A new method for minimizing cell underutilization in the process of dynamic cell forming and scheduling using artificial neural networks

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Abstract
Cell-load variation is considered as a major shortcoming in cellular manufacturing systems. It can cause long queues in front of machines and impose extra costs to the cellular layouts. In this paper the impact of inflation on cell-load variation in cellular manufacturing systems is examined. For this purpose, a new method is proposed for scheduling dynamic cellular manufacturing systems in the presence of bottleneck and parallel machines. The aim is finding the trade-off values between in-house manufacturing and using outsource services while system costs are not deterministic and may be varied from period to period by inflation. To solve the model, a hybrid Multi-layer perceptron is developed because of the high potential of outcomes to be trapped in the local optima. Our findings show that the condition of dynamic costs affects the routing of materials in process and may induce machine-load variation that yield to cell-load diversity. An increase in changing costs causes the loading level of each cell to vary, which in turn results in the development of “complex dummy sub-cells.” The results indicate that the proposed method can significantly reduce the level of cell-load variation in CMS.

Keywords: Facilities planning, Cellular manufacturing systems, Cell scheduling, Artificial neural networks

1. Introduction

The issue system imbalance is a main concern in designing and scheduling Cellular Manufacturing Systems (CMS) studies. Over allocating some machines during manufacturing periods can cause emerging machine load variation which will yield to cell load variation accordingly. Cell load variation imposes harms to a manufacturing system. For instance, while cell load variation emerges, some machines are under pressure of heavy allocating of work-loads. Hence, failures for these machines are supposed to be more than the other parallel machines which are less allocated or remained idle. As a conclusion, the emergency maintenance cost is expected to increase. Moreover, due to increasing in number of the loads for these machines, queues of WIP behind them become longer and longer. As a result these machines are risky to become bottleneck in a cell and decrease the production rate of the system. In the following subsections, some of the most important reasons for the increase in material transferring costs and the solutions provided by scientists will be investigated in detail.

Determining the best combination of machines that can be used in the consecutive operations of a part (during or after cell generation) is the aim of addressing part routing problems. Delgoshaei et al. (2016b) compared different material transferring models that are developed by scientists in the CMS problem so far. From another perspective in part routing problems, each part can be completed in more than one way because of the existence of parallel machines. Choosing different permutations of various machines inevitably causes different inter and intracellular movements and
entails material transferring costs accordingly. To minimize material transferring costs, scientists have chosen one or a combination of two strategies. The first is assigning machines to generate part families. The other is assigning parts to machines that are grouped according to function similarity or requirements. Afterward, Haleh et al. (2009) presented a hybrid Memetic algorithm and revised TOPSIS method, which is a multi-criteria decision making method for finding the best solution using similarity scores, to minimize cell load variation and inter-cellular WIP transferring. Sarker & Yu (2007) focused on the spatial coordinates in a machine-cell location problem in which bottleneck machines and parts may exist.

Another drawback that emerges during the part routing process is the underutilization of machines in cells. One reason for the emerging underutilization of some machines or cell load variation is ignoring the capacity of machines during the scheduling process. Ahkioon et al. (2009) presented a CMS where maintenance activities can affect system capacity. To overcome such drawback, they also considered using outsource services and machine relocating. But their model was failed to solve large scale problems. In some cases, cell size constraints were employed to control the addition or removal of machines in cells and to determine the best values of transferring materials within or between cells accordingly. Ariafar & Ismail (2009) addressed the problem of material transferring while the shape of the machines was assumed equal. A center-based distance calculation between machines was employed.

Aside from the strategies and solutions discussed, during the last two decades, the idea of reconfiguring cells by shifting of machines or re-arranging of part families to smooth material transferring within and between cells (or as a result of changing part demands during periods) has become noteworthy. Almost in all cases, the focus is on the modification of cell layouts during the manufacturing process to determine the best part routing. Safaei et al. (2008) investigated the issue of machine time capacity and maximum cell size in a reconfigurable dynamic CMS in which machine relocating was allowed. A few years later, Rafiee et al. (2011) developed a similar mathematical programing method for a reconfigurable manufacturing system in which more aspects of a real system, such as preventive and maintenance activities, finished and unfinished parts inventory, and defective parts replacement costs, were considered. Elmi et al. (2011) developed a situation that was previously proposed by Won & Currie (2007) in which some parts need to visit a machine more than once in a non-consecutive manner (re-entrant parts). In the proposed model, they presented a new method to schedule both bottleneck and re-entrant parts in cells. Paydar et al. (2010) considered operation sequences in a multiple travelling salesman formulation for the cell forming and machine locating problem, with multiple departures and a single destination considered.

In most real cases, part demands are different from one planning horizon to another. Such a criterion is known as dynamic part demand. Market changes, changes in product designs, and the manufacture of new products are some of the reasons for the change in part demands through different time periods. These conditions may cause emerging imbalances in part routings and bottleneck machines. They will be explained in a separate section because of their importance. Safaei & Tavakkoli-Moghaddam (2009a) also argued that machine capacity and part demands should not be considered fixed and showed how such uncertainties can influence the cell configuration through time horizon. During the scheduling of a dynamic manufacturing system, the system capacity may be inadequate to meet customer demand at a specific period. Hence, Safaei & Tavakkoli-Moghaddam (2009b) addressed a dynamic scheduling problem to find the tradeoff values between in-house production and outsourcing while cells are supposed to be reconfigurable. This time, they considered intercellular movements in addition to intracellular ones. The other solution to address part uncertainties is forming new cells as a result of market changes. This strategy was discussed by Zhang (2011). Aggregate planning while minimizing operation, inventory, and material movement costs was used. Egilmez et al. (2012) focused on uncertain operation times in D-CMS. A few years later, Egilmez & Süer (2014) evaluated the impact of risk level in an integrated cell forming and scheduling problem using Monte Carlo Simulation. Süer et al. (2010) found that the average flow time and total WIP are not always the lowest when additional machines are used. Ariafar et al. (2014) focused on the impact of dynamic product demand on facility layout problem. The main objective of the proposed model was minimizing material transferring by arranging the machine cells within the shop-floor, and the machines within each of the machine cells. Afterward, Renna & Ambriico (2015) also proposed three models for designing, reconfiguring and scheduling cells in dynamic condition of product demands. Delgoshaei et al. (2016a) used GA for scheduling CMS while part demands are dynamic and may be varied from one period to another. Delgoshaei et al. (2016c) employed a hybrid of Tabu search and simulated annealing for evaluating impacts of market changes in scheduling CMS. The literature review shows that when the part routing issue emerges, considering multi process plans, machine relocating, cell decomposition, and cell reconfiguring are the most common solutions offered by scientists. To
the best of our knowledge, no records exist to evaluate the effects of uncertain costs in part routing problems. Moreover, the time value of money can be considered as a major gap in multi-horizon planning models.

2. Research Methodology

This model is prepared to determine best trading off values between in-house manufacturing and outsourcing over planning horizon while limited backorders are allowed and all system costs are considered uncertain. During formulating the model, all system costs including group setup, operating, machine purchasing, outsourcing and backorder costs are taken into consideration. Product demands are also considered dynamic and may be vary from time to time.

2.1. Features and novelties of the proposed model

Novelties of the proposed model can also summarize as:
1) Proposing a new method for calculating inter & intra cellular material transferring while existence of bottleneck machines, parallel machines, voids and exceptional elements is possible
2) Considering uncertain costs (all costs can be changed through the manufacturing horizon)
3) Proposing a new way to find best trading off values between in-house manufacturing, outsourcing and backorders
4) Evaluating the impact of machine failures on production system
5) Evaluating impact of machine failures on part routings
6) Developing periodically scheduling plans for each machine as an outcome

2.2. Flowchart

The current model is developed in order to be able to consider preventive activities and emergency repair activities as shown by figure 1. Therefore, the algorithm starts by initiating a layout based on part families or machine groups or importing the layout like the previous model. Then sets of preventive maintenance activities are carried out according to the preventive activity lists (which will be considered as one of the imported dataset) and system capacity is calculated. Afterward, using estimation for product demands in each period, it is determined whether using subcontractors is cheaper or in-house manufacturing. In condition that using subcontractor services is cheaper, the system will assign products to subcontractors according to their capacity. Then the system will use in-house capacity to perform parts and produce products. During the in-house manufacturing, machines may break which cause them to be out of the services. The strategy is to recalculate part rotes while machine broken is happened and at the same time emergency activities will be carried out for fixing the broken machines. After completing the system capacity if there are still part demands available, the system will check whether buying new machines are more economic or using subcontractor service (if they did not used before). The rest of the part demands will be postponed to next periods as they cannot be processed further.

2.3. Mathematical model

In order to develop a model with mentioned features, a NL-MIP model which was previously presented by Delgoshaei et al. (2016a) is more developed by considering other production conditions. It is noted that Delgoshaei et al. (2016a) offered a method to temporarily freeze those machines that are more likely to be over-allocated. In this research their model is more developed by considering preventive maintenance and machine broken, depreciation of machines and human resources. Moreover, another method for reducing cell load variation is offered which is worked by calculating required extra time for bottleneck machines in cells through a manufacturing period. Similar to the previous model, in this research circumstance is considered dynamic where part demands and all system costs are not fixed and may be varied from period to period.

To find the best set of in-house manufacturing (using the system capabilities) and outsource services, the following assumptions are taken into consideration:
1) Each of the product types has a sequence of operations that must be performed respectively to produce a product.
2) The lower bound and upper bound for each cell is known in advance.
3) Machine Purchasing is allowed during the production horizon.
4) The performance of machines is not constant and will be affected by depreciation rate.
5) Preventive Maintenance is allowed through planning horizon. Machines may break down during the production horizon. The failure rate will be expressed by normal function distribution. The reliability of part routes will be considered by exponential distribution functions.
6) Using subcontractor services is allowed.
7) Inflation rate is not constant and will be expressed using increasing inflation trend.
8) The machine capacities must be considered while scheduling.
9) Backorders are allowed but restricted. The beginning inventory is considered zero and last period backorder is not allowed.

Fig. 1 Flowchart for determining the best trade off values between in-house manufacturing, outsourcing and backorder while preventive activities and repair services are considered.

**Inputs:**
- \(i\): number of parts
- \(j\): type of machines
- \(k\): number of cells
- \(l\): number of sub-contractors
- \(t\): planning periods (time slots)

**Parameters:**
- \(D_{i,t}\): demand of part \(i\) in period \(t\)
- \(D_{i,t} \sim N(\mu_{i,t}, \sigma_{i,t})\) (1)
- \(S_j\): Setup cost of machine \(j\)
- \(OP_{i,j}\): cost of processing part \(i\) using machine \(j\)
- \(OS_l\): cost of performing one part by subcontractor \(l\)
- \(BC_i\): backorder cost of part \(i\) for a period
- \(PM_j\): preventive maintenance cost of machine \(j\)
- \(EM_j\): emergency maintenance cost of machine \(j\)
- \(\alpha_i\): intracellular movement cost of part \(i\)
- \(\beta_i\): intercellular movement cost of part \(i\)
- \(K_j\): purchasing cost of machine \(j\)
$K_j$: selling cost of machine $j$

$Ir_t$: Inflation rate during period $t$ that will be calculated using randomly increasing inflation rate estimator

$$Ir_t = 1 + Ir_{t-1} \times c; \quad c \text{ is a random number between } (0,1) \quad (2)$$

$Cl$: is cell size where $Cl = length \times width \quad (3)$

**Input Matrixes:**
- Product demand ($D_{i,t} [\cdot]$)
- Batch size ($BS_i [\cdot]$)
- Machine Component Incidence Matrix ($MCIM_{i,j} [\cdot]$)
- Machine capacity ($MA_j [\cdot]$)
- Sub-contractor capability ($SC_i [\cdot]$)
- Allowed backorder ($AB_{i,t} [\cdot]$)
- Initial number of machines ($NOM_j [\cdot]$)
- Operation Cost ($OP_i [\cdot]$)
- Setup Cost ($S_j [\cdot]$)
- Intercellular Cost ($\alpha_i [\cdot]$)
- Intracellular Cost ($\beta_i [\cdot]$)
- Machine purchasing Cost ($K_j [\cdot]$)
- Depreciation Rate ($DR_j [\cdot]$)
- Preventive List ($PL_j [\cdot]$)
- Preventive Service Time ($PST_j [\cdot]$)
- Emergency Maintenance Time ($EMT_j [\cdot]$)
- Failure Rate ($FR_j [\cdot]$)
- Preventive Maintenance Cost ($PMC_j [\cdot]$)
- Outsourcing Cost ($OS_{i,t} [\cdot]$)
- Inflation Rate ($IR_{i,t} [\cdot]$)

**Variables:**
- $X_{i,f,j,k,t}$: Number of part $i$ which is performing by $f$th of machine type $j$ in cell $k$ in period $t$ (int.)
- $Z_{i,f,j,k,t}$: If part $i$ performs using $f$th of machine type $j$ in cell $k$ in period $t$ (bin.)
- $Y_{i,t}$: Number of parts which manufactured by sub-contractor $l$ in period $t$ (int.)
- $B_{i,t}$: Number of part $i$ which is decided to postpone for next period (int.)
- $N^{+}_{j,k,t}$: Number of machine type $j$ added to cell $k$ during period $t$ (int.)
- $N^{-}_{j,k,t}$: Number of machine type $j$ removed from cell $k$ during period $t$ (int.)

**Mathematical Model:**

$$\sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{f=1}^{F} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{l=1}^{L} Ir_t \cdot S_j \cdot Z_{if,jkt} \cdot (X_{if,jkt}/BS_i) + \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{j=1}^{J} \sum_{f=1}^{F} \sum_{i=1}^{I} \sum_{l=1}^{L} Ir_t \cdot MCIM_{i,j} \cdot OP_{i,j} \cdot X_{if,jkt} \cdot Z_{if,jkt}$$

$$+ \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{j=1}^{J} \sum_{f=1}^{F} \sum_{i=1}^{I} \sum_{l=1}^{L} Ir_t \cdot [(K_j^{+} \cdot N^{+}_{j,k,t}) - (K_j^{-} \cdot N^{-}_{j,k,t})] + \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{j=1}^{J} \sum_{f=1}^{F} \sum_{i=1}^{I} \sum_{l=1}^{L} Ir_t \cdot PEM_{j} \cdot PL_{j,t} + \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{j=1}^{J} \sum_{f=1}^{F} \sum_{i=1}^{I} \sum_{l=1}^{L} Ir_t \cdot (EM_{j} + S_{j}) \cdot FR_{j}$$

$$+ \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{l=1}^{L} Ir_t \cdot OS_{l} \cdot Y_{i,t} + \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{i=1}^{I} \sum_{f=1}^{F} \sum_{l=1}^{L} \sum_{j=1}^{J} Ir_t \cdot [(X_{i,j,f,k,t}/BS_{i}) - D_{i,t}] \cdot BC_{i}$$

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\[
\begin{align*}
&\sum_{t=1}^{TH} \sum_{k=1}^{K} \sum_{i=1}^{l} \sum_{m=1}^{m-1} \sum_{j=1}^{f} \sum_{f=1}^{F} \sum_{f=1}^{F} \left( y_{i} \cdot I_{R} \cdot Z_{m,i,f,j,k,t} \left( \sum_{j=1}^{j} Z_{m+1,i,f,j,k,t} \cdot X_{m+1,i,f,j,k,t} - X_{m+1,i,f,j,k,t} \right) \right) \\
&\sum_{t=1}^{TH} \sum_{k=1}^{K} \sum_{i=1}^{l} \sum_{m=1}^{m-1} \sum_{j=1}^{f} \sum_{f=1}^{F} \left( \sum_{j=1}^{j} \sum_{k=1}^{M} Z_{m+1,i,f,j,k,t} \cdot X_{m+1,i,f,j,k,t} - \sum_{j=1}^{j} X_{m+1,i,f,j,k,t} \right) \\
\text{s.t.:} \\
&\sum_{k}^{K} \sum_{j}^{J} \sum_{f}^{F} \sum_{i}^{i} \left[ \left( X_{i,f,k,t} / M \right) \right] + \sum_{t}^{T} Y_{t} + \sum_{t}^{T} B_{i,t} \geq d_{i,t} \quad \forall \ t, i; \\
X_{i,f,j,k,t} : (1 - MCIM_{i,j}) \leq 0 \quad \forall \ t, k, j, i; \\
X_{i,f,j,k,t} \leq MA_{j}, DR_{j} - PST_{j} \quad \forall \ t, k, j, i; \\
X_{i,f,j,k,t} : (1 - FR_{j,k}) = 0 \quad \forall \ t, k, j; \\
\sum_{t}^{T} Y_{t} \leq SC_{t} \quad \forall \ t, k; \\
\sum_{t}^{T} B_{i,t} \leq AB_{i,t} \quad \forall \ t, i; \\
\sum_{j}^{J} N_{j,k,t} - \sum_{j}^{J} N_{j,1,t} + N_{k,j,t-1} = N_{k,j,t} \quad \forall \ t > 1, k; \\
N_{k,j,1} = NOM_{j} \quad \forall \ k, j; \\
LP \leq \sum_{j}^{J} N_{j,k,t} \leq CL \quad \forall \ k, t; \\
\sum_{k}^{K} \sum_{i}^{i} \sum_{f}^{F} X_{i,f,k,t} \leq MA_{j}, \sum_{k}^{K} N_{k,j,t} \quad \forall \ t, j; \\
X_{i,f,j,k,t} : Y_{t}, B_{i,t}, N_{j,k,t} : \text{integer} \\
Z_{i,f,j,k,t} : \text{binary}
\end{align*}
\]

The first term of objective function represents the setup cost for each machine that may be different from period to period. The next term shows the operating cost including machinery of each part. The third sentence is to show the purchasing or removing costs of machines. The fourth and fifth sentences are developed to calculate preventive maintenance and emergency activity services costs respectively. As seen, after each emergency service, the machine is broken it cannot perform any operation. The fifth constraint is to guarantee that using sub-contractor services will not be more than their announced capacity. The sixth constraint controls the values of backorders considering the backorder limits. The seventh set of constraints ensures that the amount of purchased or removed machines will stay in a logic
manner during manufacturing horizon. The eights set of constraint represents the initial sets of each machine type in the first period. The ninth sets of constraints controls the size of cells during manufacturing process and the tenth set of operations shows that the amount of producing each part should not be more than the available amount of that machine type. The next 2 set of constraints are used to control domain of the variables.

3. A hybrid Multi-Layer Perceptron and Simulated Annealing

MLP is an improved version of the classic perceptron and can distinguish data that are not linearly separable. In optimizing problems, such characteristic can be employed to determine the weight (best values) of arcs (variables). Note that a MLP consists of multiple layers where each layer is a series of information that is fully connected to next one in a consecutive way to generate a neuron. One prominent trait of MLP is using a supervised learning method which is called back propagation. The proposed MLP has 2 layers. In the first layer, the algorithm will determines whether using outsourcing provides cheaper system costs or using in-house manufacturing. Then, a layout will be generated using memory and artificial intelligence clustering operator. This step will continues until there is no further opportunity to make a product using current layout. At the end of this section the algorithm will checks whether the amount of backorders seems logic or not and if so, the hidden layer is employed to check whether the generated solutions can improve the objective function or they can escape the local optimum. Then, the neuron will be considered activated. In the next step the bias is calculated for the neuron to update the learning function to find the quota of memory and artificial intelligence operators. The same approach will be carried out until maximum number of epochs.

3.1. First layer

The first layer is provided to determine a set weight for part routes for in-house manufacturing, outsources values to use subcontractor’s services and backorders that shows insufficient capacity of system in fulfilling a demand (figure 2). \( X_k^e \) represents the \( k^{th} \) neuron in \( e^{th} \) epoch; \( x_i \) shows the weight of in-housing the first product, \( o_i \) is the amount of outsourcing for \( i^{th} \) subcontractor, \( b_j \) represents the amount of backorder of the \( j^{th} \) product as well. During processing steps, each neuron must pass two threshold values. The first threshold value is set to check if the generated neuron \( X \) use

\[ \text{Suppose } X_k^e(x_1, x_2, ..., x_i; o_1, o_2, ..., o_i; b_1, b_2, ..., b_i) \text{ is the } K^{th} \text{ neuron in } E^{th} \text{ epoch.} \]
\[ \text{If } b(X_k^e) > A B \text{; } \forall \text{ } k \in i; \text{ } t \in T \text{ Then } T_1 = 0 \text{ (the solution is rejected)} \] 

3.1. Hidden layer and activating a neuron

Afterward, the amount of the total system costs for the generated neuron and minimum total system cost of the best solution will be compared. If this value exceeded than the objective function of the best observed neuron so far, the second threshold value check will reject the solution. Otherwise, the neuron will be ready to be activated which means the neuron will be allocated in tournament list for next epoch as indicated in figure 4.

\[ \text{a) Suppose } X_k^e(x_1, x_2, ..., x_i; o_1, o_2, ..., o_i; b_1, b_2, ..., b_i) \text{ is the } k^{th} \text{ neuron in } e^{th} \text{ epoch.} \]
\[ \text{b) If } F(X_k^e) < \min \left( F(X_{l1}^e), F(X_{l2}^e), ..., F(X_{lK}^e); F^*(X_{lK}^e+) \right) \text{ or } Y \leq LE P \]

Then \( T_2 = 1 \) (the solution is accepted)

In figure 4, the threshold value will receive 0 if the generated neuron carry’s backorders more than what allowed as inputs which means the neuron is not allowed to continue rest of the process. Otherwise, the threshold value will be 1 which means that the neuron does not have extra backorders and can follow the rest of the process.

3.2. Fitness function operator

For the heuristics and metaheuristics that designed to solve the mathematical model that developed, the objective function of each proposed model will be used as fitness function operator. Hence, the objective functions of the developed model in section 3.3 will be used as fitness function which are presented in equations 4 to 9.
Then each solution will be evaluated if it can improve the minimum total system costs observed so far. If so, the MLP will consider it as a member of tournament list.

a) Suppose \( X_{k}^{itr}(x_1, x_2, ..., x_i; o_1, o_2, ..., o_i; b_1, b_2, ..., b_i) \) is the \( k^{th} \) solution in \( itr^{th} \) epoch.

b) If \( F(X_{k}^{itr}) \leq \min\{F(X_{1}^{itr}), F(X_{2}^{itr}), ..., F(X_{k-1}^{itr}), F_{best}(X_{k-1}^{itr-1})\} \quad \forall \ k \in i \) \( (31) \)

c) Then, Tournament.list\(_{m+1} = X_{k}^{itr} \) (suppose the tournament list already has \( m \) members) \( (32) \)

### 3.3. Performance function

The performance function value is the most ideal value for total system cost gained so far. It is a border to determine the quality of the coming neurons in a way that if a neuron can pass the performance function value that gained so far, it will be a better schedule for the system. In following equations the learn parameter is a value of \( \alpha \) for next epoch.

a) Suppose \( X_k^e(x_1, x_2, ..., x_i; o_1, o_2, ..., o_i; b_1, b_2, ..., b_i) \) is the \( k^{th} \) neuron in \( e^{th} \) epoch.

b) \( F(X_k^e) < \min\{F(X_1^e), F(X_2^e), ..., F(X_{k-1}^e), F_{best}(X_{k-1}^{e-1})\} \) \( (33) \)

Then: \( \text{PERF.FCN} = F(X_k^e) \) \( (34) \)

The performance function value will then use to modify the training rate which will be explained next.

C) \( \text{LEARNPARAM}_{k+1} = \text{LEARNPARAM}_k + \left(\frac{\text{BIAS}_k}{\text{PERF.FCN}_k}\right) \) \( (35) \)
3.4. Bias

Bias shows the different earned values and what expected. Generally a simple formula for bias can be written as:

\[ X_{\text{expected}} = X_{\text{earned}} + \text{Bias}_{\text{earned}} \]  

(36)

For the proposed model, the bias is formulated by considering the performance function and the earned values for the total system costs in an epoch. The performance function is not fixed and will be updated in every epoch according to the best observed objective function.

a) Suppose \( Performance\_func_k^e = F(X_k^e) \)  

(37)

b) \( \text{Bias}_k^e = Performance\_func_k^e - F(X_k^e) \) \( \forall \, e, k > 1 \)  

(38)

3.5. Learning function

In this research, a typical Conjugate Gradient method is used. The proposed learning function is an integrated concept of memory and clustering functions. In fact the amount of bias for each neuron shows the amount of using artificial intelligence or relying on the memory for coming neurons as shown. The first operator, which is the memory operator, is inspired from the Tabu Search algorithm. The other operator that is called artificial intelligence operator for clustering remained machines after using memory function. While a neuron is to generate, the amount of memory parameter (\(\alpha\)) shows relying on memory operator and the \((1 - \alpha)\) shows the amount of relying of artificial intelligence operator. Employing this method helps the algorithm to use the good information which is achieved previously and at the same time use artificial intelligence to improve the created neuron. The function of the artificial intelligence operator is based on finding the best location for remained machines (those machines that are not allocated using memory operator) in a way that strong block diagonals can be emerged to strengthen part routings.

a) Suppose \( X_k^e(x_1, x_2, ..., x_i; o_1, o_2, ..., o_j; b_1, b_2, ..., b_l) \) is the \( k^{th} \) neuron in \( e^{th} \) epoch.

b) If \( F(X_k^e) > \min (F(X_1^e), F(X_2^e), ..., F(X_{k-1}^e); F^*(X_{k-1}^e)) \) ; \( \forall \, k \in i \)  

Then \( LEARNING\_PARAM_{k+1} = LEARNING\_PARAM_k + (\text{Bias}_k \cdot \text{PERFFCN}_k) \) (for next epoch)  

(40)

c) \( X_{k+1}^e = LEARNING\_PARAM_{k+1}(X_k^e) + (1 - LEARNING\_PARAM_{k+1}) \cdot (X_k^e) \)  

(41)

3.6. Number of neurons and epochs

Number of neurons in epoch is a pre-determined value which shows number of solutions must be completed in epoch. Number of epochs shows the number of epochs that must be passed through the searching process. It is obvious that large number of neurons in epoch increases the accuracy of the solving algorithms but at the same time it increases the time of computations. So it must be chosen in a logic manner. For the experiments in this research 3 levels of number of neurons and epochs is considered for small size, medium size and large scale problems. However the more accurate input values for parameters will be estimated using design of experiments.

3.7. Stopping criteria

The stopping criteria in the proposed MLP algorithm are set as:

1) Reaching to maximum number of pre-defined epochs.
2) If there is no choice in tournament list in epoch which means none of the solutions in the epoch can improve the fitness function so there will be no choice for improving the algorithm.

a) Suppose \( X_{k}^{itr}(x_1, x_2, ..., x_i; o_1, o_2, ..., o_j; b_1, b_2, ..., b_l) \) is the \( k^{th} \) solution in \( itr^{th} \) epoch.

b) If \( F(X_k^{itr}) > \min (F(X_1^{itr}), F(X_2^{itr}), ..., F(X_{k-1}^{itr}); F^*(X_{k-1}^{itr})) \) ; \( \forall \, k \in i \) Then \( Tournament\_list^{itr} = \emptyset \)  

(44)

4. Results and Discussion

4.1. Solving algorithms using datasets from the literature

In this research solved each experiments 50 times. In continue, to verify the proposed hybrid metaheuristic, 17
experiments are solved with data gathered from literature. The results are then compared with results of branch and bound and simulated annealing algorithm as shown by table 1. Figure 5 shows the minimizing process for some experiments in table 1.

![Fig. 5 The objective function graph of MLP-SA method for experiment number 14 in table 8](image)

In this figure, the horizontal axis indicates number of epochs which is required in searching process. The vertical axis is used to show the values of objective function of the model that is achieved in each epoch.

| Scale | No. | Problem Source | K | I | m | j | L | T | C.S | NOP | BnB | MLP-SA | Min | R | Average |
|-------|-----|----------------|---|---|---|---|---|---|-----|-----|-----|--------|-----|---|----------|
| small | 1   | Askin & Huang (2001) | 2 | 2 | 2 | 2 | 4 | 8 | [2 4] | 4454 | 4454 | 4454 | 0 | 4454 |
|       | 2   | Askin & Huang (2001) | 2 | 2 | 4 | 2 | 2 | 4 | 20 | [3 6] | 6304 | 6304 | 6304 | 0 | 6304 |
|       | 3   | Suer & Cedeno (1996) | 1 | 4 | 4 | 4 | 4 | 4 | 15 | [3 2 3 2] | 19550 | 19550 | 19550 | 0 | 19550 |
|       | 4   | Askin & Huang (2001) | 8 | 2 | 2 | 2 | 2 | 4 | 4 | [14 6] | 1245 | 1245 | 1245 | 0 | 1245 |
|       | 5   | Askin & Huang (2001) | 8 | 2 | 2 | 2 | 2 | 4 | 4 | [8 8] | 1355 | 1355 | 1355 | 0 | 1355 |
|       | 6   | Mahdavi et al. (2010) | 2 | 4 | 4 | 4 | 4 | 2 | 20 | [4 5 3 6] | 21155 | 21130 | 21130 | 25 | 2142 |
|       | 7   | Mahdavi et al. (2012) | 4 | 4 | 4 | 4 | 4 | 16 | [4 3 6 5] | 7030 | 6870 | 6870 | 160 | 6950 |
| medium | 8   | Aryanezhad et al. (2009) | 3 | 3 | 3 | 3 | 3 | 3 | 20 | [5 4 5] | 2750 | 2520 | 2520 | 230 | 2635 |
|       | 9   | Aryanezhad et al. (2009) | 5 | 4 | 5 | 5 | 4 | 4 | 8 | [4 3 2 3 3] | 5650 | 5543 | 5543 | 107 | 5596.5 |
|       | 10  | Aryanezhad et al. (2009) | 4 | 5 | 5 | 5 | 5 | 4 | 12 | [2 4 3 4 4] | 5571 | 5638 | 5571 | -67 | 5604.5 |
|       | 11  | Li et al. (2012) | 2 | 5 | 5 | 5 | 5 | 4 | 15 | [3 5 4 2 3] | 10657 | 10535 | 10535 | 122 | 10596 |
|       | 12  | Mahdavi et al. (2012) | 2 | 5 | 5 | 5 | 5 | 4 | 15 | [7 8 5 9 4] | 5706 | 5219 | 5219 | 487 | 5462.5 |
|       | 13  | Mahdavi et al. (2010) | 2 | 6 | 6 | 6 | 6 | 3 | 20 | [5 4 3 6 5 4] | 10319 | 10308 | 10308 | 11 | 10313.5 |
|       | 14  | Norman et al. (2002) | 2 | 6 | 6 | 6 | 6 | 5 | 14 | [3 5 2 4 3 4] | 9455 | 9185 | 9185 | 270 | 9320 |
|       | 15  | Askin & Huang (2001) | 2 | 8 | 6 | 6 | 8 | 4 | 30 | [3 2 2 3 2 3] | 15297 | 15237 | 15237 | 60 | 15267 |
|       | 16  | Askin & Huang (2001) | 2 | 8 | 8 | 8 | 8 | 4 | 20 | [2 4 3 5 4 2] | 17858 | 17457 | 17457 | 401 | 17657.5 |
|       | 17  | Aryanezhad et al. (2009) | 5 | 5 | 5 | 5 | 5 | 5 | 30 | [4 3 4 3 3] | 6221 | 6204 | 6204 | 17 | 6212.5 |

4.2. Discussion on evaluating and reducing impact of cost uncertainty considering machine unreliability in D-CMS

The capacity of machines should not be ignored during scheduling of cellular systems since it may affect system capacity. Comparing results in table 3, it can be found that that while machine broken is considered, the system costs increases noticeably. In this section, it is shown that using preventive maintenance plan in the CMS model can effectively reduce the cell lad variation. The proposed method follows the principle that the likelihood of machine
failure will be declined by using preventive plans. Therefore in the beginning of planning periods, the applicable periodic services will be carried out for machines based on their needs that defined by the decision maker which will reduce the possibility of the machine broken. Then, during the part routing process, the solving algorithm will check if selected machines are broken or not. If so, those machines will be removed from the candidate list. Table 3 shows the results of using preventive services with and without using preventive actions. Note that calculating the exact impact of reducing the failure rate of each machine is depended on the type of machine, historical records of failures and the environment that machines are employed which is out of the scope of this research. Since then the decreasing rate is assumed 0.5. Noted that no cell load is observed in problems 8, 14 and 16 so they do not appear in table 3.

| No | Cell load variation without preventive plan | Total | Cell load variation with preventive plan | Total | % Improve. |
|----|--------------------------------------------|-------|---------------------------------------|-------|------------|
| 1  | 1.265; 7.5; 15.037; 8.133;                 | 31.935| 14.751; 1.884; 7.75;                  | 24.385| 11.50      |
| 2  | 43.52; 7.403; 12.469; 16.664; 10.399;      | 90.455| 12.587; 16.217; 11.026; 8.419; 6.717; | 5.3; 5.3; 82.23 | 13.04      |
| 3  | 6.748; 5.895; 2.386; 0.321;               | 15.35 | 2.302; 4.534; 6.965; 9.102;           | 22.903| 13.04      |
| 4  | 3.551; 4.521; 0.808;                      | 8.88  | 4.459; 4.461;                         | 8.92  | 18.03      |
| 5  | 1.47; 1.47; 10.099; 4.929; 16.107; 4.623; | 38.698| 14.397; 14.397; 12.599; 13.604; 21.34; 0.507; | 77.15 | 11.50      |
| 6  | 2.87; 1.677;                             | 4.547 | 1.183;                                 | 1.183 | 15.25      |
| 7  | 0.419; 5.752; 1.917; 3.27; 6.26; 4.36; 11.132; 33.11 | 5.504; 1.875; 2.08; 1.823; 0.662; 3.188; 0.188; 12.613; 0.695; | 28.628 | 15.97      |
| 9  | 1.186; 8.769; 2.067; 0.139; 9.712; 2.357; | 28.535| 0.391; 10.297; 1.774; 1.112; 1.689;   | 15.263 | 17.36      |
| 10 | 1.972; 1.745;                           | 3.717 | 0.937;                                 | 0.937 | 15.97      |
| 11 | 0.556; 1.423; 3.206; 6.491; 0.446; 1.387; | 25.726| 0.8072; 0.603; 1.029; 0.029; 8.877; 5.252; 0.12; 16.7172 | 18.70 |           |
| 12 | 3.645; 0.322; 1.183; 1.006; 1.417; 1.079; | 9.765 | 4.933; 8.183; 6.726;                   | 19.842 | 15.97      |
| 13 | 1.113;                                 |       |                                        |       |
| 15 | 1.174; 0.169; 2.25;                      | 3.593 | 0.803; 0.803;                          | 1.606 | 9.91       |
| 17 | 8.174; 4.396; 1.304; 2.956;             | 16.83 | 1.429; 2.25; 1.518; 4.787; 2.633;      | 12.617 | 20.00      |

5. Conclusion

This paper presents an applicable method for scheduling dynamic cellular manufacturing systems in the presence of the cost uncertainty. The main objective of the research is evaluating the impact of uncertain cost on material transferring in dynamic CMS. For this purpose, a mathematical model is developed for determining best part routes considering different product demands in planning periods. Since the model has potential to trap in local optima, a hybrid Multi-layer Perceptron and Simulated Annealing is proposed which can effectively solve the experiments. In continue by increasing costs in different planning periods, impact of changings costs in material transferring are evaluated. It is shown that in the mentioned condition, closer set of required machines for producing a product are employed more than other parallel machines. This phenomenon can cause increasing the machine loads in such cells and may lead to machine load variation in set of closer machines. Such temporarily distortion may cause long queues in front of some machines while other parallel machines are remained idle. It is observed that inflation rate which is consider as an important cause for cost uncertainty (increasing, decreasing or wavy ways) can strengthen such distortion and hence should not be ignored in scheduling cellular systems. It is shown that proposing method can effectively reduce cell load variations in different experiments. In addition, wherever possible, it is recommended to fill out the voids by relocating the machines from far locations. However, choosing appropriate machines for relocating and filling up the voids can reduce the system costs as described before. It is found that the location of machines is an important factor in reducing the machine load and cell load variations accordingly.

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