Dynamic Cell Formation based on Multi-objective Optimization Model

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Abstract—In this paper, a multi-objective model is proposed to address the dynamic cellular manufacturing (DCM) formation problem. This model considers four conflicting objectives: relocation cost, machine utilization, material handling cost and maintenance cost. The model also considers the situation that some machines could be shared by more than one cell at the same period. A genetic algorithm is applied to get the solution of this mathematical model. Three numerical examples are simulated to evaluate the validity of this model.

Index Terms—Dynamic Cell Formation, Machine Sharing, Relocation Cost, Machine Utilization, Material Handling Cost, Maintenance Cost

I. INTRODUCTION

Traditional Cellular Manufacturing (CM) formation models usually have the assumptions that the demand and the mix/composition of the product are constant. When the demand of products fluctuates frequently, the current cell formation may not be optimal for other periods. Dynamic Manufacturing Cells (DMC) are put forward because they are easy to reorganize and suitable to the fluctuant markets. Consequently, planning horizons of Dynamic Cellular Manufacturing System (DCMS) should be divided into smaller periods. Each period is different from the other periods because they have different product mix and demands. At the beginning of each period, the manufacturing system may be reorganized. The reconfiguration includes part families and machine groups. The DCMS overcomes the disadvantages of CM system and attains the optimal configuration during most periods [1]. The reconfiguration of machine groups involves adding new machines to cells, removing existing machines from cells, changing the location of the cell and so on.

The frequent change of dynamic manufacturing cells could be uneconomical. Therefore, a mathematical model is needed to design/redesign cells in a multi-period planning horizon.

Dynamic Cell formation (DCF) is the first and most important step in the process of designing a dynamic cellular manufacturing system. In most of the DCMS models, numerous assumptions have been made. One of the most important assumptions is to assume that there is no sharable equipment. In violent market competition, many manufacturers apply the make to order production policy. Multi-varieties and small batch production are becoming the major production mode for the manufacturers. This mode requires the manufacturers have flexible manufacturing systems. It requires the manufacturing systems have enough capacity to adjust their production to fluctuant customers’ requirements.

There are many studies address the dynamic cell formation problem. Recent studies mainly focus on multi-objective cell formation problems under conditions of a multi-period planning horizon. Many models have been proposed with the aim of minimizing costs such as machines reallocation, intercellular/intracellular material handling, reconfiguration and inventory holding. Some studies put the emphasis on the tradeoff between part internal productions with part outsourcing in dynamic cell formation problem. Also, there are studies discuss the process batch size, transfer batch size for intercellular movements and transfer batch size for intercellular movements. Most DCF models suppose the manufacturing systems have enough machines and each type of machines is assigned to no more than one cell in a period. The manufacturing system cannot reassign those machine resources to other manufacturing cells when they are no longer needed in the current period. These machines stay in the manufacturing cells until the next period. But, it is impossible for enterprises to have enough amounts of these equipments. However, some expensive, rare or large equipment in manufacturing systems are needed by different kinds of parts. Idle machines also have serious negative impact on machine utilization.

In this paper, a multi-objective model of DCF which considers the machine sharing is proposed. Many factors are included in solving dynamic cell formation problem. Manufacturing cell reconfiguration is an effective method to make the manufacturing system adjust to the dynamic environment. The material handling cost is a big part of the production cost. The material cost includes intercellular material cost and intracellular material cost. Machine utilization and maintenance cost have been defined as two important factors when we evaluate the performance of a manufacturing system. The objectives of this model are relocation cost, machine utilization, material handling cost and maintenance cost. This model encourages machine sharing. The capacity of sharable machine is cut into fragments only on the logic level. Capacity fragments are assigned to manufacturing cells.
when the manufacturing cells reorganized. A genetic algorithm is applied to solve this nonlinear multi-objective model. Three examples are given to evaluate the validity of the model.

The structure of this paper is as follows: in 'Problem description and formulation', DCM model is described; in 'Implementation and experimental analyses', the GA algorithm to solve the model is presented and three numerical examples are tested; in the section ‘Conclusion’ a summary and future work are presented.

II. RELATED WORK

The concept of DCMS was first illustrated by Rheaul et al. [2]. Before this, many researches have been done for cell formation problem in uncertainty markets. Askern and Subramantan propose a three-phase method which considers the costs of the work-in-process and the inventory cycle, intra-group material handling, set-up times, and variable and fixed machine processing time costs. Firstly, part types are rendered based on process similarity. Secondly, it combines adjacent part types into groups to reduce machine requirements. Finally, it combines groups in the way that CM system can make the best use in set-up, work-in-process and material handling [3]. Shaw and Rogers develop a multi-objective models considering three different situations: (1) setting up a new system and purchasing all new machines to system, (2) reorganizing the system with existing machines, and (3) reorganizing the system with existing machines and some new machines [4]. Stoker and Yu approach at two-phase procedure considering duplicating bottleneck machines in CMS [5].

Thai and Lee present a multi-functional MP model. The model incorporates CF models and can be used in many situations [6]. Tavakkoli-Moghaddam et al. approach a mathematical model to solve the layout problem in cellular manufacturing systems. The model considers stochastic demands by minimizing the total costs of intercellular and intracellular movements [7]. Miranda and Safaei propose a nonlinear integer model of cell formation problem under dynamic conditions. They apply a neural approach based on mean field theory to solve the model. In this approach, the network weights are updated by an interactive procedure [8]. Manhattan and Javadian present a mathematical model of the facility layout problem in cellular manufacturing systems. The objective includes minimizing the total costs of intercellular and intracellular movements in both machine and cell layout problems [9]. Goncalves and Resende present an approach which combines local search heuristic with a genetic algorithm to solve machine cells and product families’ formation problems [10]. Radhakrishnan and Cheng discuss cellular manufacturing under the condition of changing product demand and resource [11]. Pilularia and Subbaraoa present a new approach (robust design) of part families and machine cells formation. The changes in demands and product mixes can be handled without any relocation by adopting this approach. This method considers a multi-period forecasting of product mix and demand and determines the cell formation by the results of the forecasting [12]. Kioon et al. present and analyze a comprehensive model of cellular manufacturing systems design problem. The model involves alternate process routings, operation sequence, duplicate machines, machine capacity and lot splitting [13]. Lokesh and Promod present a comprehensive model for the cellular manufacturing systems formation. The model integrates the cell formation problem, the machine allocation problem and the part routing problem. On top of this, they adopt a methodology based on both genetic algorithm and large-scale optimization techniques to solve the model [14]. Deference and Chen put forward a comprehensive mathematical model for the design of CMS which considers tooling requirements of the parts and tooling available on the machines. Their model integrates dynamic cell configuration, alternative routings, lot splitting, sequence of operations, multiple units of identical machines, machine capacity, workload balancing among cells, operation cost, cost of subcontracting part processing, tool consumption cost, setup cost, cell size limits and machine adjacency constraints [15]. Wu et al. propose a hierarchical genetic algorithm to solve the problem of manufacturing cells formation and the group layout of a CMS simultaneously [16]. Most of these models have a strong constraint that the needs of products are fixed over long periods. In today’s dynamic environment, the demands of parts can change very quickly.

Iraj Mahdavi et al. present an integrated mathematical model for the multi-period cell formation and production planning problem in a dynamic cellular manufacturing system. The purpose of this model is to minimize the total costs of machines, inter/intra-cell movement, reconfiguration, partial subcontracting, and inventory carrying. The trade-off between the costs of production in cell and outsourcing with cell reconfiguration is also discussed [17]. Chen proposes a mathematical model aiming to minimize the cell reconfiguration and machine constants costs in DCMS. This model also considers upper/lower bounds of cell size limitation and constant number of cells [18]. Wicks and Reasor address a model of part family/machine/cell formation problem. They address the dynamic nature of the production environment by considering a multi-period forecast of product mix and demand during the formation of part families and machine cells [19]. Balakrishnan and Cheng put forward a two-phase method to solve machine assignment problem and dynamic cell reconfiguration problem. The model considers demand fluctuations. The objectives include minimizing material handling and machine relocation costs [20]. Tavakkoli-Moghaddam further Chen’s study by considering alternative process plans, sequence of operations, machine capacity limitation and machine replication. Also, the model assumes the inter-cell movements perform in batches with the same cost. Their objectives include minimizing the total costs of machine constant/variable, inter-cell movement and cell reconfiguration [21]. Saeed Mehrabad and Safaei further Tavakkoli-Moghaddam’s study. The
model assumes the numbers of formed cells at each period are fluctuant [22].

The complexity of this algorithm has a strong impact on runtime efficiency. Fang Wan et al. present a new simplification algorithm named EQEM. This algorithm can simplify geometry model with texture [23]. Keshou Wu et al. propose a grid distributed parallel authentication model. The adoption of this model could realize simultaneous verification of grid authentication and grid behavior on upper layer of SSL and TLS protocols [24]. Ke Xu et al. a group detection algorithm for mining interesting groups in a Campus Mobile Social Network [25].

III. PROBLEM DESCRIPTION AND FORMULATION

A. Problem Descriptions

In this section, the DCF problem is illustrated as a nonlinear multi-objective programming model. The problem is formulated under the following assumptions:

B. Assumptions

The model’s assumptions are as follows:

(1) It is assumed that the parts moves in batches,
(2) The size of each batch is given;
(3) The demand of the parts is unknown but the capacity of the manufacturing can fulfill the demand;
(4) The parts can be processed at more than one type of machines;
(5) The machines can process more than one type of parts;
(6) The range of the number of the cells is given;
(7) Machine sharing is considered.

C. List of Symbols

Notations for the problems:
Indices:

\( j \) : index for part types \((j = 1, 2, ..., J)\);
\( i \) : index for operations \((i = 1, 2, ..., I)\);
\( k \) : index for machine types \((k = 1, 2, ..., K)\);
\( l \) : index for cells \((l = 1, 2, ..., L)\);
\( t \) : index for time periods \((t = 1, 2, ..., T)\);

Parameters:

\( S_k \) : cost of add machine type \( k \) to a cell;
\( R_k \) : cost of remove machine type \( k \) from a cell;
\( A_k \) : capacity of add machine type \( k \);
\( B_j \) : batch size of part type \( j \);
\( D_j \) : demand of part type \( j \) during period \( t \);
\( O_{jk} \) : cost of process part type \( j \) on machine type \( k \);
\( m_{jk} \) : maintenance cost of machine type \( k \) in cell \( l \);
\( IE_{ij}^{inc} \) : intercellular material handling cost per time;
\( IE_{i}^{inc} \) : intracellular material handling cost per time;
\( W \) : maximum number of machines in a cell;

Decision variables:

\( \alpha_{jk} = \begin{cases} 1, & \text{if operation } i \text{ of type } j \text{ is processed on machine type } k; \\ 0, & \text{otherwise} \end{cases} \)

\( \lambda = \begin{cases} 1, & \text{if the current period is the first period;} \\ 0, & \text{otherwise} \end{cases} \)

D. Four Major Objectives of DCF

Some objectives should be taken into consideration when it comes to the problem of DCF. In this paper, four objectives are considered: (1) minimizing the machine relocation cost; (2) maximizing the machine utilization rate; (3) minimizing the material handling cost; (4) minimizing the maintenance cost.

1) Machine relocation cost

The introduction of new products introduction may cause the change of product demands. Dynamic manufacturing cells can be reorganized at each period if there are changes. Then the optimal formation of the manufacturing cells should be changed according to the change of product variation. But the frequent changes of the machines in different cells may result in high costs. Therefore, it is necessary to minimize the total cost of the cell reconfiguration.

\[
\min f_i(x) = \sum_{i=1}^{I} \sum_{l=1}^{K} \sum_{k=1}^{K} (S_k Y_{lk} + R_k Z_{lk}) \tag{1}
\]

Subject to:

\[
X_{l,k,t-1} + Y_{lk} - Z_{lk} = X_{lk}, \forall k,l,t = 2, ..., T \tag{2}
\]

\[
Y_{lk} = \max \{ \lambda(X_{lk} - X_{l,k,t-1}), 0 \}, \forall k,l,t = 2, ..., T \tag{3}
\]

\[
Z_{lk} = \max \{ \lambda(X_{lk} - X_{l,k,t-1}), 0 \}, \forall k,l,t = 2, ..., T \tag{4}
\]

\[
\sum_{k=1}^{K} X_{lk} \leq W, \forall l,t = 2, ..., T \tag{5}
\]

\[
X_{lk}, Y_{lk}, Z_{lk} \in \{0, 1, 2, ..., \}, \forall k,l,t = 2, ..., T \tag{6}
\]

The objective function is given in Eq. (1) comprises two cost terms. The first term is the cost of adding the new machine to the cells at the beginning of each period. The second term is the machine removing costs at the beginning of each period. Eq. (2) means the balance of machines at the current period with the former period. Eq. (3) and (4) mean the peak number of machines added and
removed in each period. Eq. (5) states the value range of the number of machines in each period. Eq. (6) means the integrality requirement.

2) Machine utilization rate

Low machine utilization rate will raise the cost of the production. In addition, it will prolong the production cycle time. Many organizations have started adopting many methods to reduce production cost through improve machine utilization. In this paper, the optimization of machine utilization is considered. The mathematical model of the machine utilization can be expressed by above defined notations:

\[
\min f_2 = \sum_{k=1}^{K} \left( \frac{1}{\sum_{i=1}^{I} \sum_{j=1}^{J} D_{ij} C_{ik}} \right) \tag{7}
\]

Subject to:

\[
\sum_{i=1}^{I} \sum_{j=1}^{J} D_{ij} C_{ik} \leq \sum_{l=1}^{L} A_l X_{kl} \quad \forall k, t = 2, ..., T \tag{8}
\]

The objective function is given in Eq. (7) ensures some particular machines’ utilization takes higher proportions of the total utilization rate. The constraint ensures the manufacturing capacity is sufficient.

3) Material handling cost

Intracellular and intercellular material handling costs consist of the total material handling cost. In Dynamic Cellular Manufacturing Systems, intracellular material handling accounts for a very high share of total material handling cost. Reducing the martial handling cost is considered in this paper. The mathematical model of the material handling cost can be expressed by above defined notations:

\[
\min f_3 = \frac{1}{2} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{l=1}^{L} \sum_{k=1}^{K} \left[ \frac{D_{ij}}{B_j} \left( \left[ \sum_{k=1}^{K} U_{i,j,k,l} (1 - U_{i,j,k,l}) \right] I_{E,\text{intr}} \right) \right.
\]

\[
+ \frac{1}{2} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{l=1}^{L} \sum_{k=1}^{K} \left[ \frac{D_{ij}}{B_j} \left[ \left( \sum_{k=1}^{K} U_{i,j,k,l} V_{i,j,k,l} - \sum_{k=1}^{K} U_{i,j,k,l} V_{i,j,k,l} \right) I_{E,\text{intr}} \right) \right) \tag{9}
\]

Subject to:

\[
\sum_{j=1}^{J} U_{i,j,k,l} \alpha_{jk} = 1, \forall i, j, l, k, t \tag{10}
\]

\[
0 \leq X_{kl} \leq W, \forall l, k, t \tag{11}
\]

\[
U_{i,j,k,l}, V_{i,j,k,l} \in [0,1], \forall j, l, k, t \tag{12}
\]

The objective function is given in Eq. (9) minimizes the total material handling cost of the system. The constraint Eq. (10) means if operation \( l \) of part type \( j \) is assigned to one cell. Machine type \( k \) for operation \( i \) of part type \( j \) is also assigned to the cell. Eq. (11) means the peak number of machines. Eq. (12) means the integrality requirement.

4) Maintenance cost

The maintenance cost is an important factor of the total operational cost. It is also an index of the production system performance. Their values depend on the system structure as well as the utilization of the machines. In DCMS, the maintenance cost is influenced by the reconfiguration due to the frequent add and remove of alternative cells. Sharing machines will increase the maintenance cost. The mathematical model of the maintenance cost is presented as follows:

\[
\min f_4 = \sum_{i=1}^{I} \sum_{j=1}^{J} m_{i,j} X_{i,j} \tag{13}
\]

Subject to:

\[
\sum_{i=1}^{I} \sum_{j=1}^{J} m_{i,j} X_{i,j} \leq W, \forall l, k, t = 2, ..., T \tag{14}
\]

\[
X_{i,j} \in \{0,1,2,...\}, \forall k, l, t = 2, ..., T \tag{15}
\]

Eq. (14) states the valuerange of the number of machines in each period. Eq. (15) means the integrality requirement.

IV. SOLVING DCF USING GENETIC ALGORITHM

Since traditional methods cannot be used to solve such nonlinear multi-objective model as DCF, we use Genetic Algorithm (GA) [2], to solve our proposed machine shareable dynamic cell formation model. In the development process of GA, the solution representation and objective value evaluation are the two most significant factors. And we will discuss them in this section.

A. Encoding of Solution

In the GA algorithm, the encoding of a solution is the core of the algorithm. And in our model, the encoding should represent the assignment of the machines and their numbers in each cell in each period.

<table>
<thead>
<tr>
<th>TABLE I.</th>
<th>THE ENCODING OF A SOLUTION AT PERIOD ( t )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( l )</td>
<td>( n_1 ) ( n_2 ) ( n_3 ) ( n_4 ) ( n_5 )</td>
</tr>
</tbody>
</table>

More specifically, let’s consider the problem with \( T \) periods, \( K \) machines, and \( L \) cells. Then, each solution will consist of \( T \) segments; and each segment, as shown in Table 1, represents the encoding of the solution at period \( t \). Each segment includes two parts: the assignment of the machines to the cell and the number of machines in each cell in this period. Since in our model, some machines can be shared into different cells, the machines should be divided into two parts. As in Fig. I, if machine type \( k \) is un-shareable, we use \( l_k \) to denote the cell number that machine type \( k \) is assigned to; otherwise, if machine type \( m \) can be shared in \( N \) cells, we use \( l_{m1}, l_{m2}, ..., l_{mN} \) to denote, respectively, \( N \) cell numbers that machine type
has been assigned to, where \( N \) represents the maximum number of cells that machine type \( m \) can be shared. Accordingly, \( n_i \) and \( n_m \) represent the number of un-shareable machine type \( k \) and shareable machine type \( m \) assigned to the cell \( l_i \) and \( l_m \), respectively. This solution encoding style can meet all the constraints in our model except Eqs. (5), (8), (11) and (14).

### B. The Total Objective of DCF

Since four objectives in our DCF model are conflicted, and furthermore, every object has different magnitude, it is unreasonable to evaluate a solution using the direct summation of \( f_1, f_2, f_3 \) and \( f_4 \) (as defined in Eqs. (1), (7), (9) and (13)). Therefore, in this paper, we adopt and modify the global criteria method [21] to derive a total objective function of DCF as follows:

\[
F_{\text{total}} = \sum_{i=1}^{I} w_i \left( f_i - f_i^{\text{min}} \right) \frac{f_i^{\text{max}}}{f_i^{\text{max}} - f_i^{\text{min}}},
\]

(16)

where \( f_i \) is the \( i^{\text{th}} \) objective function value of a solution, as defined in the previous subsection; \( f_i^{\text{min}} \) and \( f_i^{\text{max}} \) denote the value of ideal solution and anti-ideal solution of the \( i^{\text{th}} \) objective function, respectively; and \( w_i \) represents user-defined weight of the \( i^{\text{th}} \) objective function which reflects the importance of each objective function. The ideal (resp. anti-ideal) solution is the minimum (resp. maximum) values for each objective function while meeting relative constraints. The ideal and anti-ideal solutions are not used for searching an efficient solution but for measuring the quality of generated solutions [21].

In addition, in order to meet the constraints in Eqs. (5), (8), (11) and (14), from the first to the fourth objective functions, given in Eqs. (1), (7), (9) and (13) are respectively, transformed into Eq. (17) and Eq. (18) as follows:

\[
f'_i = f_i + p_1 \sum_{j=1}^{J} \sum_{k=1}^{K} \max \left( \sum_{k=1}^{K} X_{ik} - W_i, 0 \right), \quad \text{with } i = 1, 3, 4
\]

(17)

\[
f'_j = f_j + p_2 \sum_{i=1}^{I} \max \left( \sum_{j=1}^{J} D_{ij} O_{ij} - \sum_{k=1}^{K} A_{ik} X_{ik}, 0 \right).
\]

(18)

where parameters \( p_1 \) and \( p_2 \) are used to scale the penalty terms corresponding to the constraints in Eqs. (5, 8, 11 and 14). Usually, these two parameters are set to be very large numbers.

### C. The Sub-optimization of Material Handling Cost

Since in our model, some kinds of machines can be shared in different cells, when the machine assignment has been determined, we need another sub-optimization process to decide the cells in which the operation \( i \) of part type \( j \) is assigned to produce. Also, as shown in equation (9), our material handling cost consists of two different costs: inter-cell move cost and intra-cell move cost. Thus, this sub-optimization problem can be transformed to the problem of finding the shortest path in a weighted directed graph. In our experiments, we use the standard Dijkstra algorithm to solve this shortest path problem.

Here, we use a solution of a large scale optimization problem as an example to demonstrate the sub-optimization process of our material handling cost. In this example, as shown in Table 1, the number of machine types, cells, and operations are set to be \( K = 10, L = 4, I = 5 \), respectively. For ease of presentation, we use \( M_i \) to denote the \( k^{\text{th}} \) machine type. In the example, the machine types from \( M_1 \) to \( M_6 \) are un-shareable machine types; and machine types from \( M_7 \) to \( M_{10} \) are shareable machine types. After the outer optimization process, these ten types of machines are installed into four cells, as shown in Fig. 1. Noted that, because machine types from \( M_1 \) to \( M_6 \) are un-shareable, each of these machine types are only appeared in one cell; but for machine types from \( M_7 \) to \( M_{10} \), they can be shared in more than one cells.

According to the values of parameter \( \alpha_{ik} \), the five operations of the \( 5^{\text{th}} \) part type should be processed on machine types \( M_1, M_2, M_5, M_9, M_5 \). Since machine types \( M_5, M_9 \) and \( M_{10} \) are shareable machine types, we should choose suitable cells for processing the \( 5^{\text{th}} \) part
type in its 2*, 3*, and 4* operations to reduce the material handling cost. Based on the machine locations, as shown in Fig. 2, and the machine types used by the 5* part type, the above sub-optimization process for reducing the material handling cost can be transformed into a shortest path problem as shown in Fig. 2.

In the weighted directed graph in Fig. 2, each layer, each node in the same layer, and each weighted directed edge represent, respectively, the operations of the part type, cells can be used to process the part type in each of its operations, and the inter-cell move cost or intra-cell move cost in the material handling cost. As can be seen in Fig. 2, from the second to the fourth layer (i.e. from the second to the fourth operation), we need to choose a suitable cell to process the fifth part type. Thus, finding a shortest path in this weighted directed graph equals to achieving a minimum material handling cost of this part type under the machine type locations as in Fig. 1. The red path in the graph is the shortest path derived by the Dijkstra algorithm; furthermore, its length is the material handling cost for processing this part type.

V. EXPERIMENTAL RESULTS AND DISCUSSIONS

In this section, three simulation experiments: a small scale, a medium scale and a large scale problem have been performed to evaluate the validity and efficacy of the proposed DCF model. Also, in order to compare the performance between shareable and un-shareable model, the values of the most parameters used in our model are set according to [1].

A. Experimental Parameters Settings

The number of machine types, part types, operations, cells, and periods, can be found in Table 2 in these three experiments. Most of the other parameters defined in subsection 3.1 are generated randomly between given ranges. The cost of adding, removing machines, maintenance cost of machines, capacity of machines, inter-cell and intra-cell materials handling cost, denoted as \( S_k, R_k, m_k, A_k, IE_k^{\text{inter}}, \) and \( IE_k^{\text{intra}} \), are randomly generated in \([2, 5], [0.5, 3.5], [4, 10], [20, 300], [0.1, 0.3]\) and \([0.8, 1.2]\), respectively. The demand of part type \( j \) in period \( t \), and the cost of processing part type \( j \) on machine \( k \), denoted as \( D_{kj} \) and \( O_{kj} \) are all randomly generated in \([0, 1]\). In the small scale experiment, there are 5 machine types, and we assume that machine type \( k_1 \) and \( k_2 \) are shareable machines. And in the large scale problem, among 20 machine types, we assume that machine types from \( k_7 \) and \( k_{20} \) are shareable machines. The combination of weights in the total objective function given in Eq. (16) is set to be \( w_1 = 0.2, w_2 = 0.3, w_3 = 0.3, \) and \( w_4 = 0.2 \), which reflect the importance of each objective and can be changed by users.

B. Experimental Results and Analysis

To compare the performance of our proposed model with those un-shareable machine type models, we conduct two simulations. The first case simulates the situation that some machines could be shared in more than one cell. The second case simulates the situation that all the machine types are allocated to one cell at most.

<table>
<thead>
<tr>
<th>Part/machine/cell/period</th>
<th>5/5/2/2</th>
<th>10/6/3/2</th>
<th>20/10/4/3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Machin e un-shareabl e</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cell reorganization cost</td>
<td>13.4808</td>
<td>56.108</td>
<td>141.9874</td>
</tr>
<tr>
<td>Machine utilization rate</td>
<td>0.3808</td>
<td>0.4627</td>
<td>0.5734</td>
</tr>
<tr>
<td>Material handling cost</td>
<td>1.2618</td>
<td>47.1938</td>
<td>316.478</td>
</tr>
<tr>
<td>Maintenance cost</td>
<td>86.2929</td>
<td>363.2399</td>
<td>849.5706</td>
</tr>
<tr>
<td>Machin e shareabl e</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cell reorganization cost</td>
<td>10.3281</td>
<td>35.4699</td>
<td>75.5454</td>
</tr>
<tr>
<td>Machine utilization rate</td>
<td>0.217</td>
<td>0.2894</td>
<td>0.3842</td>
</tr>
<tr>
<td>Material handling cost</td>
<td>0.1232</td>
<td>3.9667</td>
<td>25.9521</td>
</tr>
<tr>
<td>Maintenance cost</td>
<td>91.5532</td>
<td>474.1037</td>
<td>1167.56</td>
</tr>
</tbody>
</table>

The results of these two simulations are shown in Table 2. From Table 2, we can find that the comparisons of these two simulations, the objectives of the model of considering shareable machine types are much better in total costs. Fig. 3 shows two comparisons between shareable and un-shareable model. Fig. 4 shows the values for each sub-objective functions and the total objective function of large scale simulations during the process.

As can be seen in Fig. 4, when the machine types can be shared by more than one cell, the total objective of our
shareable model is much better than the un-shareable model. And the objectives of machine utilization and material handling cost in shareable machine types are far more superior to the unshareable one.

The shareable machine can be used in more than one cell; their working hours will be extended. Thus, their maintenance costs will increase. When the manufacturing system reorganized, the physical location of the shareable machine may not change. That’s because not every cell changes their formation at each period. So cell reorganization cost in shareable situation is lower than the un-shareable one. If parts processed on shareable machine and moved to next cell in which the shareable machine also be used, the intercellular material handling cost will transfer to the intracellular material handling cost. It will decrease the overall material handling cost.

The reason that machine utilization rate increased can be explained as follows. The machine should immediately be released once the operation is processed. If a machine is assigned to only one cell in one period, the other cells which also need the machine will wait in a queue until the machines are available for the next period.

In the machine shareable systems, there are some other advantages. Firstly, shareable systems can produce more parts. In the case of system capacity is enough; the machine can be shared in two or more cells in one period to achieve higher utilization. Furthermore, the quantities of expensive, rare or large equipments in the manufacturing systems may not be sufficient for each cell. And thus, these kinds of machines should be shared in more than one cell to increase their utilizations.

VI. CONCLUSIONS

This paper addresses the dynamic cell formation problem (DCF) with the consideration of machine sharing. To solve the problem of DCF under the conditions of multi-period planning horizons, a nonlinear multi-objective mathematical model is adopted to deal with the four conflict objectives. Since DCF is a NP-hard problem, a GA algorithm is developed. In order to evaluate the efficiency of the model, three numerical examples are tested. The results show that compared with the situation of the machine type which cannot be shared by more than one cell, the multi-objective result of experiments which simulate machine being shared by more than one cell is much better. The future extension of the study will consider overhead costs at different situations. Also, more analysis of the interferences of the objectives is to be considered.

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