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A New Mathematical Model in Cell Formation Problem with Consideration of Inventory and Backorder: Genetic and Particle Swarm Optimization Algorithms

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Abstract

Cell Formation (CF) is the initial step in the configuration of cell assembling frameworks. This paper proposes a new mathematical model for the CF problem considering aspects of production planning, namely inventory, backorder, and subcontracting. In this paper, for the first time, backorder is considered in cell formation problem. The main objective is to minimize the total fixed and variable costs, including the machine related costs, intercellular movements, deviation between the levels of cell utilizations, inventory, backorder, and sub-contracting costs. The presented mathematical model is validated using GAMS software, and various test problems are solved by Genetic Algorithm (GA) and Discrete Particle Swarm Optimization (DPSO) algorithm. The performance of the algorithms is compared with the results obtained by the GAMS. The results demonstrate, there is no significant difference between the results of algorithms. Finally, some sensitive analyses are carried out to analyze the effects of backorder and inventory holding costs.

Keywords

Backorder, cell formation, inventory control, production planning.

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Introduction

Due to today's competitive conditions, companies should produce various types of products in small lot sizes. Group Technology (GT) is a manufacturing philosophy trying to produce efficiently by taking advantage of similarity of manufacturing processes. Cellular Manufacturing System (CMS) is a creative manufacturing strategy based on the GT concept. This method is employed to increase flexibility and efficiency of the manufacturing system, simultaneously. The advantages of using CMS include reduction of setup time, reduction of work-in-process and inventory, material movement reduction, improvement of quality, reduction in production lead time, and better supervisory control.

Most production environments have to deal with variations in the operating parameters along the planning horizon, such as in the product demand. Manufacturers are also confronted with constraints, conditions, and costs, such as facility capacity limits (i.e., time), machine costs (i.e., purchase and maintenance), inventory holdings, backorder, and subcontracting. In this condition, the act of managing and controlling resources and balancing them among subsequent periods to minimize cost is known as *Production Planning* (PP). The main goal of production planning is to minimize the costs of production over the planning horizon, which include fixed and variable production costs, inventory, shortage, and subcontracting costs. The main restraints of the production planning problem include: (1) The inventory balance at each given time period, which is moderated by the inventory or shortage from a prior period, production, subcontracting, and demand; and (2) capacity limits.

Majority of recent studies consider CMS and PP sequentially or independently (Chattopadhyay et al., 2013). However, considering the CMS and PP simultaneously is critical for manufacturers in real competitive production environments (Sakhaii et al., 2016). Variations in the production volume and mixture of products and introduction of new products lead to the necessity of integration of the CMS and PP

(Hassan Zadeh et al., 2014). In a CMS, the sequence of operations has a critical effect on material handling and the inter-cell and intra-cell movement costs. As an example, consider Figure 1 which demonstrates the effect of the operation succession on the material movements. Operations 1 and 3 of part 10 (P10) are processed on Machine 5 (M5) in Cell 1, and Operation 2 of P10 is processed on Machine 7 (M7) in Cell 2. Therefore, the processing route of Part 10 includes two inter-cell movements. Processing Part 4 in Cell 2 needs two intra-cell movements. Therefore, the design of the production system depends on the operational planning of the resources (Hassan Zadeh et al., 2014).

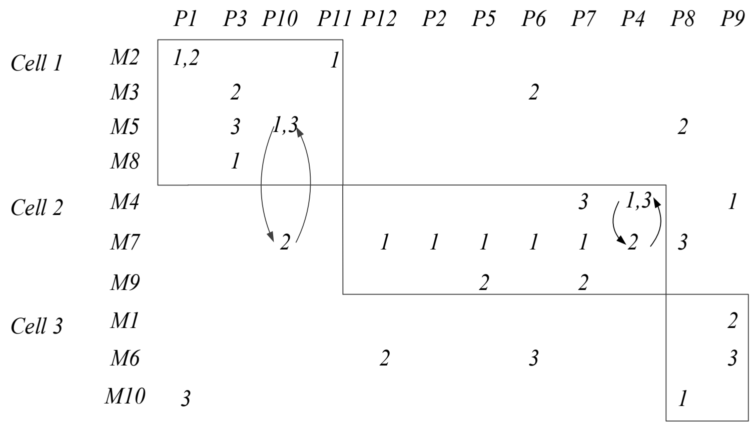

Figure 1. The intra/inter-cell material movement.

This paper addresses the Cell Formation Problem (CFP) which is extended by considering aspects of production planning such as inventory, backorder, and subcontracting. The proposed model determines the optimal inter-cell and intra-cell formation layout and the production planning simultaneously. The rest of this paper is organized as follows. A review of the CFP literature is provided in Section 2. Problem formulation is presented in Section 3. Section 4 describes the proposed solution approaches. The parameters of the algorithms are tuned in Section 5. Verification of the proposed model and the performance of the developed solution algorithms are presented in Section 6. Finally, the concluding remarks and directions for future research are provided in Section 7.

Literature Review

In this section, the literature related to cell formation problem is reviewed. Defersha and Chen (2006) addressed a comprehensive model and proposed a two-stage Genetic Algorithm (GA) to form the manufacturing cells. They attempt to minimize machine related costs, inter-cell material movement costs, subcontracting costs, and system reconfiguration costs. The proposed GA creates separate cells in the first step and enhances the initial solution in the second step. Rafiee et al. (2011) addressed a mathematical model for the integrated cell formation to minimize the sum of machine related cost, cell reconfiguration cost, maintenance, material handling, and subcontracting costs, as well as replacement cost of defective parts. The model considers alternative routes, machine capacity constraints, cell size constraints, and machine breakdowns. Safaei et al. (2008) proposed a mixed integer programming model for the CF problem. The objective function was to minimize the machinery fixed and variable costs, inter-cell and intra-cell movements, and reconfiguration costs. Dalfard (2013) proposed a nonlinear mathematical model for a dynamic CF problem to minimize the number and average length of inter-cell and intra-cell movements. They combined simulated annealing and branch-and-cut algorithm to solve the proposed model.

Krishnan et al. (2012) proposed three steps for cell layout problem. In the first step, they tried to group the machines into cells in order to minimize inter-cell and intra-cell movements costs. In the second step, two heuristic methods were used to assign the parts to the cells based on the first step solution. Finally, a GA is employed to determine the optimum inter-cell and intra-cell layouts. Wu et al. (2008) employed hybridization techniques which combine SA and GA algorithms to solve their proposed model. Durán et al. (2010) combined PSO with a data mining technique to solve the CF problems.

Shirzadi et al. (2017) addressed a new multi-objective model in CF by assuming the demand under fuzzy condition. The model minimizes machine related costs, inter-cell movements costs, subcontracting, and also balancing the intracellular workload. Delgoshaei and Gomes

(2016) proposed a new mathematical model for short-term scheduling in a dynamic condition to determine the optimum schedule of manufacturing plant and outsourcings. The results demonstrate that uncertainty of system costs have a significant effect on the parts' routing. Eguia et al. (2017) addressed an integer linear model in CMS by considering alternative routing, multiple time horizons, and cell load variation. They considered cell load variation in two phases. In the first, they considered the machine cell design to assign machines into machine cells, and in the second, the cell loading has been considered to determine the routing mix and the allocation of tools.

Chang et al. (2013) solved the CF problem while considering alternative routing by a Tabu search algorithm in two steps. In the first step, CF and layout problems are simultaneously solved, and in the next, the machine layout for each cell is formed. Tavakkoli-Moghaddam et al. (2012) proposed a mathematical model for multi-criteria scheduling problem. They used the scatter search method to solve the proposed model. Mahdavi et al. (2010) proposed a new model to consider CF and cell layout problems simultaneously. They aimed to minimize costs of intra-cell forward and backward movements and inter-cell travel distance. They proposed weights for inter-cell and intra-cells movements and considered the weight of inter-cell movements more than intra-cell movement. Mahdavi et al. (2013) attempted to minimize the number of void and exceptional elements in a machine-part-worker assignment matrix. They considered the ability of workers in performing various jobs in the proposed mathematical model. Rezazadeh and Khiali-Miab (2017) proposed a new model in CMS to minimize the costs, enhance the quality of parts, and improve the reliability of the designed system. They used a cost method as a logical relation in order to consider the reliability. Moreover, they utilized a two-layer GA to obtain the optimum solutions.

Azadeh et al. (2017) consider human factors in designing dynamic cellular manufacturing system. The main objective is to minimize the total costs, inconsistency in the decision-making style of operators, and the cell load variation. Rabbani et al. (2017) proposed a bi-objective model in dynamic cell formation problem by considering the total cell load variation and some fixed and variable costs. They applied a Multi-Objective Scatter Search (MOSS) to find local Pareto-optimal frontier. Moreover, Mahdavi et al. (2012) proposed a mathematical model to solve the CF and operator assignment problems using a goal programming approach.

Table 1. Summary of Related Literature.

Articles	Intra-cell layout	Inter-cell layout	Outsourcing	Setup-cost	Inventory	Backorder	Cell load variation
Defersha & Chen (2006)	✓	✓					✓
Saidi-Mehrabad & Safaei (2007)	✓				✓		
Rafiee et al. (2011)	✓	✓	✓				
Tavakkoli-Moghaddam et al. (2012)	✓	✓	✓		✓		✓
Chang et al. (2013)	✓	✓	✓				
Mahdavi et al. (2013)	✓	✓		✓			
Hassan Zadeh et al. (2014)		✓	✓	✓			✓
Delgoshaei & Gomes (2016)		✓	✓		✓		✓
Sakhaii et al. (2016)	✓	✓	✓	✓			
Shirzadi et al. (2017)	✓	✓		✓	✓		
Rabbani et al. (2017)		✓	✓	✓	✓		✓
Rezazadeh & Khiali-Miab (2017)		✓	✓		✓		
Azadeh et al. (2017)	✓	✓	✓		✓		✓
This study		✓	✓	✓	✓	✓	✓

Table 1 illustrates the features of some related literature of the cell formation problem. As mentioned in the literature section, the cell formation problem with regard to production planning has not been considered in the previous studies. As the best of our knowledge, for the first time, in this paper, the effects of inventory holding and backorder costs on cellular manufacturing system have been considered.

Problem Definition

In this section, the proposed mathematical integrating CFP and PP model is presented. The proposed model makes contributions to CFP in two ways. First, it integrates cellular manufacturing problem with production planning problem. For the first time, the backorder is considered in the CFP. Second, the effect of inventory holding and backorder costs is demonstrated. In the proposed model, several parts should be produced and each part requires a number of operations which can be processed on different machines. Each part's demand in each period is known. Machines are multi-process with limited capacities; that is, by considering available tools, machines can process various operations. Moreover, the processing time of each operation on each machine is known. The maintenance cost of machines is known and constant. The material handling cost is considered to be independent of the traveled distance. Subcontracting is allowed with a specified cost; the total or a portion of the demand can be subcontracted. The workload assigned to machines should be balanced within cells based on the time spent on the parts. The extra inventory and delayed order are allowed. The setup cost for each part is considered but machine installation and breakdown times are ignored. Other attributes of the proposed model are summarized as follows:

- The demand of each part type is known per period.
- Machines' capacities are known and constant.
- The processing time for all the operations on each machine type is known.
- Machine maintenance and purchase costs are known and constant.

- The operation cost for each machine type per hour is known and constant.
- Machines can be procured to certain numbers and with a constant cost at the beginning of each time period.
- The batch size of parts is known and constant and movement cost for each part type is known and deterministic.
- The subcontracting of parts is allowed. Thus, total or portion of demand can be subcontracted with a known cost.
- The minimum and maximum cell sizes are given.
- The inventory holding and backorder are allowed with known costs. Therefore, the demands can be satisfied in the preceding or succeeding periods.
- The cost of setup operation required to produce each part type is known and constant.

Mathematical Model

Indices

c	Index of manufacturing cells (c=1,…,C)
m	Index of machine types (m=1,…,M)
p	Index of part types (p=1,…,P)
h	Index of time periods (h=1,…,H)
j	Index of operations belonging to part type p (j=1,…,O_p)

Parameters

D_{ph}	Demand for part p in period h
a_{jpm}	Binary variable that is equal to 1; if operation j of part type p can be conducted on machine type m, and is equal to 0 otherwise.
t_{jpm}	Processing time of operation j of part type p on machine type m
UB	Maximum cell size
LB	Minimum cell size
S_p	Subcontracting cost for part type p
T_m	Time capacity of machine type m in each period

α_m	Purchase cost of machine type *m*
M_m	Maintenance cost of machine type *m*
β_m	Operation cost per time unit per machine type *m*
γ_p	Inventory holding cost for part type *p*
A_p	Setup cost of part type *p*
α_p	Moving cost for part type *p*
λ_p	Backorder cost for part type *p*
β_p	Batch size for part type *p*
L	A sufficiently large positive number
S	Cost for each variation in cell load

Decision variables

X_{jpmch}	1, If operation *j* of part type *p* is performed by machine *m* in cell *c* in period *h*; 0 otherwise.
$I^{+}_{p,h}$	Inventory level of part type *p* kept in period *h*, and carried over to period *h+1*
$I^{-}_{p,h}$	Backorder level of part type *p* in period *h*
SC_{ph}	The quantity of part type *p* subcontracted in period *h*
Z_{ph}	1, If part type *p* is planned to be produced in period *h*; 0 otherwise
N_{mch}	Number of machines type *m* required in cell *c* in period *h*
Q_{ph}	Production volume of part type *p* in period *h*
W_{jpmch}	The workload associates with operations of part type *p* for machine *m* in cell *c* in period *h*
W^{-}_{jpch}	Average intra-cell workload associates with operations of part *p* in cell *c* in period *h*
y'_{ph}	Auxiliary variable;1 if $I_{ph} \geq 0$; 0 otherwise

$$\begin{aligned}\text{Min } Z = &\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{m=1}^{M} N_{mch} M_m + \sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{m=1}^{M} N_{mch}\alpha_m + \sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{j=1}^{J_p}\beta_m t_{jpm} Q_{ph} X_{jpmch} \\ &+ \frac{1}{2}\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{j=1}^{Jp-1}\alpha_p\left\lceil\frac{Q_{ph}}{\beta_p}\right\rceil\left|\sum_{\mathrm{m}=1}^{M} X_{(j+1)pmch} - \sum_{\mathrm{m}=1}^{M} X_{jpmch}\right| + \sum_{h=1}^{H}\sum_{p=1}^{P} y_p I^{+}_{p,h} \\ &+ \sum_{h=1}^{H}\sum_{p=1}^{P}\lambda_p I^{-}_{p,h} + \sum_{h=1}^{H}\sum_{p=1}^{P} A_p Z_{ph} + \sum_{h=1}^{H}\sum_{p=1}^{P} S_p SC_{ph} + \sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{j=1}^{Jp}\left|w_{jpmch} - \bar{w}_{jpch}\right| s\end{aligned} \quad (1)$$

$$\sum_{m=1}^{M}\sum_{c=1}^{C} a_{jpm} X_{jpmch} = Z_{ph} \qquad \forall j,p,h \qquad (2)$$

$$Q_{ph} \le Z_{ph} L \qquad \forall p,h \qquad (3)$$

$$\sum_{p=1}^{P}\sum_{j=1}^{Jp} t_{jpm} X_{jpmch} Q_{ph} \le N_{mch} T_m \qquad \forall m,c,h \qquad (4)$$

$$N_{mch} \le \sum_{p=1}^{P}\sum_{j=1}^{J_p} a_{jpm} X_{jpmch} \qquad \forall m,c,h \qquad (5)$$

$$Q_{ph} + I_{p,h-1} - I_{p,h} + SC_{ph} = D_{ph} \qquad \forall p,h \qquad (6)$$

$$I^{+}_{p,h} - I^{-}_{p,h} = I_{p,h} \quad ; I_{p,H} = 0 \qquad \forall p,h \qquad (7)$$

$$I^{+}_{p,h} \le L y'_{ph} \qquad \forall p,h \qquad (8)$$

$$I^{-}_{p,h} \le L(1 - y'_{ph}) \qquad \forall p,h \qquad (9)$$

$$X_{jpmch} \le a_{jpm} \qquad \forall j,p,m,c,h \qquad (10)$$

$$LB \le \sum_{m=1}^{M} N_{mch} \le UB \qquad \forall c,h \qquad (11)$$

$$w_{jpmch} = \left(t_{jpm} Q_{ph} X_{jpmch}\right)/T_m \qquad \forall j,p,m,c,h \qquad (12)$$

$$\bar{w}_{jpch} = \left(\sum_{m=1}^{M} w_{jpmch} N_{mch}\right)/\left(\sum_{m=1}^{M} N_{mch}\right) \qquad \forall j,p,c,h \qquad (13)$$

$$\begin{aligned}&\delta_{ph}, B_{ph}, I_{ph} \ge 0 \quad , \quad Z_{ph}, y'_{ph} \in \{0,1\} \qquad \forall p,h \\ &X_{jpmch} \in \{0,1\} \qquad \forall \mathrm{j,p,m,c,h}\end{aligned} \qquad (14)$$

Equation (1) is the objective function. The first eight terms in Equation (1), respectively, represent machine purchase, maintenance, operating, material handling, inventory, backorder, setup, and outsourcing costs. The last term is the cost corresponding to the deviation of each machine workload from the cell average over the planning horizon. The cell load variation in single route CMS is calculated as the difference between the workload on the machine and the average load of the corresponding cell (Venugopal & Narendran, 1992). This is considered in the objective function in order to improve the balance of the workload between cells and smoothen the materials flow.

Equations (2) and (3) ensure assignment of each operation to the cell and the machine which has the required tool, if the part is to be produced at the given period. Equations (4) and (5) ensure machine capacity constraints and the demand is satisfied. Equations (6) to (9) are the inventory balance relationships between two consecutive periods. If $I^{+}_{ph} \geq 0$, the result is a surplus in inventory which incurs holding cost; and if $I^{-}_{ph} \geq 0$, a shortage of inventory is implied leading to backorder cost. The Amount of I_{ph} is zero in the last period of planning horizon. Equations (8) and (9) ensure that the two variables I^{+}_{ph} and I^{-}_{ph} do not simultaneously get a positive value. Equation (10) ensures assignment of each operation to a machine by considering the required tools. Equation (11) reflects the upper and lower bounds of the cell size. Equations (12) and (13) identify the workload for each machine type in each cell and the average intra-cell workload, respectively. Equation (14) represents the binary and non-negativity integer requirement of the decision variables.

Linearization

Equation (4) and the third term of Equation (1) can be linearized via introducing a non-negative variable as $\varphi_{jpmch} = Q_{ph} \times X_{jpmch}$ and the following constraint set:

$$\varphi_{jpmch} \le L\, X_{jpmch} \qquad \forall j,p,m,c,h \qquad (15\text{ a})$$

$$\varphi_{jpmch} \le Q_{ph} \qquad \forall j,p,m,c,h \qquad (15\text{ b})$$

$$\varphi_{jpmch} \ge Q_{ph} - L\left(1 - X_{jpmch}\right) \qquad \forall j,p,m,c,h \qquad (15\text{ c})$$

$$\varphi_{jpmch} \ge 0 \qquad \forall j,p,m,c,h \qquad (15\text{ d})$$

The fourth term of Equation (1) can be linearized by introducing two non-negative variables τ^{+}_{jpch} , τ^{-}_{jpch} and also a binary variable ϑ_{jpch}. So, the term $\left|\sum_{\mathrm{m}=1}^{M} X_{(j+1)pmch} - \sum_{\mathrm{m}=1}^{M} X_{jpmch}\right|$ is replaced by $\tau^{+}_{jpc} + \tau^{-}_{jpc}$ through adding Equation (16).

$$\sum_{\mathrm{m}=1}^{M} X_{(j+1)pmch} - \sum_{\mathrm{m}=1}^{M} X_{jpmch} = \tau^{+}_{jpch} - \tau^{-}_{jpch} \qquad \forall j,p,c,h \qquad (16\text{ a})$$

$$\tau^{+}_{jpch} \le L\,\vartheta_{jpch} \qquad \forall j,p,c,h \qquad (16\text{ b})$$

$$\tau^{-}_{jpch} \le L\left(1 - \vartheta_{jpch}\right) \qquad \forall j,p,c,h \qquad (16\text{ c})$$

$$\vartheta_{jpch} \in \{0,1\} \qquad \forall j,p,c,h \qquad (16\text{ d})$$

Where, L is a large positive number.

Determine Complexity of Problem

As computation point of view, the proposed model is complex. Clearly, the complexity of the problem is positively correlated to the number of machines, parts, operations, and length of the planning horizon. In the proposed model, each part type requires j operations and each operation can be processed on k alternative machines. Supposing that all part types have demand in all periods, thus, each part can be produced through K^{j} alternative plans; for all parts, in each period, there are $\left[k^{j}\right]^{p}$ alternative plans. Thus, there are $\left[k^{j}\right]^{pH}$ alternative to allocate part-operations to machines. To estimate the solution space size of the proposed model, we assume that demand of each part type is either satisfied by in-house production, or by completely subcontracting the production. Therefore, each part type can be produced through $K^j + 1$ alternative plans, and then there are $\left[k^j + 1\right]^{pH}$ alternative plans for parts in the whole planning horizon. Also, we assume the inventory and backorder are allowed. Therefore, each part type can be produced through $K^j + 1 + (H-1)$ alternative plans. Accordingly, in the easy case, there are $\left[k^j + H\right]^{PH}$ allocation combinations, in which $\left[k^j + H\right]^{PH} + W$ and W is a polynomial as:

$$W = \sum_{i=1}^{H\times P} \binom{H\times P}{i} \left(K^j \right)^{H\times P-i} H^i$$

Solution Approach

Cell formation problem is an example of a non-polynomial-hard (NP hard) problem (Rabbani et al., 2017). Thus, these problems especially large-sized ones, are hardly solved using exact solutions. Meta-heuristic algorithms are commonly used to achieve high-quality solutions for these types of problems. In this study, GA and DPSO algorithms are employed. To validate the model and the meta-heuristic algorithms, test problems are solved using GAMS software, GA, and DPSO algorithms and a comparison is drawn between them. As mentioned in the literature review, GA is commonly used to solve the CFP; we also employed the DPSO algorithm to compare its performance with GA algorithm.

Genetic Algorithm

Genetic algorithm (GA) was introduced by Holland (1975). GA is an evolution-based computation technique (Yousefi et al., 2017). It operates on a population of individuals, each of which presenting a possible solution to the optimization problem. GA attempts to generate improved or suitable individuals, that are solutions, by combining the best features of the current genes by the natural selection mechanics and genetic operators. Actually, GA searches the feasible space to find optimal or near-optimal solutions (Rabbani et al., 2016). In this paper, to employ GA, four principal factors are considered which are explained in the followings.

Solution chromosome

The chromosome structure represents a feasible solution. Each chromosome is comprised of the two following genes for each period.

1. The matrix E_{jpm} is the related gene to assign operations to the machines. It is designed for every period and means operation j for part p is performed by machine m when the corresponding element equals to 1. For example, the term E_{123}=1 means Operation 1 of Part 2 is processed on Machine 3. Table 2 shows the micro structure of a chromosome in the proposed GA, where D=max{ k | k=||K_{jp}||} with parameter ||K_{jp}|| as the set of alternative machines for operation j of part p, Q(i) is production volume of part type i, $SC(i)$ is subcontracting of part i, and $I^{+}(i)$ and $I^{-}(i)$ are backorder and inventory of part i, respectively. The sign ♯ represents the number of the cells in which the operation is processed. This matrix and the value of D yield the value of the binary variable X_{jpmch}.

Table 2. Micro Structure of a Chromosome in the Proposed GA.

Part 1				**Part 2**				**…**	**Part m**			
Q(1)				Q(2)					Q(m)			
SC(1)				SC(2)				…	SC(m)			
I^{+}**(1) or** I^{-}**(1)**				I^{+}(2) or I^{-}(2)				…	I^{+}(m) or I^{-}(m)			
Op.1	Op.2	…	Op. j	Op.1	Op.2	…	Op. j	…	Op.1	Op.2	…	Op. j
Cell numbe r ♯	Cell numbe r ♯	…	Cell numbe r ♯	Cell numbe r ♯	Cell Numbe r ♯	…	Cell Numbe r ♯	…	Cell numbe r ♯	Cell numbe r ♯	…	Cell numbe r ♯
E_{111}	E_{211}	…	E_{j11}	E_{121}	E_{221}	…	E_{j21}	…	E_{1p1}	E_{2p1}	…	E_{jp1}
E_{112}	E_{212}	…	E_{j12}	E_{122}	E_{222}	…	E_{j22}	…	E_{1p2}	E_{2p2}	…	E_{jp2}
.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.
E_{11D}	E_{21D}	…	E_{j1D}	E_{12D}	E_{22D}	…	E_{j2D}	…	E_{1pD}	E_{2pD}		E_{jpD}

2. Matrix $\left[N\right]_{m\times c}^{h}$ consists of genes indicating the number of available machines in each cell in period h. Elements of matrix [N] are calculated by Equation (17).

$$N_{mch} = \left\lceil \frac{\sum_{p=1}^{P}\sum_{j=1}^{Jp} t_{jpm} X_{jpmch} Q_{ph}}{T_m} \right\rceil \qquad \forall m,c,h \qquad (17)$$

Initial solution.

As mentioned previously, GA is a population-based algorithm, and requires an initial population to conduct the evolution process. In the proposed GA, the initial population is generated in a random fashion; for each part type in each period, Q_{ph} and SC_{ph} are drawn from the uniform distribution $U(0, \sum_{h=1}^{H} D_{ph})$. In the next step, the parts' operations are randomly assigned to available cells. Then, with respect to the parameter a_{jpm}, the parts' operations are randomly assigned to available machines. Finally, the inventory or backorder values are calculated using Equation (6).

Improved GA operators

To generate new solutions from those existing in the current generation, genetic operators are used. Since a matrix format is used as the chromosome structure in this paper, the three well-known genetic operators, crossover, mutation, and inversion are applied in two approaches called columnar and linear. In each iteration, an operator is applied to the matrix E_{jpm} of the given chromosome, and then the other variables related to E_{jpm} are updated. The cases of columnar and linear are described in the followings.

1. *Columnar*. In this approach, two rows of the matrix are chosen arbitrarily. Then, the operator is applied to the selected columns. For instance, in Figure 2, Rows 3 and 4 of matrix E_{jpm} are chosen and then the inversion operator is applied.

0	0	0	0
0	0	0	0
1	0	1	1
0	1	0	0
0	0	0	0
0	0	0	0

⟹

0	0	0	0
0	0	0	0
1	1	0	1
0	0	1	0
0	0	0	0
0	0	0	0

Figure 2. Inversion operator in the horizontal direction.

2. *Linear*. In this approach, two columns of a matrix are chosen arbitrarily. Then, the operator is applied to obtained new columns. For example in Figure 3, the result of using inversion operator on the Columns 3 and 4 is shown on the right side.

1	0	0	0
0	0	0	1
0	1	1	0
0	0	0	0
0	0	0	0
0	0	0	0

$\Longrightarrow$

1	0	0	0
0	0	0	0
0	1	0	0
0	0	1	0
0	0	0	1
0	0	0	0

Figure 3. **Result of employing inversion operator.**

Arithmetic crossover operators.

Arithmetic crossover operators, implemented in Arkat et al. (2007), is used to produce two offspring by combining two selected parents, as shown in Equation (18).

$$\begin{cases} C_1 = aP_1 + bP_2 \\ C_2 = bP_1 + aP_2 \end{cases} \qquad 0 \le a \le 1,\ \ b = 1 - a \tag{18}$$

Where, C_1 and C_2 are offspring of P_1 and P_2, and $a = U(0,1)$. To obtain the necessary integer representation of the variables, the Equation (19) is used:

$$\left(a\left[P\right]_{ij} + b\left[P\right]_{ij}\right) = \begin{cases} a\left[P\right]_{ij} + b\left[P\right]_{ij} & if \left[P\right]_{ij} > \left[P\right]_{ij} \\ a\left[P\right]_{ij} + b\left[P\right]_{ij} & if \left[P\right]_{ij} \le \left[P\right]_{ij} \end{cases} \tag{19}$$

Flow chart of the proposed GA is demonstrated in Figure 4, and the pseudo code is presented in Figure 5.

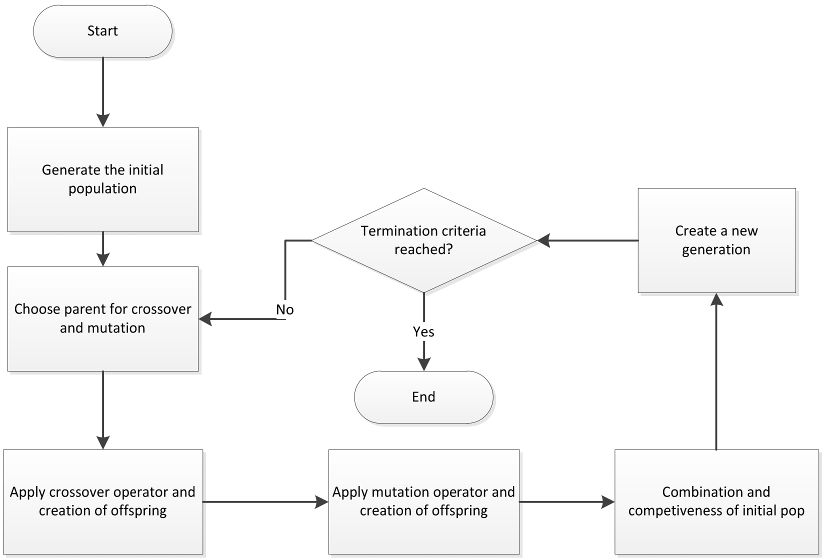

Figure 4. **Flow chart of proposed GA.**

Initialize parameters *F, T*
Initialize counters *p*=1(population counter), t=1(generation counter)
Do
Generate generation t as F feasible solution X_1^t , X_2^t ,…, X_f^t
If N_{mch} > UB Regenerate generation
population fitness values is calculated as F (X_1^t), F (X_2^t),…, F (X_f^t)
population fitness is normalized as $Z_1, Z_2, \ldots, Z_f$ where $Z_i = \frac{F(X_i^t)-\mu_t}{\delta_t}$
If $Z_i \leq 0$ select mating pool of solution X_i
Do (generate offspring for new generation)
Select two chromosomes of the present mating pool
Operate crossover of choose chromosome
Choose one chromosome of the previous population
Operate mutation of selected chromosomes
If N_{mch} > UB omit the selected chromosomes
End if
Loop until $(p \leq F)$
t=t+1
Loop until$(t \leq T)$

Figure 5. **Pseudo code of the GA algorithm**

Particle Swarm Optimization (PSO)

PSO is an evolutionary computation technique formulated by Kennedy and Eberhart (1997). In this algorithm, the best population in the swarm influences the communal performance. The particles move with a convincing constitution and discover the global best answer after certain iterations, because PSO is a population-based move with convincing algorithms and influential evolutionary particles in this algorithm to adopt the leadership of the group, which is the best of cost. PSO has received a lot of attention from researchers due to its considerable ability in solving large-scale optimization problems.

Discrete Particle Swarm Optimization (DPSO)

DPSO is different from PSO in two ways. The first difference is that in the DPSO, particles of the algorithm include several binary variables. The second difference is that in the DPSO algorithm, the velocity should be changed considering the value of probability. Let $P_i^t = (p_{i1}{}^t, p_{i2}{}^t, ..., p_{iD}{}^t)$ and $P_g^t = (p_{g1}{}^t, p_{g2}{}^t, ..., p_{gD}{}^t)$ be the local best (*pbest*) and global best (*gbest*) at iteration *t*, respectively. the velocity of each particle is calculated by Equation (20):

$$v_{id}{}^t = v_{id}{}^{(t-1)} + c_1 r_1 (p_{id}{}^t - x_{id}{}^t) + c_2 r_2 (p_{gd}{}^t - x_{id}{}^t) \qquad (20)$$

Where, C_1 and C_2 (random uniform number in [0, 1] interval) are the knowledge learning factor and social learning factor, respectively. Moreover, r_1 and r_2 are the randomly generated vectors (Kennedy et al., 2001). v_{id}^t is the velocity of particle *i* in iteration *t* in direction *d*; P_{id}^t is the best prior position of particle *i* in iteration *t* at direction *d*; P_{gd}^t is the best foregoing position among all the particles in iteration *t* at direction *d*. By considering the value of $X_{jpmch} \in \{0,1\}$, each particle alters its velocity and acquires a new velocity. In DPSO, the particles are presented as binary variables. For the value of velocity for each particle, Kennedy et al. (2001) declared that the value of velocity in each particle is between 0 and 1, and represented Equation (21) which calculates as follow:

$$s\left(v_{id}^{t}\right)=\frac{1}{1+\exp\left(-v_{id}^{t}\right)} \tag{21}$$

Where, $s(v_{id}{}^{t})$ announces the probability of taking value 1 by bit x_{id}^{t} . To prevent $s(v_{id}{}^{t})$ value taking 0 or 1, a fixed V_{max} is employed to constraint the range of v_{id}^{t} which is $v_{id}^{t} \in [-V_{max}, +V_{max}]$. Usually V_{max} is set to 4. In this paper, the structure of the solution representation used in DPSO is the same as the structure of the chromosomes in GA, and the methods discussed for GA are also applied in DPSO. The flow chart of the proposed DPSO algorithm is shown in Figure 6.

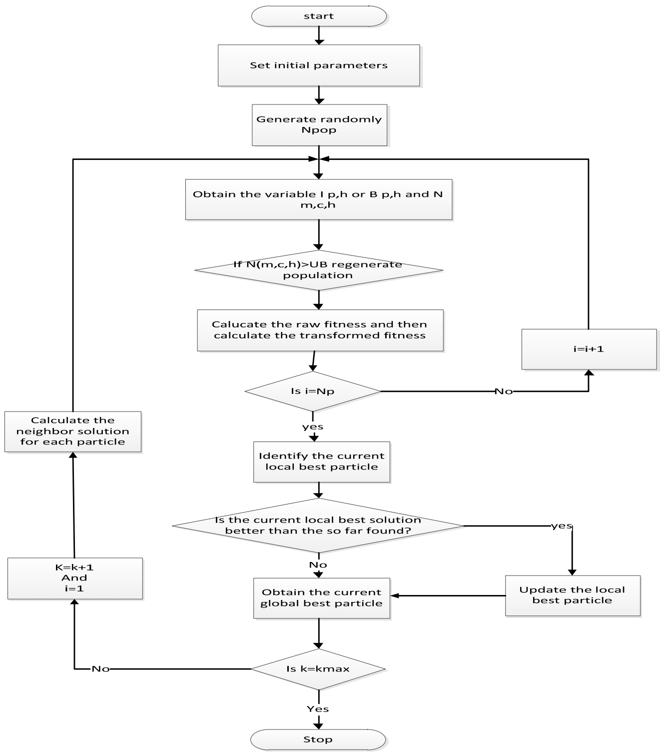

Figure 6. Flowchart of the proposed DPSO algorithm.

Parameter Tuning

Trial and error attempts are commonly used to find optimum parameter sets of GA and DPSO algorithms. The efficient parameter set can improve the ability of meta-heuristic methods (Rabbani et al., 2016).

Generally, the primary parameters of GA are population size (N_{pop}), crossover probability (p-crossover), and mutation probability (p-mutation). In the DPSO algorithm, C_1, C_2 are cognitive and social parameters with a positive value, and w is called inertia weight. Taguchi methods are structured statistical method used in this paper for tuning these parameters. The obtained value of the parameters are shown in Table 3.

Table 3. Tuned Parameters of Algorithms.

GA		DPSO	
Parameter	Value	Parameter	Value
N_{pop}	200	N_{pop}	250
p-crossover	0.6	C_1	2
p-mutation	0.5	C_2	3
		w	1 or 2

Numerical Experiments

Eleven test-problems are used to validate the proposed model. Table 4 shows the general assumption about the parameters used to generate these test-problems. The complete results for two test-problems solved by GAMS 24.1 software are presented in this section. Also, the performance of the proposed GA and DPSO algorithm is compared with GAMS. The GA and DPSO algorithms are coded in MATLAB and all computations are run on a PC with Intel Core Duo II 2.6 GHz processor and 4 GB of RAM.

Table 4. Parameter Value Ranges Used in Generating the Test-Problems.

Parameter	Value	Parameter	Value
D_{ph}	U (0, 1000)	λ_p	U (20, 50)
α_m	U (1000, 2000)	α_p	U(10,15)
β_m	U (1, 10)	A_p	U (100, 200)
M_m	U (5, 20)	γ_p	U (10, 30)
β_p	U (10, 40)	S_p	U (10, 30)
a_{jpm}	0 or 1	$\sum_m a_{jpm}$	2

Test-problems 2 and 4 are described in more details to clarify the solution procedure. The attributes of test-problems are mentioned in Table 11. Table 5 includes the information about Test-problem 2 consisting of three part types, four machine types, and two periods. The processing time of each operation for all part types of Test-problem 2 is presented in Table 5. Tables 6, 7 and Figure 7 illustrate the optimal solution of Test-problem 2. As shown in Figure 7, Machine type 2 should be duplicated in Cell 1 in Period 1. The first and second operations of Part 1 are processed in Cell 1, and the third operation is processed in Cell 3. All the operations of Part type 2 are processed in Cell 2; and all operations of Part 3 are processed in Cell 3. In Period 2, the first and second operations of Part type 1 are processed in Cell 1, the third one is processed in cell 2, and all the operations of PART type 2 are processed in Cell 2. The total cost elements are illustrated in Table 6. As shown in Table 7, the demand for Part type 3 in Period 2 is satisfied in Period 1 by producing 300 units. Thus, Part type 3 is not produced in Period 2. Generally, because inventory cost is low, most of the demand of the Period 2 is fulfilled in Period 1.

Table 5. Data of Test-Problem 2.

Machine info					P1			P2			P3		
T_m	α_m	M_m	β_m		1	2	3	1	2	3	1	2	3
500	1800	50	9	M1	0.81			0.78		0.84			0.46
500	1500	60	7	M2		0.85	0.47		0.56		0.87	0.59	
500	1800	80	5	M3	0.73	0.93	0.48			0.79		0.57	
500	1700	50	9	M4				0.81	0.78		0.25		0.31
D_{ph}			Period1			300			600			200	
			Period2			350			700			500	
β_p						35			25			20	
A_p						130			140			150	
S_p						13			12			15	
γ_p						14			13			14	
λ_p						40			39			30	
C=3	UB=4												

Table 6. Cost Elements in Optimal Solution of Test-Problem 2.

Z^*	Machine constant	Machine variable	Inter-cell moves	Inventory	Backorder	Subcontracting	Setup	Deviation between cells utilization
49835	14150	25450	1025	3710	0	4690	690	120

Table 7.
Optimal Solution of Example 2.

	h=1			*h*=2		
	P1	P2	P3	P1	P2	P3
Q_{ph}	450	250	300	450	430	
S_{ph}	200	120		50		
I_{ph}	100	70	100			
D_{ph}	550	300	200	600	500	100

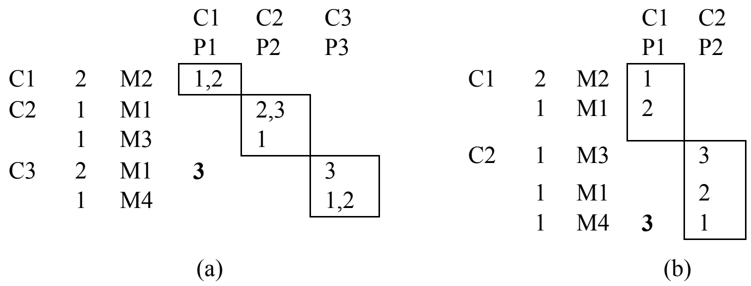

Figure 7. **Optimal cell configuration of example 2: (a) period 1 (b) period 2.**

Table 8 shows the information about Test-problem 4 consisting of five part types, five machine types, and three periods. Tables 9, 10, and Figure 8 show the optimal cell configuration of Test-problem 4. As shown in Table 10, a portion of Part type 4's demand in Period 3 is satisfied by producing 600 units and subcontracting 120 units in Period 2, and the other portions are satisfied by producing 350 units and subcontracting 50 units in Period 3. Furthermore, 60 units of the demand of Part type 3 in Period 2 are produced in Period 3 as backorder demand. On the other hand, the inventory of Part type 2 in

Period 1 is 440 units, which is held in Period 2 to satisfy the demand of Period 2. Generally, due to the low inventory cost, a large portion of the demand of all part types is satisfied in Periods 1 and 2. Table 9 illustrates breakdown structure of the costs of Test-problem 4.

Table 8. Data of Test-Problem 4.

Machine info				P1			P2			P3			P4			P5		
T_m	α_m	β_m		1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
500	1900	5	M1		0.75		0.58	0.65	0.39			0.56	0.56	0.81			0.26	
500	1600	8	M2		0.79					0.92	0.56	0.38			0.76	0.41	0.63	
500	1700	7	M3	0.71		0.54		0.74					0.48					0.59
500	1800	6	M4			0.66	0.8			0.14								
500	1200	9	M5	0.64					0.91		0.48			0.67	0.64	0.12		0.75
D_{ph}		Period1			350			800			210			0			220	
		Period2			420			720			650			220			0	
		Period3			410			0			400			900			300	
β_p					30			20			20			40			45	
S_p					18			13			17			15			25	
γ_p					15			11			25			17			13	
λ_p					41			40			30			36			34	
A_p					150			140			130			160			170	
C=3	UB=4																	

Table 9. Cost Elements in the Optimal Solution of Test-Problem 4.

Z^*	Machine constant	Machine variable	Inter-cell moves	Inventory	Backorder	Subcontracting	Setup	Deviation between cells utilization
106380	24500	47230	875	23390	1800	6775	1630	180

Table 10. Optimal Solution of Test-Problem 4.

	h=1					h=2					h=3				
	P1	P2	P3	P4	P5	P1	P2	P3	P4	P5	P1	P2	P3	P4	P5
Q_{ph}	350	915	210		220	390	280	590	600	300			460	350	
S_{ph}		325							120					50	
I_{ph}		440				410		-60*	500	300					
D_{ph}	350	800	210	0	220	420	720	650	220	0	410	0	400	900	300

* Backorder

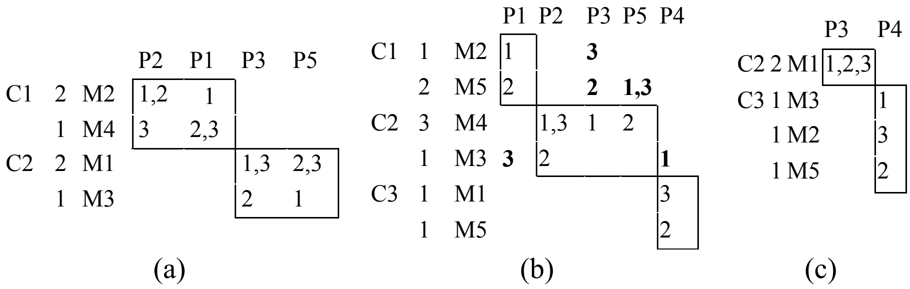

***Figure 8*. Optimal cell configuration of Example 4: (a) Period 1 (b) Period 2 (c) Period 3.**

To compare the results of the meta-heuristic method, 11 test-problems were solved using GA, DPSO, and GAMS. The obtained results are shown in Table 11. Because of the enormous number of constraints and variables, GAMS is not able to solve some of test problems within a reasonable time. The problems that GAMS cannot solve in a span of 4 hours are Test-problems 6, 9, 10, and 11. The results show that the GA and DPSO have the ability to find rational solutions with respect to solutions obtained by GAMS. Figures 9 and 10 illustrate the comparison between the methods in terms of CPU time and the objective function value; the performances of GA and DPSO are similar and can compete with the GAMS software, especially in large-sized problems.

Table 11. Comparison of GA and DPSO Algorithms with GAMS.

Test NO.	Example info (Part×Machine, Cell, Period)	GAMS		GA		DPSO	
		Objective	CPU Time (sec)	Objective	CPU Time (sec)	Objective	CPU Time (sec)
1	*2×2,C=2,H=2*	14150	65	15510	35	15602	32
2	*3×4,C=3,H=2*	49715	440	52690	174	52684	164
3	*4×3,C=3,H=3*	95423	442	101148	185	101213	191
4	*5×5,C=3,H=3*	106380	1256	112475	464	112521	451
5	*8×6,C=3,H=2*	412305	1568	438123	410	438326	387
6	*8×7,C=3,H=3*	N/A		652498	487	652365	498
7	*9×8,C=3,H=2*	658974	4532	700004	651	700125	647
8	*10×10,C=3,H=2*	680616	6278	721453	912	721536	903
9	*12×10,C=3,H=2*	N/A		785423	1356	785514	1381
10	*20×15,C=3,H=2*	N/A		812632	3845	812456	3805
11	*20×20,C=4,H=2*	N/A		954127	4785	953689	4852

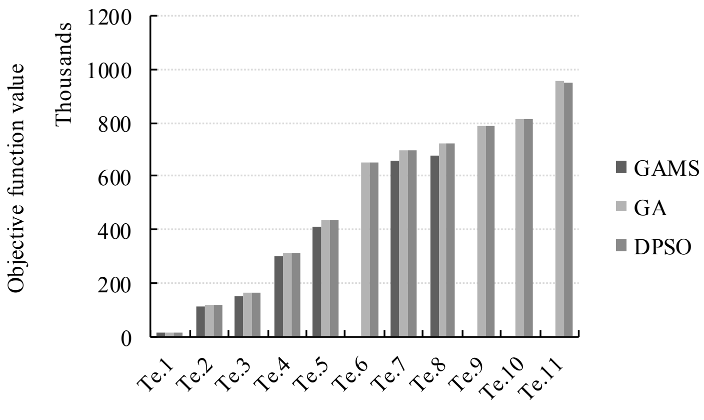

Figure 9. Comparing objective function value between GAMS, GA and DPSO.

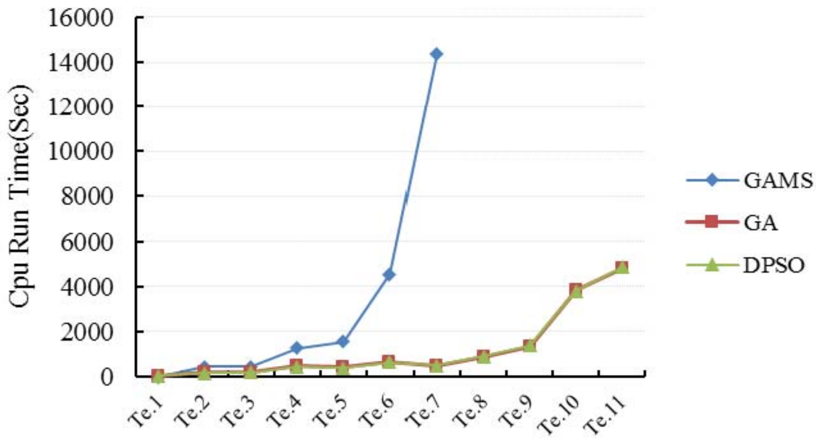

Figure 10. Comparing CPU time of GAMS, GA and DPSO.

Sensitivity Analysis

Most of the industrial plants cope with inventory and backorder whose costs are decisive in production planning. Thus, in the proposed model, inventory and backorder are considered. To further explore the effects of the inventory and backorder costs on the optimum solution, two sensitivity analyses on inventory holding and backorder costs are conducted respectively. The impact of the inventory holding and backorder costs on the overall costs are analyzed. These analyses are based on Test-problem 4. To conduct the sensitivity analyses, in each step, 20 units are added to the inventory holding and backorder costs respectively. This procedure is continued in six steps and the results are illustrated in Table 12 and Figure 11.

As shown in Table 12, the first step for the analysis of the inventory holding cost involves increasing the objective function value by 1130 units. Tables 13 and 14 demonstrate the optimal solution for the first step of the inventory analysis. As shown in Table 14, by increasing the inventory holding cost, the amount of the inventory held in each period decreases. Moreover, increasing the inventory holding cost results in fulfilling the demands of each part type in the current or subsequent period rather than prior periods. Moreover, as it can be inferred from Table 13, the setup and machine-related costs such as constant and variable costs are increased compared to the initial situation, which led to an increase in the objective function value. As it can be inferred from Table 12, by increasing backorder cost, the amount of objective function is increased. Moreover, for all part types the amount of the backorder is decreased, which leads to the satisfaction of the part types in the current or the prior periods rather than the subsequent periods. For the inventory holding sensitivity analysis, the amount of setup cost is increased. Moreover, by increasing the amount of backorder cost, the amount of subcontracted parts are increased. Because of avoiding backorder, a number of parts which should be produced at the current time are increased and moreover, due to machine capacity, the amount of subcontracted parts is increased. Subsequently, this leads to an increase in objective function value. Figure 11 demonstrates the changes in the objective function by increasing the unit cost of inventory and backorder.

Table 12. The Results of Sensitivity Analysis.

The value added to inventory cost ($\Delta_{\gamma p}$)	Amount of change in cost function (Δ_z)	$\frac{\Delta_z}{\Delta_{\gamma p}}$	The value added to backorder cost ($\Delta_{\beta p}$)	Amount of change in cost function (Δ_z)	$\frac{\Delta_z}{\Delta_{\beta p}}$
20	1130	56.5	20	874	43.7
40	1920	48	40	1356	33.9
60	2560	42.67	60	1954	32.56
80	3050	38.13	80	2432	30.4
100	3470	34.7	100	2654	26.54
120	3640	30.33	120	2784	23.2

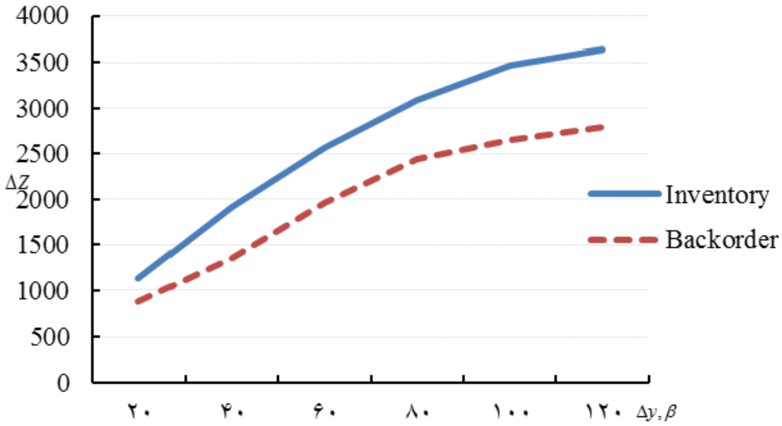

Figure 11. **Sensitivity analysis of inventory and backorder cost.**

Table 13. Cost Structure of Test-Problem 4 When the Unit Inventory Cost Is Increased by 20.

Z^*	Machine constant	Machine variable	Inter-cell movement	Inventory	Backorder	Subcontracting	Setup	deviation between cells
107510	29530	57325	1025	10150	1800	5660	1780	240

Table 14. Optimal Solution of Test-Problem 4 When the Unit Inventory Cost Is Increased by 20.

	h=1					h=2					h=3				
	P1	P2	P3	P4	P5	P1	P2	P3	P4	P5	P1	P2	P3	P4	P5
Q_{ph}	350	950	210		220	420	400	590	500		310		460	510	300
S_{ph}		170							110		100				
I_{ph}		320						-60*	390						
D_{ph}	350	800	210	0	220	420	720	650	220	0	410	0	400	900	300

* Backorder

In this paper, for the first time, backorder is considered in the cell formation problem. In order to obtain the significance and effect of considering backorder in cell formation problem, the obtained results of this paper are compared with obtained results of Rabbani et al. (2017) where backorder is not considered. The results demonstrate that by considering reasonable value for backorder cost, the amount of objective function is less than the amount of objective function obtained by Rabbani et al. (2017). Finally, comparison of the results of this paper and Rabbani et al.'s (2017) demonstrates that considering backorder can improve the amount of objective function and enhance the flexibility of production planning.

Conclusion

In this paper, a new mathematical model for the cell formation problem by integrating the production planning problem is proposed. The proposed model covers important manufacturing features including inventory holding, cell load variation, and especially backorder. The proposed model can determine the optimum cell formation and production planning, simultaneously. The objective function of the proposed model consists of minimizing the total fixed and variable costs including the purchasing, operation, and maintenance costs, inter-cell movement costs, minimizing the backorder, inventory and subcontracting costs, and minimizing the costs of deviations between the levels of cell utilization. The proposed model was validated by applying it to test-problems using GAMS software. Since, this problem is an NP-hard problem, finding the optimal solution is impossible in large-scale problems. Thus, GA and DPSO algorithms are employed to solve the proposed model. The computational results demonstrated that GA and DPSO have the ability to find near-optimum especially when GAMS fails to obtain any solution for large-size test-problems. The results demonstrated that GA had a relatively better performance than DPSO.

Besides the innovation in the proposed model, for the first time, the effects of inventory holding and backorder costs on cellular manufacturing problem have been considered. The results of the numerical experiments and the sensitivity analyses demonstrate that considering inventory and backorder has a significant effect on the optimum solution of the cell formation problem, because they provide the condition in which some portion of the demand of a period can be satisfied in a prior or subsequent period. Moreover, for further research one can study Multi Attribute Decision Making (MADM) techniques and recent approaches in part families' formation. Considering lead time for receiving parts from subcontracting can also be another interesting addition to the proposed model. Considering the dynamic form of cell formation, incorporating uncertainties in the demand and machine availability, and using multi-objective optimization techniques can also be suggested for future studies.

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