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Designing a Manufacturing Cell System by Assigning Workforce

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Abstract:

Purpose: In this paper, we have proposed a new model for designing a Cellular Manufacturing System (CMS) for minimizing the costs regarding a limited number of cells to be formed by assigning workforce.

Design/methodology/approach: Pursuing mathematical approach and because the problem is NP-Hard, two meta-heuristic methods of Simulated Annealing (SA) and Particle Swarm Optimization (PSO) algorithms have been used. A small randomly generated test problem with real-world dimensions has been solved using simulated annealing and particle swarm algorithms.

Findings: The quality of the two algorithms has been compared. The results showed that PSO algorithm provides more satisfactory solutions than SA algorithm in designing a CMS under uncertainty demands regarding the workforce allocation.

Originality/value: In the most of the previous research, cell production has been considered under certainty production or demand conditions, while in practice production and demand are in a dynamic situations and in the real settings, cell production problems require variables and active constraints for each different time periods to achieve better design, so modeling such a problem in dynamic structure leads to more complexity while getting more applicability. The contribution of this paper is providing a new model by considering dynamic production times and uncertainty demands in designing cells.

Keywords: cell production, group technology, particle swarm optimization, simulated annealing

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1. Introduction

Nowadays, in a global competitive environment, the companies tend to offer products at lower cost and higher quality for challenging with the competitors. In the recent decades, methods and production strategies have significantly changed, in comparison to the early half of the twentieth century. One of the changes that many companies have used is cellular manufacturing (CM). Group Technology (GT) is a well-known idea that includes both advantages of mass and small-scale production settings (Karthikeyan, Saravanan & Ganesh, 2012). GT is a philosophy of production that identifies the similar products and collects them in a certain group for reaching the benefits of their similarities in design and manufacturing. Components are gathered in clusters based on their designing, features and geometric shapes within product groups which as a result, the system performance improves significantly. CM is a GT application to help companies cope with global challenges. CM has been created to meet market demand due to the inefficiency of traditional production systems. Therefore, cellular manufacturing system (CMS) is a more efficient solution with higher quality than the other methods. CMS groups similar products into product groups and allocates the necessary machines to the production cells. The main objective of CM is identifying machine cells and product groups and assigning the product groups to machine cells in order to minimize the costs. In designing of a CM, four important decisions should be made: cell formation, group layout, group scheduling, and resource allocation (Rafiee, Rabbani, Rafiei & Rahimi-Vahed, 2011).

In this research, a mathematical model is presented for designing a random cell production system which demands parameters and processing times are probable and have a normal distribution. The CMS deals with the grouping of products and allocation of them to the cells and the allocation of machines to cells, but another important factor in the CMS is workforce, which should be allocated to the cell. For this reason, the problem changes from a two-dimensional to three-dimensional state. This paper constructed as follows: literature review in section 2, methodology in section 3, a numerical example in section 4, comparison of algorithms in section 5, and conclusion in section 6.

2. Literature Review

Aalaei and Davoudpour (2015) have studied a revised multi-choice goal programming for incorporating dynamic virtual cellular manufacturing into supply chain management. Nouri and Hong (2013) have researched on development of bacterial foraging optimization algorithm for cell formation in cellular manufacturing system considering cell load variations. Karthikeyan et al. (2012) have provided a GT machine cell formation problem in scheduling for cellular manufacturing system using Meta-Heuristic method. Singh and Rajamani (2012) described about a cellular manufacturing system by taking into account designing, planning and controlling. Mahdavi, Aalaei, Paydar and Solimanpur (2012) have studied a new mathematical model for integrating all incidence matrices in multi-dimensional cellular manufacturing system. Chang, Wu and Wu (2013) have provided an efficient approach to determine cell formation, cell layout and intra-cellular machine sequence in cellular manufacturing systems. Li, LI and Gupta (2015) have developed to solve the multi-objective flow-line manufacturing cell scheduling problem using hybrid harmony search. Brown (2014) has evaluated a capacity constrained mathematical programming model for cellular manufacturing with exceptional elements. Hamedi, Esmaeilian, Ismail and Ariffin (2012) have studied about capability-based virtual cellular manufacturing systems formation in dual-resource constrained settings using Tabu Search. Kia, Khaksar-Haghani, Javadian and Tavakkoli-Moghaddam (2014) solved a multi-floor layout design model of a dynamic cellular manufacturing system by an efficient genetic algorithm. Shirazi, Kia, Javadian and Tavakkoli-Moghaddam (2014) have described about an archived multi-objective simulated annealing for a dynamic cellular manufacturing system. Egilmez, Suer and Huang (2012) have researched a stochastic cellular manufacturing system design subject to maximum acceptable risk level. Mohammadi and Forghani (2014) have provided a novel approach for considering layout problem in cellular manufacturing systems with alternative processing routings and subcontracting approach. Kia, Baboli, Javadian, Tavakkoli-Moghaddam, Kazemi and Khorrami (2012) have solved a group layout design model of a dynamic cellular manufacturing system with alternative process routings, lot splitting and flexible reconfiguration by simulated annealing. Novas and Henning (2014) have integrated scheduling of resource-constrained flexible manufacturing systems using constraint programming. Vivaldini, Rocha, Beker and Moreira (2015) have studied a comprehensive review of the dispatching, scheduling and routing of AGVs. Duan, Mao and Duan (2016) have provided an improved artificial fish swarm algorithm optimized by particle swarm optimization algorithm with extended memory. Gülcü and Kodaz (2015) have investigated a novel parallel multi-swarm algorithm based on comprehensive learning particle swarm optimization. Ngan and Tan (2016) have developed photovoltaic multiple peaks power tracking using particle swarm optimization with an artificial neural network algorithm. Tang, Li and Luo (2015) have studied a multi-strategy adaptive particle swarm optimization for numerical optimization. Zhang, Zhang and Li (2014) have improved artificial fish swarm algorithm. Dastmalchi (2017) have studied an optimization of micro-finned tubes in double pipe heat exchangers using particle swarm algorithm. Yuan and Yin (2015) have analyzed a convergence and rates of convergence of PSO algorithms using stochastic approximation methods. Dai, Tang and Giret (2013) have studied energy-efficient scheduling for a flexible flow shop using an improved genetic-simulated annealing algorithm. Li et al. (2013) have provided a simulated annealing based genetic local search algorithm for multi-objective multicast routing problems. Ku, Hu and Wang (2011) have modeled a simulated annealing based parallel genetic algorithm for the facility layout problem.

Considering the recent researches and the existing gap, this paper is extending a dynamic structure in different time periods, and operation times are deterministic with a defined distribution.

3. Model Description

The objective of the model is allocating the workforce for operating a defined job on a specific machine in the cells. Considering the uncertain demands in the real world, in this model the demands are assumed under uncertainty and an acceptable risk. As a novelty, the model is formulated based on a dynamic structure in different periods. For more compatibility with real life, operation times are deterministic with defined distributions.

Model notations are described in the Table 1:

j	demand
p	product
l	labor
m	machine
c	cell
h	time periods

Table 1. Model notations

Model parameters are described in the Table 2:

Parameter	Description
ρ_{pml}	If a machine can operate pth product with lth labor will take 1, otherwise will take 0
∂_{ℓ}^{k}	If pth product needs to mth machine will take 1, otherwise will take 0
υ_{vk}	Upper bound for number of machines in kth cell
ℓ_{k}	Lower bound for number of machines in kth cell
ℓ_{lk}	Lower bound for number of labors in kth cell
ℓ_{p}^{k}	Lower bound for number of products in kth cell
τ_{m}	Number of available machines
ε_{lh}	Available time for labors in hth time period
Δ_{mh}	Available time for mth machine in hth time period
T_{pml}	Time required for processing pth product with lth labor on mth machine
D_{pjh}	Market demand for pth in hth time period
H_{ph}	Cost rate for pth product's inventory in hth time period
a_{mh}	Cost rate for mth machine's maintenance in hth time period
f_{p}	Fix cost for producing pth product
χ_{p}	Cost rate for pth product's inventory
I_{j}	Cost rate for jth demand supply

Table 2. Description of model parameters

Model variables are described in the Table 3:

Variable	Description
X_{pkh}	If p^{th} product be processed in h^{th} time period at k^{th} cell will take 1, otherwise will take 0
Y_{mkh}	If m^{th} machine be allocated to k^{th} cell in h^{th} time period will take 1, otherwise will take 0
Z_{lkh}	If l^{th} labor be allocated to k^{th} cell in h^{th} time period will take 1, otherwise will take 0
R_{pmlkh}	If p^{th} product be allocated to l^{th} labor in h^{th} time period at k^{th} cell will take 1, otherwise will take 0
Q_{ph}	Number of p^{th} products in h^{th} time period
B_{pjh}	Number of p^{th} products in h^{th} time period to supply the demand
N_{mkh}	Number of m^{th} machine in k^{th} cell in h^{th} time period
K_{ph}	If p^{th} product be produced in h^{th} time period will take 1, otherwise will take 0

Table 3. Description of model variables

$$\boldsymbol{Min(F)} = \sum_{h=1}^{H}\sum_{p=1}^{P}\chi_p H_{ph} + \sum_{h=1}^{H}\sum_{k=1}^{C}\sum_{m=1}^{M} a_{mh}N_{mkh} + \sum_{h=1}^{H}\sum_{p=1}^{P} f_p K_{ph} + \sum_{h=1}^{H}\sum_{j=1}^{J}\sum_{p=1}^{P} I_j[B_{pjh}]$$

The objective function (F) aims to minimize the total costs. The first part is minimizing the inventory cost, the second part is minimizing the maintenance cost, the third part is minimizing the fix production cost, and the last part is minimizing the demand supply cost.

The constraints of the model are,

$$\begin{aligned}&\sum_{h=1}^{H}\sum_{k=1}^{C}\sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{l=1}^{L} X_{pkh}\,Y_{mkh}(1-Z_{lkh})R_{pmlkh}\\&\quad+\sum_{h=1}^{H}\sum_{k=1}^{C}\sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{l=1}^{L} 2\times(1-X_{pkh})Y_{mkh}(1-Z_{lkh})R_{pmlkh}\\&\quad+\sum_{h=1}^{H}\sum_{k=1}^{C}\sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{l=1}^{L}(1-X_{pkh})Y_{mkh}Z_{lkh}R_{pmlkh}\\&\quad+\sum_{h=2}^{H}\sum_{l=1}^{L}{}^{1}/_{2}\left|\sum_{k=1}^{C}Z_{lkh}-\sum_{k=1}^{C}Z_{lk(h-1)}\right|\leq limit\end{aligned}\qquad(1)$$

$$\sum_{k=1}^{C}\sum_{m=1}^{M}\sum_{p=1}^{P} R_{pmlkh}T_{pml}Q_{ph}\leq \varepsilon_{lh}\qquad \forall\, l,h \qquad(2)$$

$$\sum_{l=1}^{L}\sum_{p=1}^{P} R_{pmlkh}T_{pml}Q_{ph}\leq N_{mkh}\Delta_{mh}\qquad \forall\, m,k,h \qquad(3)$$

$$B_{pjh}\leq D_{pjh}\qquad \forall\, p,j,h \qquad(4)$$

$$\sum_{j=1}^{J} B_{pjh} = Q_{ph} + I_{ph-1} - I_{ph}\qquad \forall\, p,h \qquad(5)$$

$$\sum_{k=1}^{C} R_{pmlkh} \leq \rho_{pml} \qquad \forall\, p,m,l,k \tag{6}$$

$$\sum_{k=1}^{C}\sum_{l=1}^{L} R_{pmlkh} = K_{ph}\partial_{pm} \qquad \forall\, p,m,h \tag{7}$$

$$\sum_{k=1}^{C} N_{mkh} \leq \tau_m \qquad \forall\, m,h \tag{8}$$

$$\ell_k \leq \sum_{m=1}^{M} N_{mkh} \leq \mathcal{V}_k \qquad \forall\, k,h \tag{9}$$

$$\sum_{p=1}^{P} X_{pkh} \geq \ell_{pk} \qquad \forall\, k,h \tag{10}$$

$$\sum_{l=1}^{L} Z_{lkh} \geq \ell l_k \qquad \forall\, k,h \tag{11}$$

$$\sum_{k=1}^{C} X_{pkh} = K_{ph} \qquad \forall\, p,h \tag{12}$$

$$\sum_{k=1}^{C} Z_{lkh} \leq 1 \qquad \forall\, l,h \tag{13}$$

Constraint (1) ensures the optimal cell allocation which is required to be less than a defined limit.

Constraint (2) ensures that the total allocated time is less than the labor available time.

Constraint (3) ensures that the total allocated time is less than the machine available time.

Constraint (4) ensures that the number of products is less or equal to market demand.

Constraint (5) describes relationship among inventory level at the start of period, number of production and amount of assignment to market.

Constraint (6) ensures that a labor is only assigned to one machine-cell-product.

Constraint (7) ensures that a labor can perform related jobs on different machines.

Constraint (8) prevents from allocating machines to cells more than its capacity.

Constraint (9) prevents from allocating machines to cells more than its capacity by considering cell capacity.

Constraint (10) describes limitation of cell for producing the products.

Constraint (11) describes limitation of workforce capacity.

Constraint (12) investigates the possibility of production pth product in a defined period at different cells somehow produce in one cell.

Constraint (13) defines that every machine-product-labor assigns to one cell.

4. Numerical Example

Now, for analyzing the model capability and validation a numerical example is provided and solved. The required parameters are shown in below tables (Tables 4 to 8) and then the model are solved with PSO and SA algorithms.

Three type machines are considered that can do the jobs, but all machines cannot do all jobs. For example, the machine I disables to produce the products 4, 5, and 6. On the other hand, product 1 can be assigned to all machines, but product 5 can only be assigned to machine III. Table 4 shows the product assignment to machine. Whenever a product be assigned to a machine will take 1, otherwise it will take 0.

Four labors are considered in this example. This means that the available labors for assigning machines are four persons. Every labor has some abilities and experience who enable them for assigning to some machines. For instance, labor 1 can be assigned to machines I, and III but labor 4 can only be assigned to machine II. Table 5 shows the labor assignment to machines. As above-mentioned, the number 1 shows assignment and number 0 shows non-assignable.

The number of available machines for each type can be variable, also the cost rates for maintenance are different for each period. In this example, the number of machine-type are identical, but the maintenance cost rate in different periods and idle cost are unequal. Table 6 shows the machine availability for all types, maintenance cost rates by periods, and idle cost (whenever a machine doesn't work according to a planning).

Product	Machine-type		
	I	II	II
1	1	1	1
2	1	1	0
3	1	0	1
4	0	1	1
5	0	0	1
6	0	1	0

Table 4. Product assignment to machines

Labor	Machine-type		
	I	II	III
1	1	0	1
2	1	0	0
3	0	1	1
4	0	1	0

Table 5. Labor assignment to machines

Machine-type	Information				
	Number of available machines	Maintenance cost (first period)	Maintenance cost (second period)	Maintenance cost (second period)	Idle cost
I	2	520	500	650	350
II	2	510	560	540	400
III	2	550	600	520	430

Table 6. Machine availability and maintenance cost

Although four labors are considered in assigning, but the number of available labors in different periods is less than four. Also the idle cost rate is unequal for different periods. It imposed from difference between labors' abilities and experience. As well, the available time for all labors are identically considered. Table 7 shows the labor availability and idle cost.

Demand, inventory cost, and shortage cost by periods have an important role in assigning the jobs and labors to machines. Whenever the number of production is more than the demand the model will be faced with inventory cost, and whenever demand is more than the number of production the model will be faced with shortages. Table 8 shows the demand, inventory cost, and shortage cost by periods that for this example, it considered that there are three periods.

Number of available labors	Idle cost (first period)	Idle cost (second period)	Idle cost (third period)	Available time (first period)	Available time (second period)	Available time (third period)
2	400	450	450	40	40	40
2	420	465	465	40	40	40
2	415	475	475	40	40	40
2	430	480	480	40	40	40

Table 7. Labor availability and idle cost

Demand (first period)	Demand (first period)	Demand (third period)	Inventory cost (first period)	Inventory cost (second period)	Shortage cost (first period)	Shortage cost (second period)
0	500	1550	1	1	14	14
600	800	1000	2	2	12	12
1200	1000	500	3	3	10	10
1200	900	900	4	4	8	8
1400	900	600	5	5	7	7
1500	600	1000	6	6	6	6

Table 8. Demand, inventory cost, and shortage cost

Now, the particle swarm optimization algorithm steps are described as follows.

Particle swarm optimization algorithm steps:

1. Initialize population with random particles and velocity vector.
2. Select optimal variables and set constraints domain.
3. Calculate the fitness value for each particle by finite values.
4. Evaluate the fitness values.
5. Update personal best and global best.
6. Update particles position and velocity.
7. Produce next swarm of particles.
8. While the satisfactory termination conditions is be fulfilled, the results will be optimal and algorithm will be stopped.

   End while.
9. While the satisfactory termination conditions is not be fulfilled, will go back to step 3.

   End while.

Considering the PSO steps the model is computed by MATLAB. The population is defined 1000 and the maximum iteration is limited to 20. In the other words, the stop condition is defined based on the iteration. Table 9 shows the results for each iteration, which is declining to iteration 15 and after that is fixed. As a result, the global optimum solution is reached at iteration 15 and its value is equal to 2945.

Iteration	The best fitness function
1	6021.5
2	5963.5
3	5043.5
4	5043.5
5	5043.5
6	5043.5
7	5043.5
8	4942.5
9	4351
10	4351
11	3898.5
12	3898.5
13	3898.5
14	3460
15	**2945**
16	2945
17	2945
18	2945
19	2945
20	2945

Table 9. The best fitness function with 1000 papulation and 20 iterations

The convergence graph is shown in Figure 1 based on the best fitness versus iteration.

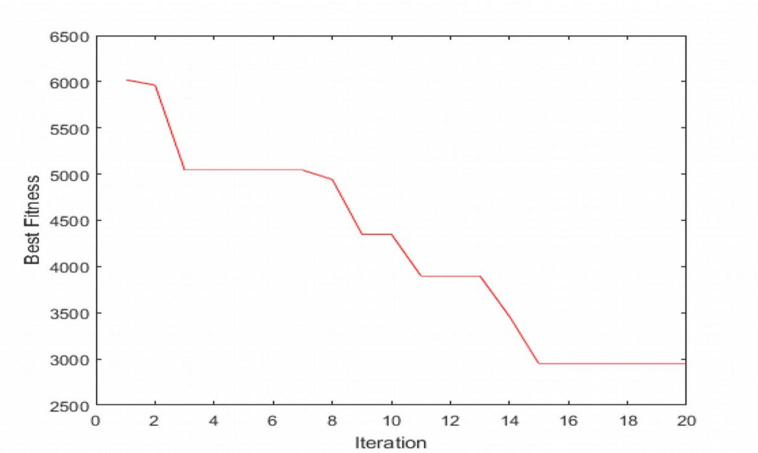

Figure 1. PSO algorithm Convergence graph

Also, the simulated annealing algorithm steps are described as follows.

Simulated annealing algorithm steps:

1. Initialize temperature T, random starting point.
2. While cool iteration <= max iteration.
3. Cool iteration = cool iteration +1.
4. Temp iteration = 0.
5. While temp iteration <= nrep.
6. Temp iteration = temp iteration +1.
7. Select a new point the neighborhood.
8. Compute current cost (of this new point).
9. σ= current cost – previous cost.
10. If σ<0, accept neighbor, else accept with probability exp. (-σ/T).

End while.

T= α * T (0< <1).

End while.

For SA algorithm the iteration parameter is defined 50. By running the algorithm in MATLAB, the best solution for each iteration is computed and finally the global optimal solution is archived at iteration 7 and its value is 5937.5. Table 10 shows the best fitness function results for every iteration.

Iteration	The best fitness function	Iteration	The best fitness function
1	7579	26	5937.5
2	6860.5	27	5937.5
3	6860.5	28	5937.5
4	6860.5	29	5937.5
5	6860.5	30	5937.5
6	6724.5	31	5937.5
7	**5937.5**	32	5937.5
8	5937.5	33	5937.5
9	5937.5	34	5937.5
10	5937.5	35	5937.5
11	5937.5	36	5937.5
12	5937.5	37	5937.5
13	5937.5	38	5937.5
14	5937.5	39	5937.5
15	5937.5	40	5937.5
16	5937.5	41	5937.5
17	5937.5	42	5937.5
18	5937.5	43	5937.5
19	5937.5	44	5937.5
20	5937.5	45	5937.5
21	5937.5	46	5937.5
22	5937.5	47	5937.5
23	5937.5	48	5937.5
24	5937.5	49	5937.5
25	5937.5	50	5937.5

Table 10. Best fitness function with 50 iterations

Then, the convergence graph is shown in Figure 2 based on the best fitness versus iteration.

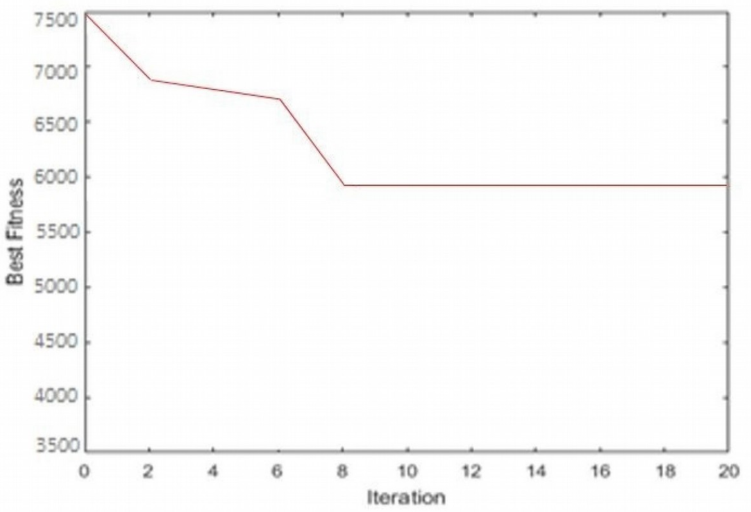

Figure 2. SA Algorithm Convergence graph

5. Comparison of Algorithms

Now, the comparison of two methods based on the crucial factors is important. In this research, the main objective is to minimize the total costs by considering the workforce allocation. Thus, the algorithm that provides the least cost has the better procedure and can be used for solving the model. Also, another important factor is time. The running time is limited. In the other words, the available time for solving the model by considering the large-scale is not unlimited, so the algorithm with less time running is better than another algorithm. However, Table 11 shows the results for two algorithms which the optimum objective function for PSO algorithm is 2945 and for SA algorithm is 5937.5, also running time for PSO is 300 seconds and for SA is 330 seconds. As a result, PSO algorithm has given a better output than SA algorithm by considering the objective function and running time.

Also, comparisons of the decision variables are shown in Tables 12 to 14. Optimum allocations for (If p^{th} product be processed in h^{th} time period at k^{th} cell will take 1, otherwise will take 0) in two algorithms are shown in Table 12. For instance, by considering PSO algorithm product 5 is only produced at third period and is produced in cells 1, 3, and 4. On the other hand, for SA algorithm, product 5, is produced at periods 1, 2, and 3. Also at first period product 5, is produced in cells 1 and 4, at second period is produced in cells 1, 3, and 4, and at third period is produced in cells 1, 2, and 3.

Optimum allocations for (If m^{th} machine is allocated to k^{th} cell in h^{th} time period will take 1, otherwise will take 0) in two algorithms are shown in Table 13. For example, by considering PSO algorithm machine-type 1 at first period is allocated to cells 1 and 2, also at third period is allocated to forth cell. In contrast, for SA algorithm machine-type 1 at first period is allocated to cells 1 and 4, also at second period is allocated to forth cell.

Algorithm	Objective function (optimal)	Running time (second)	Population	Iteration
PSO	2945	300	1000	20
SA	5937.5	330	-	50

Table 11. Comparison of algorithms (summary results)

PSO	1^{th} period				2^{th} period				3^{th} period			
Product	Cell				Cell				Cell			
	1	2	3	4	1	2	3	4	1	2	3	4
1	0	0	1	0	1	0	1	0	1	0	1	1
2	1	1	0	1	0	0	1	0	1	1	0	1
3	1	0	0	1	1	1	0	0	0	1	0	0
4	1	0	1	0	1	0	1	1	0	0	0	1
5	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**1**	**0**	**1**	**1**
6	1	0	0	0	1	0	1	0	1	1	0	1
SA	1^{th} period				2^{th} period				3^{th} period			
Product	Cell				Cell				Cell			
	1	2	3	4	1	2	3	4	1	2	3	4
1	1	1	1	1	1	1	0	0	0	1	0	0
2	0	0	1	0	0	0	0	1	1	0	1	0
3	0	0	0	1	1	1	0	0	1	1	0	0
4	0	0	1	0	1	1	1	1	1	1	0	1
5	**0**	**1**	**0**	**1**	**1**	**0**	**1**	**1**	**1**	**1**	**1**	**0**
6	0	1	1	0	0	0	1	0	0	1	0	0

"1" shows allocation
"0" shows non-allocation

Table 12. Optimal allocations for in PSO and SA algorithms

PSO	1^{th} period				2^{th} period				3^{th} period			
Machine	Cell				Cell				Cell			
	1	2	3	4	1	2	3	4	1	2	3	4
1	**1**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**1**
2	0	1	1	1	1	0	0	0	0	0	0	1
3	1	1	1	1	1	0	0	0	1	0	0	1
SA	1^{th} period				2^{th} period				3^{th} period			
Machine	Cell				Cell				Cell			
	1	2	3	4	1	2	3	4	1	2	3	4
1	**1**	**0**	**0**	**1**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**
2	1	1	1	0	1	0	1	1	1	0	0	0
3	0	0	1	1	0	1	0	1	1	1	1	1

"1" shows allocation
"0" shows non-allocation

Table 13. Optimal allocations for in PSO and SA algorithms

Optimum allocations for (If l^{th} labor is assigned to k^{th} cell in h^{th} time period will take 1, otherwise will take 0) in two algorithms are shown in Table 14. For instance, by considering PSO algorithm labor 2 at first period is assigned to cells 1 and 3, also at second period is assigned to forth cell and at final period is assigned to first cell. In contrast, for SA algorithm labor 2 at first period is assigned to all cells, also at second period is assigned to cells 3 and 4, and at find period is assigned to forth cell.

PSO	1^{th} period				2^{th} period				3^{th} period			
	Cell				Cell				Cell			
Labor	1	2	3	4	1	2	3	4	1	2	3	4
1	1	0	1	0	0	1	1	0	1	0	0	0
2	**1**	**0**	**1**	**0**	**0**	**0**	**0**	**1**	**0**	**0**	**1**	**0**
3	1	1	1	1	0	1	1	1	0	1	1	0
SA	**1^{th} period**				**2^{th} period**				**3^{th} period**			
	Cell				**Cell**				**Cell**			
Labor	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
1	0	1	0	0	1	0	1	0	0	0	1	1
2	**1**	**1**	**1**	**1**	**0**	**0**	**1**	**1**	**0**	**0**	**0**	**1**
3	1	0	0	1	0	1	1	0	1	0	0	0

· "1" shows allocation

· "0" shows non-allocation

Table 14. Optimal allocations for in PSO and SA algorithms

6. Conclusion

In this paper, a new model has been proposed in the cellular manufacturing system for minimization of costs regarding the limited number of cells to be formed by assigning workforce, which has been solved with two meta-heuristic algorithms. Considering the model should be solved in the large-scale, the exact solvers cannot reach the global optimal solution. However, two proposed algorithms including PSO and SA for solving the model have been used. Although the best fitness function using both algorithms reached, the elapsed runtime and the value of global best have the significant difference. Since the fitness function and time are the crucial factors in this study, the algorithm with lower fitness function and runtime is more efficient. Considering these factors the PSO algorithm with fitness function 2945 and the runtime 330 seconds is the optimal solution for the present study. Also, the optimal allocation of products, labors, and machines have been presented for both algorithms that show the difference between PSO and SA procedures. The present study can be used to planning the allocation in many industries which can reduce the total cost. As well, the industrial managers can reach to an optimal allocation considering the uncertain demands in the real world. The further research can link and extend this model to a scheduling and supply chain system. Also, some parameters including setup cost, start and finish time, due date, tardiness can be considered, and then the model is formulated again.

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