						
13	Saraswat et al. (2015)	SR	S	✓	C													✓		
14	Rafiei et al. (2014a), Rafiei et al. (2014b)	SM	B	✓	C	✓						✓		✓		✓		✓		
15	Proposed Model	SM	S	✓	C	✓	✓			✓				✓		✓	✓	✓	✓	

[a] SM: Machine selection for Cell; SR: Selection of Routs.
[b] B: Binary data; S: Sequence data.
[c] C: Certain; U: Uncertain.

the reliability of cellular manufacturing systems. Yadollahi, Mahdavi, Paydar, and Jouzdani (2014) considered machine repairing, failure rate, intercellular, forward intracellular, backward intracellular movements and machine purchase cost for cell formation problem and solved the model with augmented ε constraint method.

The cellular manufacturing system is a sub domain of production planning and control and the integration of CMS with other areas of production planning such as resource planning, job assignment and inventory management is becoming popular. Safaei and Tavakkoli-Moghaddam (2009) focused on CF and production planning simultaneously to minimize machine, inter/intra-cell movement, reconfiguration, partial subcontracting, and inventory carrying cost. Shirazi, Fazlollahtabar, and Mahdavi (2010) developed six sigma based multi-objective optimization technique to minimize the material flow intra and inter-loops and minimization of maximum amount of intercellular flow, considering the limitation of AGV work-loading in CMSs. Torabi and Amiri (2012) used fuzzy adaptive ranking and possibility programming in hybrid CMS and formed cells to minimize the total of operational costs, machines allocating costs (involving both buying new machines and allotting existing machines to cells), inter-cell material. Mehdizadeh and Rahimi (2016) studied a simultaneous problem of cell formation and job assignment to minimize intercellular, intracellular, machine relocation, forward flow ratio, and operator related costs and solved problem using multi-objective simulated annealing and multi-objective vibration damping optimization.

Work-In-Process is the basic performance measure of any manufacturing system. WIP has been the key issue in the all domains of production planning and control. Performance measures of the average WIP has been extensively used for scheduling problems of manufacturing system and details can be found in (Kim & Lee, 2001; Papadopoulos & Vidalis, 2001; Pramanik, 2006; Tsourveloudis, 2010). Most of the researchers have considered average WIP of a system as a performance measure however WIP varies with respect to time in system and its absolute value at any instant of time cannot be measured directly using analytical approaches. Cell formation on the basis of direct WIP minimization is very rare. However, indirect WIP minimization objectives exist in literature for example Rafiei, Rabbani, Nazaridoust, and Ramiyani (2014b) designed a dynamic CMS using nonlinear mixed integer programming and minimized, machine purchasing and operation costs, intercellular moves, machine relocation, machine transferring cost and average work-in-process(Batch size). Saraswat et al. (2015) considered average WIP for layout of machines insides cells in which machines were already assigned. Table 1 shows the comparison of proposed cell formation problem with previous literature.

It is clear from the literature that the performance measure of value added work in process VAWIP in cell formation context has not been found so far (to the best of our knowledge). However, use of VAWIP minimization along with average WIP minimization can be found in other manufacturing contexts such as flow shop scheduling. Yang and Posner (2010) developed a mathematical model for WIP and value added costs for flow shop and Aziz, Bohez, Pisuchpen, and Parnichkun (2013) scheduled a flow shop to minimize value added work in process using petrinets and also their models were specific to limited set of machines and parts and cannot be applied to complex manufacturing systems. It is clear from the literature that the performance measure of value added work in process VAWIP in cell formation context has not been found so far (to the best of our knowledge). However, use of VAWIP minimization along with average WIP minimization can be found in other manufacturing contexts such as flow shop scheduling. Yang and Posner (2010) developed a mathematical model for WIP and value added costs for flow shop and Aziz et al. (2013) scheduled a flow shop to minimize value added work in process using petrinets and also their models were specific to limited set of machines and parts and cannot be applied to complex manufacturing systems.

Table 2
Solution method.

No	Solution Method	No	Solution Method
1	League Championship algorithm	10	Augmented ε-constraint method
2	Dynamic Programing with Simulated annealing	11	Tabu search and GA
3	Linear Programming	12	Mixed integer Programming
4	NSGA II and Simulated annealing	13	Simulated annealing
5	Mixed-Integer Programming	14	Mixed Integer Programming
6	Discrete bacteria foraging algorithm	15	Simulation Integrated GA
7	Dolphin Echolocation Algorithm		
8	Simulated annealing with GA		
9	Percentage Multi Choice Goal Programing		

Table 2 is linked with Table 1 which shows the solution method adopted for cell formation problems in previous literature.

The performance measure of value added WIP is more realistic than average WIP. As the value of WIP is not constant at each stage of production due to the application of labor, time, and machining energy at each stage Aziz et al. (2013). Therefore cell formation is done on the basis of value added WIP minimization and in current research the consideration of material handling cost and energy costs are included to compute the value of WIP at each stage of production so as to minimize that cost.

The genetic algorithm is hybridized with discrete event simulation to solve this model which is more dynamic and provides more realistic results. GA has been used along with simulation for flow shop scheduling by Al Kattan and Maragoud (2008) but used in two separate steps: first, applied GA and then, applied simulation to near optimum results. In this paper GA and the simulation have been integrated in such a way that each individual in each generation is evaluated using discrete event simulation. WIP of complex systems at particular time and machine cannot be measured directly using analytical methods therefore, GA is integrated with simulation to achieve desired results. So SHGA is a good optimizer for those performance measures which cannot be measured analytically.

3. Mathematical model formulation

This section includes model assumption, syntax and notations, variables, objective function and constraints. The Mathematical model presented in this section is further elaborated with the help of a case study of cell formation in automobile spare parts industry.

3.1. Model assumptions

The following are the assumptions for this model.

1. Throughput time of each individual part on machine is composed of move time from the previous machine to that machine or (in case of 1st machine it is time from storage to 1st machine) plus process time of part on machine and setup time of part on machine.
2. Launching sequence of parts into the system must be predetermined according to the due date.
3. Arrival time of parts in system is deterministic.
4. Cycle time is designed according to the number of parts required per unit time but number of machines is not increased to meet product demands.

5. Machine duplication is not allowed.
6. Demand of parts is already known.
7. No of cells to be formed are known.
8. AGVs are used for material handling of parts between machines and the capacity of each AGVs is same
9. The selection and required number of material handling devices is already decided by the management.

3.2. Mathematical model

3.2.1. Indices

j:	machine type	j = 1, 2, 3, ..., m
i:	part type	i = 1, 2, 3, ..., n
k:	cell type	k = 1, 2, 3, ..., c
j_p:	previous machine in sequence	j_p = 1, 2, 3, ..., m−1
o:	operation type	o = 1, 2, 3, ..., O
z:	chromosome	z = 1, 2, 3, ..., Z
v:	material handling device (AGV)	v = 1, 2, 3, ..., V
$x_i = j_p - j$:	sequencing subscript (difference of previous and current machine in a route of part "i")	

3.2.2. Parameters

C_{ij}:	value added cost on part "i" at machine "j"
W_{ij}:	work-in-process of part "i" at machine "j"
TT_{ij}:	throughput time of part "i" on machine "j"
$T_{c(ij)}$:	cycle time of part "i" on machine "j"
PH:	planning Horizon during which demand is to be met
D_i:	demand of part "i"
S_h:	hours per shift
t_{mx_i}:	transportation time of part "i" between machine "j" and previous machine "j_p" in sequence
P_j:	rated power of machines
P_v:	rated power of material handling device (AGVs)
$t_{o(ij)}$:	operation time of part "i" on machine "j"
$t_{s(ij)}$:	setup time of part "i" on machine "j"
U:	electricity unit cost per kilowatt hours
E_{ij}:	exit time of part "i" from machine "j"
ART_{ij}:	arrival time of part "i" on machine "j"
SRT_{ij}:	service start time of part "i" on machine "j"
Q_{ij}:	waiting/Queue time of part "i" on machine "j"
L:	minimum number of machines in cell "k"
U:	maximum number of machines in cell "k"
Y_{ij}:	1 if part "i" is assigned to machine "j" 0 otherwise
F_{fz}:	fitness function value of chromosome z
f_{vu}:	function value of chromosome u
AV:	achieved value
BV:	best value

3.2.3. Decision variables

$$Y_{jk} = \begin{cases} 1 & \text{if machine "j" is in cell k} \\ 0 & \text{if machine "j" is not in cell k} \end{cases}$$

3.2.4. Objective function

The objective of this research is to find an optimal assignment of machines in cell to minimize the value added work in process (VAWIP). According to little's law relationship between WIP, Cycle Time and Throughput time is given by (McKenna, 1989) and is shown in Eq. (1)

$$W_{ij} = \frac{TT_{ij}}{T_{c(ij)}} \tag{1}$$

Planned cycle time which is defined by Aziz et al. (2013) is given in Eq. (2)

$$T_{c(ij)} = \frac{PH}{D_i} \tag{2}$$

Material handling cost and energy (electricity) cost of machines is considered as value adding cost to WIP. Although material handling is considered as non-value added activity but there is a slight difference between the term "Value added WIP(VAWIP)" and the term of "Value added or Non-Value added activities" in manufacturing. The elimination or reduction of non-value added activities is desirable. Value added WIP comes from addition of any cost added to WIP stage by stage. Scope of this research is to minimize value added WIP (VAWIP) at each stage regardless of that cost came from value added activity or non-value added activity. Eq. (3) is cost function.

$$C_{ij} = \frac{U}{60000} \times ((P_v \times t_{mx_i}) + (P_j \times t_{o(ij)})) \tag{3}$$

Eq. (3) shows the material handling cost and production cost. Material handling is measured by the electricity consumption of AGVs and production cost is composed of electricity consumption by machines. Cost function takes value of time in minutes. Using Eqs. (1) and (3) final objective function is shown in Eq. (4). Y_{ij} is process sequence dependent input parameter it is "1" if part visit machine otherwise "0" and Y_{jk} is binary decision variable.

$$F = \sum_{k=1}^{c}\sum_{j=1}^{m} Y_{jk} \sum_{i=1}^{n} C_{ij} \times W_{ij} \times Y_{ij} \tag{4}$$

3.2.5. Constraints

As this integer linear programming model has been integrated with discrete even simulation (DES) so there are two types of constraints. Constraint in Eqs. (5) and (6) are assignment constraints while constraints in Eqs. (7)–(14) are used in simulation during evaluation of objective function.

$$\sum_{k=1}^{c} Y_{jk} = 1 \quad \forall_j \tag{5}$$

$$\sum_{k=1}^{c} Y_{ij} = 1 \quad \forall_i \tag{6}$$

$$(t_{o(ij)} + t_{s(ij)} + Q_{ij}) - TT_{ij} \leqslant 0 \tag{7}$$

$$TT_{ij} = \begin{cases} E_{ij} - E_{i(j-1)} & \text{if part "i" arrives at machine "j" from "j} - 1\text{"} \\ E_{ij} - E_{(i-1)j} & \text{if part "i" directly comes to machine "j" from storage} \end{cases} \tag{8}$$

$$SRT_{ij} - \mathrm{Max}(E_{i(j-1)} + t_{mx_i}, E_{(i-1)j}) = 0 \tag{9}$$

$$E_{(i-1)j} - ART_{ij} > 0 \tag{10}$$

3.2.6. Non-negativity constraints

$$TT_{ij} > 0 \tag{11}$$

$$T_c > 0 \tag{12}$$

$$Q_{ij} > 0 \tag{13}$$

3.2.7. Bounds

$$\mathrm{L_k} \leqslant \sum_{\mathrm{j=1}}^{\mathrm{m}} \mathrm{Y_{jk}} \leqslant \mathrm{V_k} \quad \forall_k \tag{14}$$

Eq. (4) is objective function. The Constraint in Eq. (5) ensures that each machine must be assigned to a one machine cell. Eq. (6) shows that each machine can process only one part at a time. Eq. (7) illustrates that throughput time of part "i" on machine "j" must be either equal to sum of processing and setup time or greater than it. Eq. (8) focuses that if the part directly comes from storage then throughput time is equal to exit time of part from that machine if it comes from another machine then throughput time is difference of exit times of both machines. Eq. (9) ensures that part will be processed only when the machine has completed processing of the previous part. Eq. (10) tells that queue of part will be generated only when part arrives before the machine is busy in processing other part. Eqs. (11)–(13) are non-negativity constraints which restrict throughput time, cycle time and queue time of parts to be positive. Eq. (14) is lower and upper bound of cell. Term $\sum_{j=1}^{m} Y_{jk}$ denotes total number of machines assigned to a cell k while "$\mathrm{L_k}$" and "$\mathrm{U_k}$" shows the lower and upper cell capacity.

4. Simulation integrated hybrid genetic algorithm (SHGA)

Simulation Integrated Hybrid Genetic Algorithm (SHGA) is modified Genetic Algorithm in which discrete event simulation (DES) and GA are integrated. In SHGA each individual in a population is evaluated using discrete event simulation (DES). There are specific performance measures of complex manufacturing system such as WIP, Utilization, idle Time, wait time (Fujimoto, 1990). SHGA is best for optimizing the performance measures of those systems which change their state with the passage of time. As the WIP of any part at any machine at any instant of time cannot be measured analytically due to change in state, so to optimize these systems discrete event simulation (DES) must be integrated with optimization technique. Combining discrete even simulation (DES) with GA provides better results as compared to combining the simulation with other approaches such as linear programming or mixed integer programming. Therefor discrete event simulation (DES) is integrated with GA. The Model developed in the last section is used to minimize the VAWIP in CMS of discrete parts using SHGA. Complete procedure of SHGA can be seen in Fig. 1 This schematic diagram is step by step procedure of Simulation integrated hybrid genetic algorithm (SHGA) which evaluates the function and provides a solution with minimum VAWIP.

4.1. Pseudo code of simulation integrated hybrid genetic algorithm

Following pseudo code is used to develop a simulation integrated hybrid genetic algorithm to solve the mathematical model in section.

```
Initialize
If system is manufacturing system then
  Define Variables and parameters
 • Define number of part and number of machines
 • Define process routing of parts
 • Define objective function
 • Define constraints and bounds
Initialize SHGA
 • Set priority of parts arrival on machine
 • Randomly generate initial population
 • Evaluate each individual's fitness using simulation
 • Calculate average fitness function of entire population
Select selection criteria
  Stochastic sampling selected
  Define pointers distance using cumulative probability and
   random start point.
If   Pointer position is greater than
  Cumulative probability of fitness function of "ith"
   chromosome
And   pointer position is less than
  Cumulative probability of fitness function of "i+1th"
   chromosome then
  Select the chromosome
Else   reject it
  Generate new population considering constraints and bounds
  Crossover
  Mutation
  Evaluate Function value of new population using simulation
  Check the constraints while evaluating population
  Calculate average fitness function of entire population
If   Function value of Elite individual's start to repeat in ten
   successive generations
  Terminate the algorithm.
```

4.2. Case study of cell formation in automobile industry

This section provides a case study of an automobile industry which produces different parts for motorcycles, cars, and tractors and was facing a problem of higher WIP. This model helped to design the layout of industry and form cells to minimize VAWIP. The study was carried out on fifteen machines on which twenty parts could be manufactured. Machines in industry were randomly oriented and it took time to take one part from one machine to another one due to which more WIP introduced in the system.

4.3. Input Parameters of the model

In order to use this algorithm for the above model, process routings of parts, process time, setup times, move times, demand of each part, number of cells to be formed, and costs of electricity, must be known. The demand of each part type is known and is shown in Table 3 and Table 4 shows the process routing of parts. The movement of parts through cells is modeled as entity, parts arrive in system and go to server (machine) as defined by process routing if server is busy then part waits for its processing. After processing on a certain machine, the part is sent to the next machine as defined in process routing. Priority of processing of parts is defined, for example, P1 is required to complete before P2 and P2 must be completed before P3 is complete.

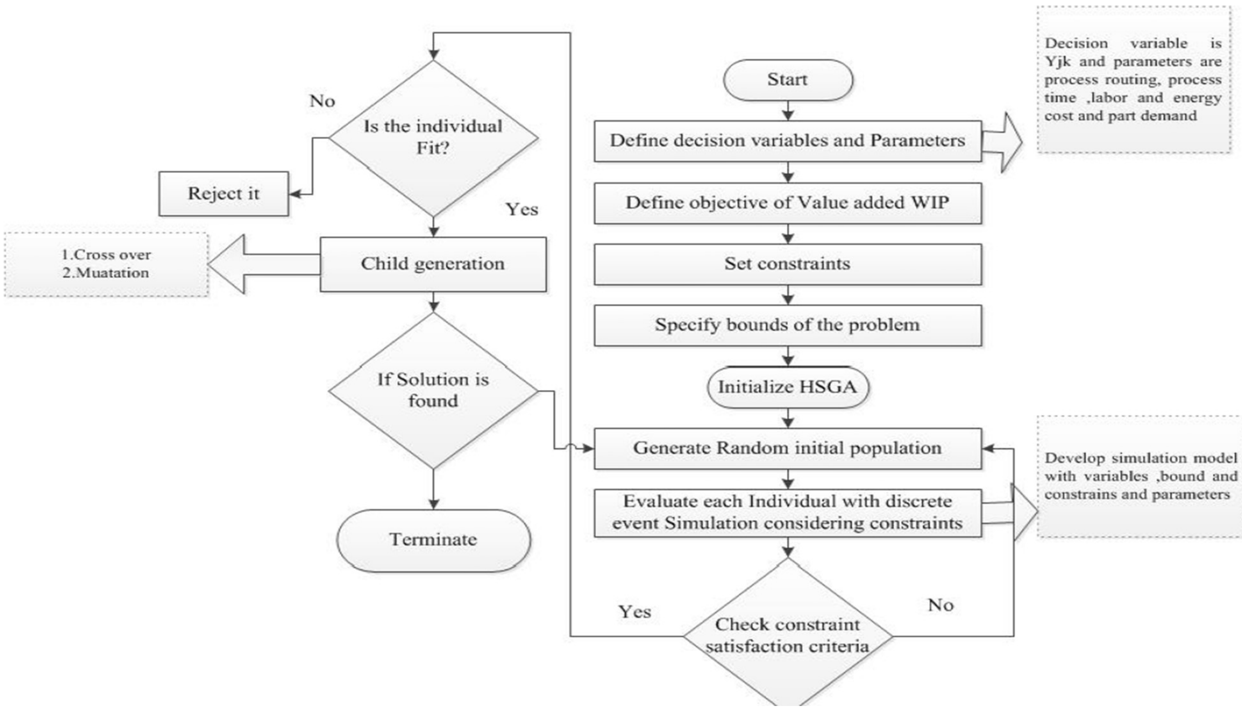

Fig. 1. Schematic diagram of simulation integrated hybrid genetic algorithm.

Table 3
Demand of parts from customers.

Parts	Customer Demand	Parts	Customers Demand
P1	8000	P11	5670
P2	7500	P12	5680
P3	6800	P13	7000
P4	9700	P14	8600
P5	10,000	P15	9200
P6	9780	P16	8400
P7	5670	P17	6900
P8	7860	P18	9000
P9	9870	P19	9900
P10	7650	P20	8760

The simulation integrated hybrid genetic algorithm (SHGA) is programmed in MATLAB R2015a version, using personal computer with 4 GB RAM and 2.67 GHz processor. The inputs for simulation are process routing, operation times, and setup times and demand of parts over planning horizon. In the current model planning horizon is one month in which twenty-six days are working days and each day comprises of eight hour shift. There is a lunch break of thirty min daily. The total planning horizon is 11,700 min.

The rated power of each AGV is 5966 W. The rated power of machines which can be seen in Table 5 and process time of parts on machines is shown in Table 6.

Table 4
Process routing of parts.

Part	1st Process	2nd Process	3rd Process	4th Process	5th Process	6th Process
P1	M2	M3	M8	M6	M10	M13
P2	M4	M8	M5	M1	M11	M14
P3	M1	M2	M6	M12	M11	M7
P4	M7	M4	M3	M10	M12	M15
P5	M5	M6	M1	M13	M14	M15
P6	M8	M11	M14	M3	M1	M9
P7	M10	M9	M12	M7	M2	M4
P8	M3	M4	M11	M15	M13	M6
P9	M2	M1	M6	M11	M8	M15
P10	M10	M12	M14	M15	M3	M5
P11	M9	M12	M4	M1		
P12	M5	M7	M11	M2		
P13	M4	M8	M10	M13		
P14	M1	M5	M7	M15		
P15	M6	M3	M9	M24	M12	
P16	M5	M4	M2	M12		
P17	M15	M14	M1	M6	M10	
P18	M3	M10	M14	M15	M1	
P19	M7	M5	M3	M8	M12	
P20	M2	M6	M14	M15	M8	

Table 5
Rated powers (W).

Machine #	Rated power	Machine #	Rated Power	Machine#	Rated Power
M1	2984	M6	2238	M11	5968
M2	2238	M7	2238	M12	5968
M3	2984	M8	5968	M13	4476
M4	2084	M9	2238	M14	6714
M5	3730	M10	3730	M15	2238

Table 6
Process times.

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15
P1	0	2.65	1.11	0	0	2.95	0	4.68	0	4.03	0	0	3.48	0	0
P2	1.18	0	0	2.81	3.04	0	0	5.6	0	0	5.09	0	0	5.71	0
P3	2.68	1.34	0	0	0	3.73	6.85	0	0	0	4.52	3.75	0	0	0
P4	0	0	2.75	2.46	0	0	3.38	0	0	5.4	0	4.63	0	0	4.18
P5	2.154	0	0	0	3.53	3.43	0	0	0	0	0	0	4.77	6.06	4.97
P6	6.13	0	5.91	0	0	0	0	1.89	4.36	0	3.05	0	0	1.68	0
P7	0	5.54	0	6.01	0	0	2.08	0	5.44	3.63	0	2.55	0	0	0
P8	0	0	5.32	6.21	0	2.29	0	0	0	0	5.96	0	1.72	0	3.52
P9	6.51	6.14	0	0	0	2.29	0	3.78	0	0	5.97	0	0	0	2.45
P10	0	0	7.47	0	1.87	0	0	0	0	5.77	0	1.49	0	2.32	4.2
P11	5.07	0	0	4.42	0	0	0	0	6.13	0	0	4.65	0	0	0
P12	0	6.28	0	0	5.86	0	7.62	0	0	0	5.59	0	0	0	0
P13	0	0	0	6.03	0	0	0	5.85	0	8.37	0	0	7.48	0	0
P14	7.8	0	0	0	5.78	0	6.76	0	0	0	0	0	0	0	7.95
P15	0	0	8.65	0	0	6.14	0	0	6.1	0	0	8.23	0	6.79	0
P16	0	5.51	0	5.9	3.88	0	0	0	0	0	0	4.39	0	0	0
P17	4.81	0	0	0	0	6.59	0	0	0	7.07	0	0	0	4.62	3.47
P18	2.79	0	6.79	0	0	0	0	0	0	6.95	0	0	0	4.42	2.96
P19	0.45	0	1.5	0	3.65	0	2	4.74	0	0	0	4.55	0	0	0
P20	0	5.3	0	0	0	3.34	0	4.32	0	0	0	0	0	6.22	5.88

4.4. Genetic representation

Fig. 2 Shows the genetic representation, crossover, and mutation procedures for a cell formation problem with fifteen machines.

In Fig. 2 Chromosome 2 1 3 4 2 1 3 4 3 1 1 2 4 3 2 means that machine M1 is assigned cell two, M2 is assigned cell 1 and so on. The double point crossover is used for crossover and mutation point is selected randomly. The transportation time of parts between machines or cells largely depends on weights of parts and some other features such as size or volume. Therefore travel time of AGVs for different parts within cell and between cells varies accordingly. Let us consider an example of chromosome 413214324143241 and part P1. It can be seen from Table 4 that P1 visits machines M2, M3, M8, M6, M10 and M13 and M2 is in cell 1, M3 is in cell 3, M8 is in cell 2, M6 is in cell 4, M10 is in cell 1 and M13 is in cell 2 so part will take 0.6 min as shown in Table 7, if it

Fig. 2. Genetic representation and reproduction.

Table 7
Inter and intracellular travel time of each part (minutes).

Parts	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Intracellular travel time	0.3	0.28	0.28	0.45	0.7	0.275	0.75	0.725	0.45	0.325
Intercellular time	0.6	0.55	0.55	0.9	1.4	0.55	1.5	1.45	0.9	0.65
Parts	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20
Intracellular travel time	0.3	0.75	0.33	0.625	0.575	0.7	0.5	0.85	0.575	1.125
Intercellular time	0.6	1.5	0.65	1.25	1.15	1.4	1	1.7	1.15	2.25

Table 8
Best solution/elite individual.

Generations	Best SOLUTION															Cost
56	4	3	3	4	2	3	3	1	2	3	4	2	4	1	1	580,293
57	4	3	3	4	2	3	3	1	2	3	4	2	4	1	1	580,293
58	4	3	3	4	2	3	3	1	2	3	4	2	4	1	1	580,293
57	4	3	3	4	2	3	3	1	2	3	4	2	4	1	1	580,293

moves from M2 to M3 and same time will be consumed if part move from M3 to M8, M8 to M6, M6 to M10, and M10 to M13. If machines were in same cell then it would take an average of 0.3 min same is true for all parts with different process routing.

4.5. Fitness function

The fitness of a chromosome in a population is usually measured by probability of fitness of individual which is ratio of the function value of chromosome to sum of function values of all chromosomes Eq. (15) shows calculation of fitness value of a chromosome.

$$F_{fo} = \frac{f_{vz}}{\sum_{z=1}^{Z} f_{vz}} \tag{15}$$

Population size in this numerical is 10.

4.6. Constraints satisfaction

This problem is a constrained problem. The constraints must be satisfied while evaluating the individuals in the population. Table 8 shows the solution achieved in last in last four generations.

It can be seen from Table 4 that part P1 first visits machine M2, then M3, M8, M6, M10 and at last visits M13. The processing time which consists of setup time and operation is shown in Table 6. Using the process routing of all parts from Table 4 and process time from Table 6 a simulation model is developed which can be seen in Table 9. Consider the best solution that is 433423312342411. This individual shows that machine M1 is assigned to cell "4", M2 is assigned to cell "3" and so on. Now look at Table 9 keeping in view process routing, process time, and the individual. Note that individual is a scenario of simulation of CF.

As part directly comes to M2 so the second term of Eq. (9) becomes zeros so constraints in Eq. (9) and (10) are satisfied. Similarly, constraints for other parts and machine are also satisfied. It can be observed that TT_{ij}, T_c and Q_{ij} are always positive. The constraint in Eq. (14) shows the lower and upper bound of number of machines assigned to a cell. It is clear from best solution 433423312342411 that numbers of machines assigned to cell "1" is three. Three machines are assigned to cell "2". Five machines are assigned to cell "3" and four machines are assigned to cell "4". At least one machine can be assigned to cell and at most five machines can be assigned to single cell so Eq. (14) is satisfied.

4.6.1. Satisfaction of constraints for part P2 between machine M4 and M8

Consider the part P2 and Table 9. In this case

Table 9
Discrete event simulation for evaluation of chromosome/individual.

Parts #	Start	M1	Exit	Start	M2	Exit	Start	M3	Exit	Start	M4	Exit	Start	M5	Exit
P1	0	0	0	0	2.65	2.65	2.65	1.41	4.06	0	0	0	0	0	0
P2	19.08	1.73	20.81	0	0	0	0	0	0	0	2.81	2.81	15.49	3.59	19.08
P3	20.81	2.68	23.49	23.49	1.89	25.38	0	0	0	0	0	0	0	0	0
P4	0	0	0	0	0	0	52.895	3.65	56.545	49.535	3.36	52.895	0	0	0
P5	34.215	3.554	37.769	0	0	0	0	0	0	0	0	0	19.08	3.53	22.61
Parts #	Start	M6	Exit	Start	M7	Exit	Start	M8	Exit	Start	M9	Exit	Start	M10	Exit
P1	9.34	3.55	12.89	0	0	0	4.06	5.28	9.34	0	0	0	12.89	4.33	17.22
P2	0	0	0	0	0	0	9.34	6.15	15.49	0	0	0	0	0	0
P3	25.38	4.005	29.385	38.755	7.4	46.155	0	0	0	0	0	0	0	0	0
P4	0	0	0	46.155	3.38	49.535	0	0	0	0	0	0	56.545	5.85	62.395
P5	29.385	4.83	34.215	0	0	0	0	0	0	0	0	0	0	0	0
Parts #	Start	M11	Exit	Start	M12	Exit	Start	M13	Exit	Start	M14	Exit	Start	M15	Exit
P1	0	0	0	0	0	0	17.22	4.08	21.3	0	0	0	0	0	0
P2	20.81	5.365	26.175	0	0	0	0	0	0	26.175	6.26	32.435	0	0	0
P3	33.685	5.07	38.755	29.385	4.3	33.685	0	0	0	0	0	0	0	0	0
P4	0	0	0	62.395	5.53	67.925	0	0	0	0	0	0	67.925	5.08	73.005
P5	0	0	0	0	0	0	37.769	5.47	43.239	43.239	7.46	50.699	73.005	5.67	78.675

$E_{28} = 15.49$
$E_{24} = 2.81$

Hence from Eq. (8) throughput time of part two at machine eight can be computed

$TT_{28} = 15.49 - 2.81 = 12.68$

As the part P2 arrive arrives at 2.81 but machine is not available so part waits for 6.53 min for processing.

$Q_{28} = 9.34 - 2.81 = 6.53$
$t_{o(28)} + t_{s(28)} = 6.15$

Now the constraints in Eq. (7) is again satisfied

$(6.15 + 6.53) - 15.49 \leqslant 0$

For constraint in Eq. (9)

$SRT_{28} = 2.81$
$E_{24} = 2.81$

$E_{18} = 9.34$

So putting values in Eq. (9) satisfy the constraint

$15.49 - \text{Max}(2.81 + 9.34) = 0$

As there are total of fifteen machines and twenty parts so the problem size is 20×15 but due to large size only 4×15 is shown in Table 9.

For constraint in Eq. (10)

$ART_{28} = 2.81$
$E_{18} = 9.34$
$9.34 - 2.81 > 0$

Similarly, all constraints can be satisfied for all parts and machines.

4.7. Selection criteria for new generation

For the next generation stochastic sampling is used in which chromosomes with the fittest value are selected for the next generation and weaker chromosomes are rejected by replacing them with mutant elites. The probability of crossover is 0.6 and mutation is 0.2 while there is 20% elitism for all generations.

4.8. Stopping criteria

Termination criteria for SHGA were repetition of the same elite chromosome in ten successive generations. The minimum number of machines that can be placed in a cell is one and maximum is five. SHGA provided an excellent way to find solution of CMS problems, Fig. 3 Shows the reduction of average function value and observed minimum function or best value over the 57th iteration or generations. Fig. 3 means, 57th generation has the best individual with 590,293 $ objective function value.

5. Results and discussion

Simulation integrated hybrid genetic algorithm provided an efficient solution to the cell formation problem. The best function value of cost of value added work in process (VAWIP) is achieved at 57th generation and it cannot be preceded to higher generations because function value of elite chromosome started to repeat.

As generation progressed from parent generation to 57th generation, the minimum observed function value of chromosomes within populations went on decreasing this trend can be seen in Fig. 3. In 57th generation a chromosome (433423312342411) with minimum function value of $ 590,293 was observed which is the best cost achieved with SHGA. Table 10 shows the binary decision variables of the best solution.

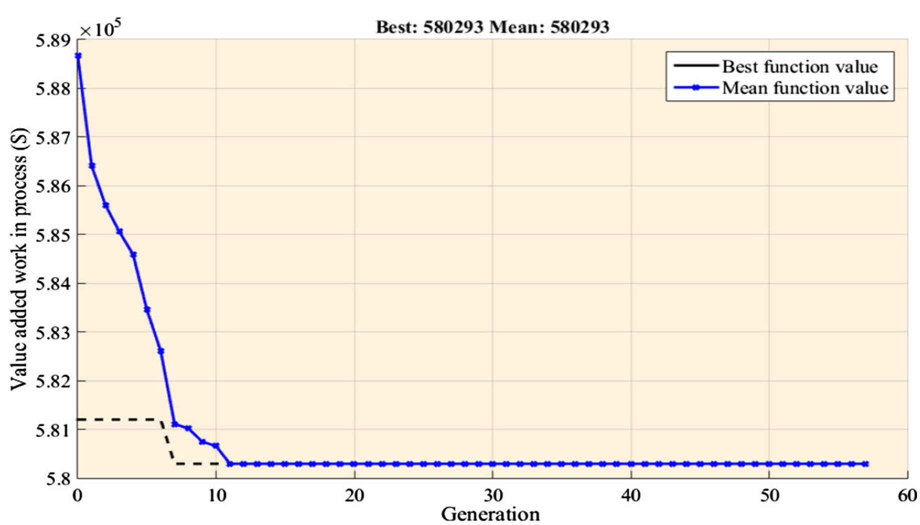

Fig. 3. Generations.

Table 10
Best solution.

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15
C1	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1
C2	0	0	0	0	1	0	0	0	1	0	0	1	0	0	0
C3	0	1	1	0	0	1	1	0	0	1	0	0	0	0	0
C4	1	0	0	1	0	0	0	0	0	0	1	0	1	0	0

Table 11
Decoded solutions.

Machine#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Cell Assigned	4	3	3	4	2	3	3	1	2	3	4	2	4	1	1

Table 12
Comparison of proposed method with other algorithm.

Algorithm	Solver Package	Best Solution	Iterations	Computational time (s)
SHGA	MATLAB R2015a	580293.3217	57	13.164
Branch and Bound	ILOG IBM CPLEX Optimizer	586945.6581	23	14.457
Branch and Bound	Excel Solver	581901.0813	6578	37.346

Table 13
Percentage gap of performance measures of algorithm.

Algorithm	Solver Package	% Gap		
		Best Solution	Iterations	Computational time
SHGA	MATLAB R2015a	0.0000	59.6491	0.0000
Branch and Bound	ILOG IBM CPLEX Optimizer	1.1334	0.0000	8.9438
Branch and Bound	Excel Solver	0.2763	99.6503	64.7512

The solution can be achieved by decoding the elite chromosome in 57th generation as in Table 11.

SHGA helped in making decision and it was decided that machine M8, M14, and M15 must be assigned to cell 1, M5, M9, and M12 should be assigned to cell 2, Machines M2, M3, M6, M7 and M10 must be placed in cell 3 while machines M1, M4, M11 and M13 must be placed in cell 4.

5.1. Computational efficiency of SHGA

To evaluate the performance and efficiency of proposed algorithm it must be compared with some other well-known algorithms. The efficiency of SHGA is measured by solving the same case study explained in Section 4 with branch and bound algorithm. Discrete event simulation is integrated with branch and bound algorithm and problem is solved in two different solvers such as ILG IBM CPLEX Optimizer and Excel solver on a PC of 4 GB RAM and 2.67 GHz processor. The results of algorithms from solvers along with number of iteration and computation time are shown in Table 12.

The quality of solution for each algorithm is computed with the percentage gap as shown in Eq. (16)

$$\%Gap = \frac{AV - BV}{AV} \times 100 \tag{16}$$

Consider the "SHGA" . The solution value of SHGA is the minimum among all other solution values obtained from other solvers. Therefore

$$BV = 580293.32; \quad AV = 580293.32$$

From Eq. (16) the percentage gap is "0". Similarly, in term of number of iterations, CPLEX provides better results but function value is higher than SHGA value. Table 13 shows the percentage gap of each performance measure of all algorithms.

The % Gap of SHGA in term of solution value and computation time is zero which indicates the results of SHGA are best as compared to other algorithms. Therefore in term of solution value the performance of SHGA is better than excel solver and performance of excel solver is better than Cplex.

$$HSGA < Excel\ solver(B\&B) < CPLEX(B\&B)$$

In term of number of iterations performance of cplex is better than SHGA but SHGA performs better than excel solver. Finally, the performance of SHGA in term of computation time is better than the others

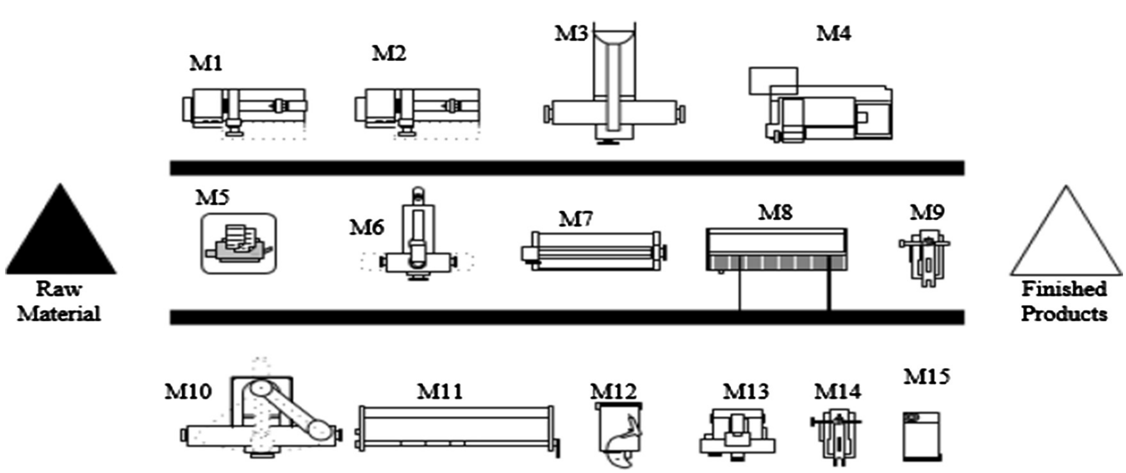

Fig. 4. Existing layout of machining unit.

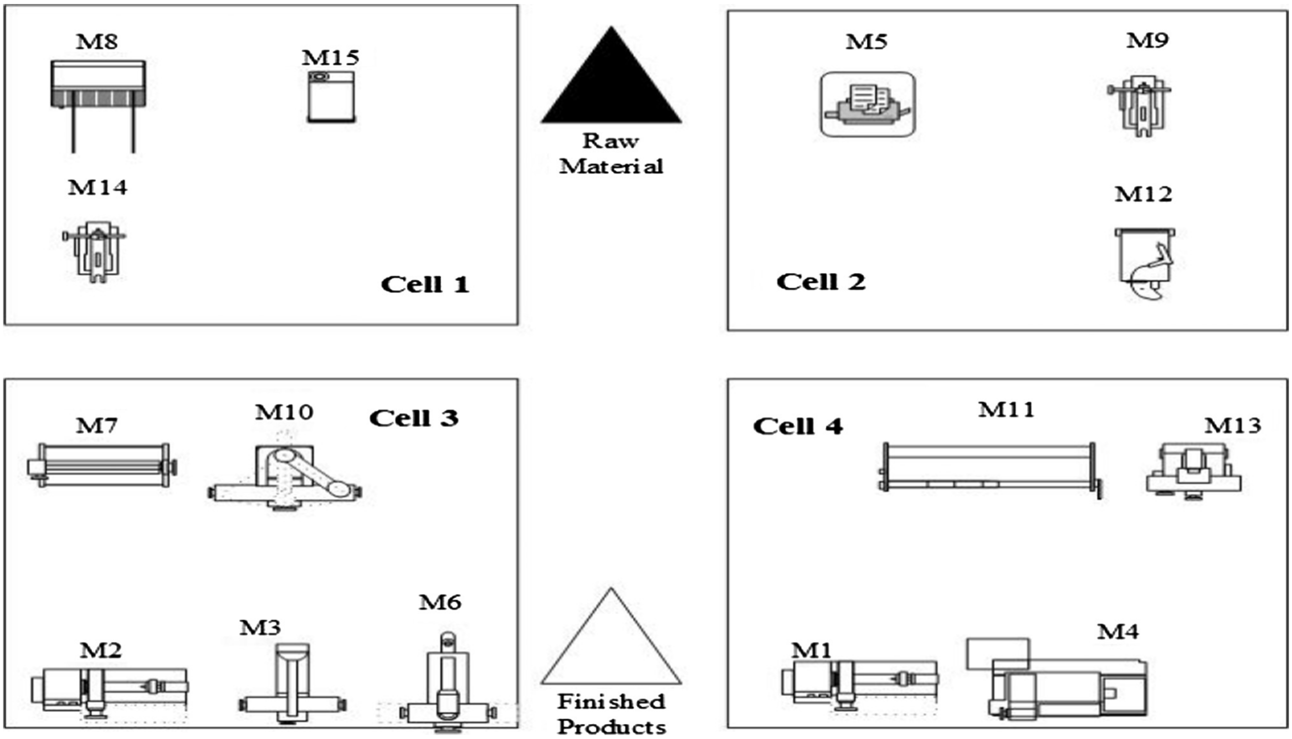

Fig. 5. Proposed cellular layout.

$$CPLEX(B\&B) < HSGA < Excel\ solver(B\&B)$$

While the performance of SHGA in term of computation time is better than the others

$$HSGA < CPLEX(B\&B) < Excel\ solver(B\&B)$$

Hence it is concluded that integration of Genetic algorithm with simulation provides better results in term of solution and computation time than the integration with branch and bound algorithm.

5.2. Comparison with existing system

In existing system machines were randomly located within manufacturing facility. Fig. 4 Shows the initial layout of matching section of automobile spare parts industry. Discrete event simulation is used to compute value added work in process VAWIP. The value added WIP of existing system was $634574.345.

After cell formation in system it comes to be $580293.3217 and this indicates 8.55% reduction of value added work-in-process (VAWIP). Cellular layout machining unit of automobile spare parts industry is shown in Fig. 5.

6. Conclusion

A simulation integrated hybrid genetic algorithm (SHGA) is proposed for layouts design in cellular manufacturing systems (CMS) to minimize VAWIP. The objective of cell formation is the minimization of value added WIP (VAWIP) which includes the production and material handling cost. A case study of automobile spare parts industry is also provided as a numerical example. The data used in this paper is taken from auto part manufacturing firm and analysis is carried out using SHGA which resulted in 8.55% reduction in cost. SHGA provides a solution for making decision about placement of each machine to proper cell which would minimize VAWIP. If Industry implements the results and rearrange the machines according to new design suggested then it will provide substantial reduction of VAWIP. Cell formation (CF) approach can be used in industry in two cases: first the company is installing its new setup, second the company is upgrading from job shop to CMSs. In up gradation of flow shop in cellular manufacturing system various issues arise, for example if cost of up gradation is more than cost of cell formation then it is better not to upgrade the system. If such a type of problem occurs then system must be scheduled to get the optimal results instead of cell formation. The future research includes the idle time of machine minimization with the consideration of job sequencing and scheduling with the assignment of machines in cells for cellular flexible manufacturing systems.

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