# A Mathematical Approach to the Design of Cellular Manufacturing System Considering Dynamic Production Planning and Worker Assignments

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## ABSTRACT

# A Mathematical Approach to the Design of Cellular Manufacturing System Considering Dynamic Production Planning and Worker Assignments

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Due to increasing international competition, shorter product life-cycles, variable demand, diverse customer needs and customized products, manufacturers are forced from mass production to the production of a large product mix. Traditional manufacturing systems, such as job shops and flow lines, cannot provide such requirements efficiently coupled with flexibility to handle these changes. Cellular Manufacturing (CM) is an alternate manufacturing system combining the high throughput rates of line layouts with the flexibility offered by functional layouts (job shops). The benefits include reduced set-up times, material handling, in-process inventory, better

product quality, and faster response time. The benefits of CM can only be achieved by sufficiently incorporating the real-life structural and operational features of a manufacturing plant when creating the cellular layout. This research presents integrated CM models, with an extensive coverage of important manufacturing structural and operational features.

The proposed Dynamic Cellular Manufacturing Systems (DCMSs) model considers several manufacturing attributes such as multiperiod production planning, dynamic system relocation, duplicate machines, machine capacities, available time for workers, worker assignments, and machine breakdowns. The objective is to minimize total manufacturing cost comprised of holding cost, outsourcing cost, intercell material handling cost, maintenance and overhead cost, machine relocation cost as well as salary, hiring, and firing costs of the workers. Numerical examples are presented to show the performance of the model.

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# LIST OF SYMBOLS

*Sets:*

Index set of part types

$p = \{1, 2, 3 \ldots P\}$

Index set of workers

$w = \{1, 2, 3 \ldots W\}$

Index set of machine types

$m = \{1, 2, 3 \ldots M\}$

Index set of cells

$c = \{1, 2, 3 \ldots C\}$

Index set of time periods

$t = \{1, 2, 3 \ldots T\}$

*Model Parameters:*

| | |
|---|---|
| $D_{pt}$ | Demand for part type $p$ in time period $t$ |
| $V_p^{inter}$ | Intercell movement cost of part type $p$ |
| $\mu_{mpw}$ | = 1, if machine type *m* is able to process part type *p* with worker *w*,<br>= 0, otherwise. |
| $\lambda_{pm}$ | = 1, if part type *p* needs machine type *m,*<br>= 0, otherwise. |
| $U_p$ | Outsourcing cost per unit of part type *p* in period *t*. |
| $t_{pmw}$ | Processing time part type $p$ on machine type $m$ with worker type $w$ |
| $T_{mt}$ | Time capacity of one machine of type $m$ for one time period $t$ |
| $LL_c$ | Minimum number of machines limit in cell $c$ |
| $UL_c$ | Maximum number of machines limit in cell $c$ |
| $LW_c$ | Minimum size of cell $c$ in terms of the number of workers |
| $R_m^+$ | Relocation cost of installing one machine of type $m$ |
| $R_m^-$ | Relocation cost of removing one machine of type $m$ |
| $L^p$ | a large positive number |
| $H_{pt}$ | Part holding cost per part type $p$ per time period $t$ |
| $A_m$ | Quantity of machine type $m$ available at time period $t=1$ |
| $A_w$ | Number of worker type $w$ available |
| $RW_{wt}$ | Available time for worker type $w$ at time period $t$ |
| $S_{wt}$ | Salary cost of worker type $w$ within period $t$ |
| $HI_{wt}$ | Hiring cost of worker type $w$ within period $t$ |
| $F_{wt}$ | Firing cost of worker type $w$ within period $t$ |
| $OV_m$ | Machine maintenance overhead cost of machine type $m$ per unit time in time period $t$ |
| $OP_m$ | Procurement cost per machine type m |
| $\gamma_m$ | Operating cost per unit time per machine type m |
| $£_p$ | Internal production cost per part type p |

*Model Decision Variables*

$N_{mct}$ Number of type $m$ machines to present at cell $c$ at beginning of time period $t$

$Y_{mct}^{+}$ Number of type $m$ machines added in cell $c$ at beginning of time period $t$

$Y_{mct}^{-}$ Number of type $m$ machines removed from cell $c$ at beginning of time period $t$

$BN_{mt}$ Number of machines of type m procured at time t

$A_{mt}^{*}$ Quantity of machine type m available at time period t after accounting for machines that hav been procured

$Q_{pt}$ Number of part inventory of type $p$ kept in time period $t$ and carried over to period *(t+1)*

$\beta_{pt}$ Production volume of part type p to be produced in time period t

$O_{pt}$ Number of parts to be outsourced at time period t.

$L_{wct}^{+}$ Number of workers of type $w$ added to cell $c$ during period $t$

$L_{wct}^{-}$ Number of workers of type $w$ removed from cell $c$ during period $t$

$N_{wct}$ Number of workers of type $w$ allotted to cell c in period $t$

$v_{pct}$ = 1, if part type p is processed in cell c in period t.

= 0, otherwise.

$z_{pmwct}$ = 1, if part type p is to be processed on machine type m with worker w in cell c in period t.

= 0, otherwise.

# LIST OF ACRONYMS

| | | |
|---|---|---|
| AAA | - | Assignment Allocation Algorithm |
| AI | - | Artificial Intelligence |
| ALC | - | Average Linkage Clustering |
| ANN | - | Artificial Neural Network |
| BEA | - | Bond Energy Analysis |
| CF | - | Cell Formation |
| CFA | - | Component Flow Analysis |
| CFP | - | Cell Formation Problem |
| CI | - | Cluster Identification |
| CLC | - | Complete Linkage Clustering |
| CLS | - | Candidate List Size |
| CM | - | Cellular Manufacturing |
| CMS | - | Cellular Manufacturing Systems |
| DCA | - | Direct Clustering Algorithm |
| EA | - | Evolutionary Algorithm |
| FIFO | - | First-In-First-Out |
| GA | - | Genetic Algorithm |
| GAP | - | Generalized Assignment Problem |
| GT | - | Group Technology |
| JIT | - | Just-In-Time |
| MGI | - | Machine Group Identification |

| | | |
|---|---|---|
| NP | - | Non-Polynomial |
| PFA | - | Production Flow Analysis |
| PFI | - | Part Family Identification |
| PF/MC | - | Part Family/Machine Cell |
| ROC | - | Rank Order Clustering |
| SA | - | Simulated Annealing |
| SLC | - | Single Linkage Clustering |
| TS | - | Tabu Search |
| WIP | - | Work In Progress |

# Chapter 1

## Introduction

In the past few decades, there has been an increasing worldwide awareness towards productivity improvement. Advanced countries are moving towards the progressive concept and philosophies in the manufacturing area. The main interest of such changes lies in decentralization of the activities hitherto carried out in an autocratic and bureaucratic manner in the production units. A new style of operation and a new environment in the work place conductive to improvement in such factors as flexibility, efficiency, management-worker relation, team work and job satisfaction are becoming important for survival in the international market. Group Technology (GT) has emerged as one of the manufacturing philosophies to address such requirements.

Group Technology (GT) is a manufacturing technique in which the parts having similarities in geometry, manufacturing process and/or functions are assembled together. The group of similar parts is known as part family and the group of machineries used to process an individual part family is known as machine cell (Selim *et al.* 1998).

### 1.1. Cellular Manufacturing

Cellular Manufacturing (CM) is an application of group technology in manufacturing in which similar parts are classified into part families and different machines are assigned into machine cells. Cellular Manufacturing System (CMS) presents a better performance in satisfying the demand of mid-volume and mid-variety products mixed rather than job shops or flow lines. There are many benefits of cellular manufacturing for a company if applied correctly, which will be discussed later in this chapter. CMSs have emerged to cope with such production requirements and have been successfully implemented with good results. It is important for companies that use CMS to invest sufficient time in the design and planning phase of any CMS implementation. The benefits of CMS can only occur to the company if strategic decisions are based upon results obtained from models that accurately describe its structural and operational features (Greene and Sadowski, 1984). CM has been applied successfully in different manufacturing fields on numerous numbers of products, for example, agriculture and construction equipment, seals, and hospital and medical equipment.

A functional or process layout (a job shop) does well in the case where the variety among the products is so high (approximately there is no similarity between products) and the production volume for each product is low. Figure 1-1 shows the design layout of such a configuration, where the machines of the same type are grouped together in one department (Work Centre) which will be responsible to make a specific operation for all parts that need these or some of these operations. The products have to move between the work centers in order to complete all the required operations. From this we can conclude that the job shop system involves considerable material handling which cause rapid increases in the production cost as well as the in waiting times. In such systems, just 5-10% of the whole time that is spent on the product is a productive time and the remaining is just waiting (wasted, non-productive) time. Also, this increases the number of work in process (WIP) products, hence, low throughput (Wemmerlov and Hyer, 1986).

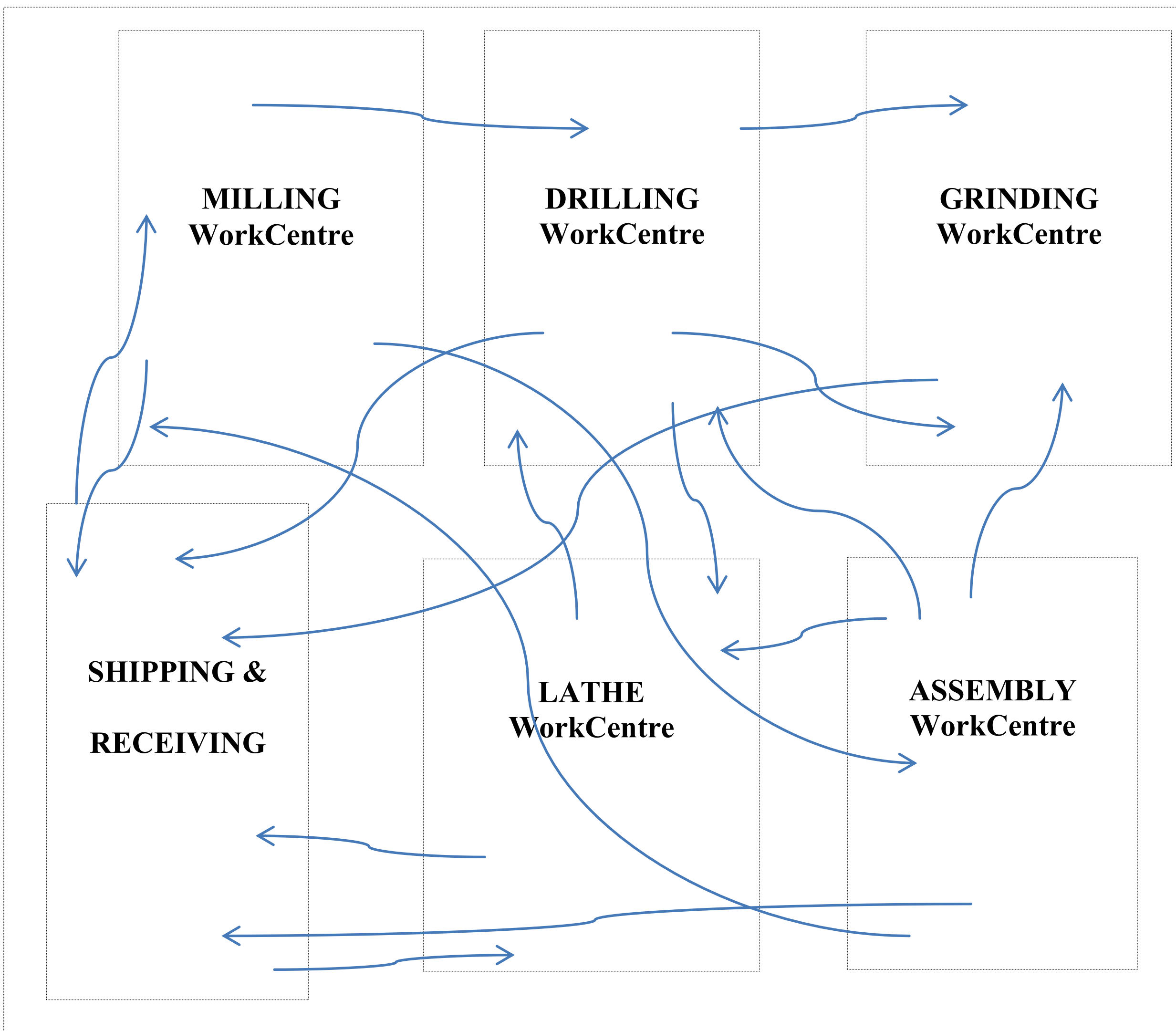



**Figure 1-1 : A functional layout (job shop)**

The concept of a line layout (a flow line) is based on minimizing the distance that people, information, and material move. This system deals with the high volume production but low variety mix, such a system has low flexibility to deal with the customization products. It performs well in mass production industry or assembly industry. A specific number of lines is performed such that each line produces a specific product, where the arrangement of the machines in each line depends on the operations sequence of the product which is assigned to that line (Kusiak, 1987).

For example, if we have a milling machine in the first line we cannot use it just to the product which assigned to the first line even though it has available time. Hence, we need a specific machine for each line, which means a large investment machine cost. Major drawback of flow lines is the lack of flexibility. They are not suitable to produce products for which they are not designed for. If the design of the product is changed, a major relocation of the line may be required. If new products are introduced, it may be absolutely essential to open a new line with additional investment. In Figure 1-2 we can see a typical layout of the flow line system.

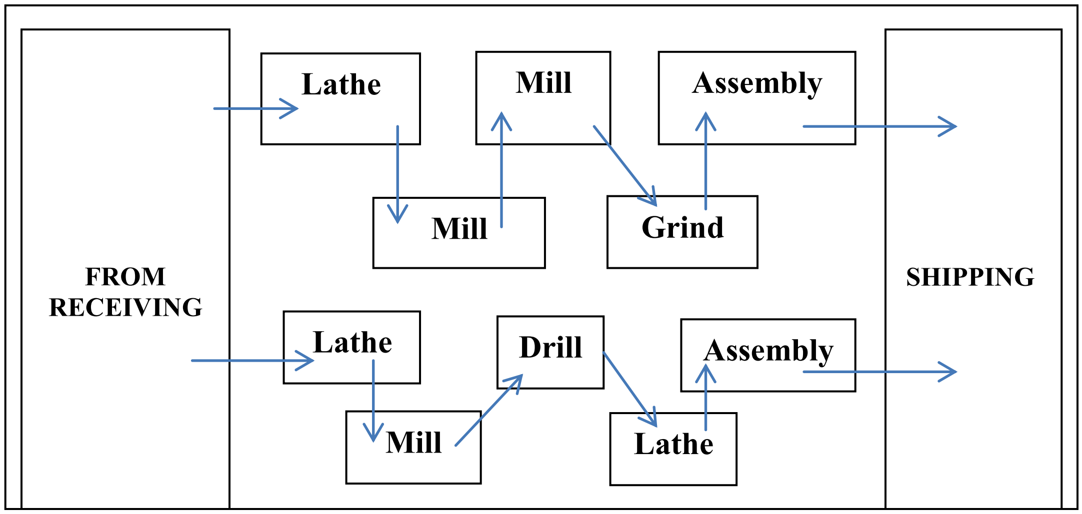



**Figure 1-2 : A line layout (flow line)**

We conclude that neither the job shop nor the flow line systems perform well in the case of mid-volume and mid-variety products mix. CM is an approach that helps to build a variety of products with as little waste as possible. A cell is a group of workstations, machine tools, or equipment arranged to create a smooth flow so families of parts can be processed progressively from one workstation to another without waiting for a batch to be completed or requiring additional handling between operations. But simply, cellular manufacturing groups together machinery and a small team of staff, directed by a team leader, so that all the work on a product or part can be accomplished in the same cell eliminating resources that do not add value to the product (Ah kioon, 2007). Figure 1-3 shows the formulation of the CMS. Figure 1-4 presents a comparison between the three systems (flow line, cellular, and job shop) when perform with regard to the products variety and the demand volume.

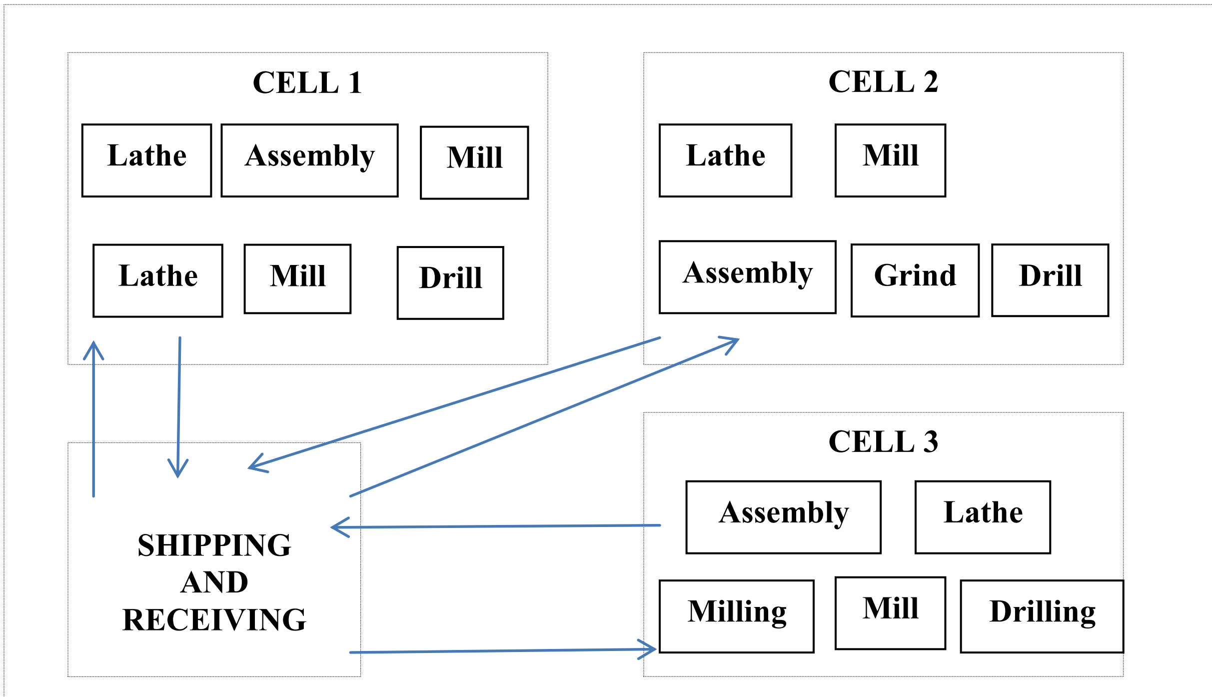



**Figure 1-3 : A cellular (group) layout**

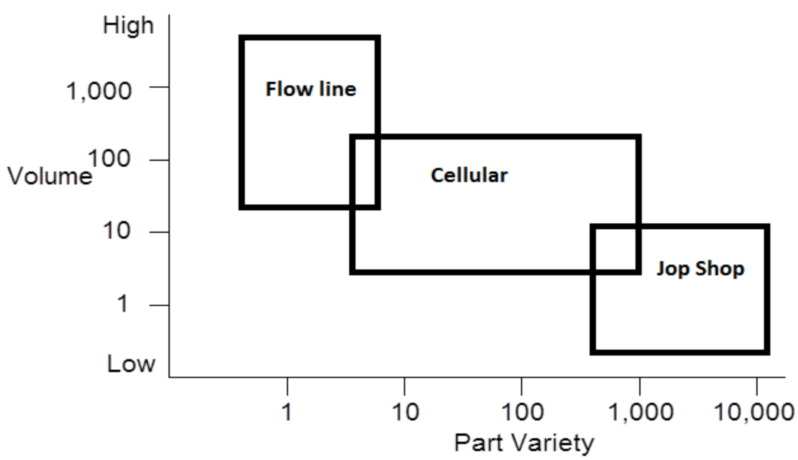



**Figure 1-4: Systems comparison**

Therefore, CM is a manufacturing system which can produce medium-volume and medium-variety part types more efficiently and economically than the other types of manufacturing systems. The product design and demand characteristics have to justify the implementation of any CM system since the latter is not a universal panacea to all of the challenges inherent to modern day manufacturing (Selim *et al.* 1998). For instance, products that have very large production volumes are better processed using pure flow lines. Moreover, products fetching small production volumes coupled with widely varying part processing operations do not warrant the need for CM systems.

## 1.2. Benefits of Cellular Manufacturing

Cellular manufacturing offers substantial benefits to companies. These benefits include Ahkioon (2007):

1. **Reduction in material handling and transit time.** Since all of the operations that the product needed will perform in the same cell this means that no material handling between the cells and also the product will not wait the whole batch to move to the next operation because the movement occur one by one.

2. **Reduction in throughput times.** In CM systems, parts are moved between cells in small batches and within each cell individual parts can be moved to the next machine after completing their operation on the previous machine. This contributes in significantly reducing the waiting times. Furthermore, CM leads to

an easier identification of bottlenecks since the material flow within each cell can be better tracked. Therefore, this is conducive in enabling delivery due dates to be met and in providing better customer lead times.

3. **Reduction in setup times and lot size.** Since a manufacturing cell is designed to manufacture a part family (parts having the same processing requirements: required operations, tolerances, machine tool capacities, similar shapes and sizes), it can accommodate the standardization of equipment, tools, jigs and fixtures. The parts can, therefore, be quickly processed without the need to redesign tools for that matter. Moreover, the use of adapters and generic fixtures significantly reduces the time required to change tools and fixtures. Owing to the considerable reduction in setup times, it also becomes more economical to operate using smaller lot (batch) sizes.

4. **Reduction in WIP and finished goods inventory.** The decrease in setup time leads to an increase capacity of the machines as well as a decrease in WIP inventories. Less WIP is easier to manage and allows the manufacturer to operate with shorter lead time this lead to production on just-in-time (JIT), and then a reduction in finished goods inventory could be achieved.

5. **Reduction in space.** Since we got a reduction in WIP and finished goods inventory, on the other hand, since we have a similar products need similar tools, all of these lead to decreasing in the space required.

6. **Better production scheduling and response to product design changes**. Reductions in setup times and lot sizes, simplified material flow and the ability of cells to be reconfigured quickly (through standardized equipment) effectively make production scheduling and product design changes significantly more manageable. When a new part is introduced, the designer can use the database for existing part families which are similar in processing requirements. The aggregation of machines into cells reduces the number of work centers that have to be scheduled. Owing to the relative independence of the cells, changes in the production scheduling or design of a particular product line can be better addressed within one cell instead of the whole production facility.

7. **Better product quality**. Since parts are manufactured in small lot sizes, any quality defects can be immediately tracked and addressed within a cell, without having to stop production in other cells. Also, quality improvement circles within each cell can be more effective since the latter consists of a team of operators working together on a daily basis and who are aware of their increased job responsibility and ownership.

8. **A better socio-technical environment**. Better employee satisfaction, labor relations, worker motivation and reduced employee absenteeism and turnover have been achieved as a result of enhanced job enrichment and status

(Brandon, 1996). In fact, within a cell, this is made possible thanks to higher levels of variety, identity, significance, autonomy and feedback.

CM is also one of the methods of implementing lean manufacturing as it paves the way to small manufacturing lot sizes (batch manufacturing) and improved machine changeover and setup times. A cellular layout is also a typical pre-requisite for achieving just-in time (JIT) production since it helps achieve a decrease in inventory, work-in-progress (WIP).

### 1.3. Research Objectives and Contributions

The design of a cellular manufacturing system consists of three main phases (Dimopoulos and Zalzala, 1998) as shown in figure 1-5.

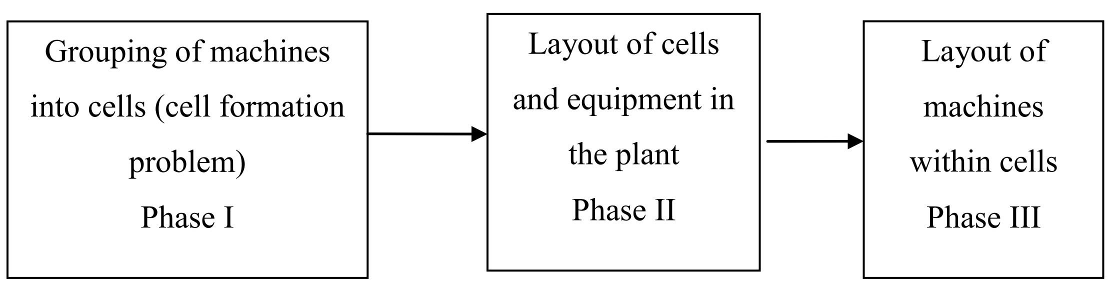



**Figure 1-5 : Main stages in the design of a cellular manufacturing system**

This research focuses on the first phase of CM design where part families and machine cells are formed, followed by the assignment of the former to the latter. The effectiveness of this phase is related to several decisions in the CM design process. These manufacturing decisions are related to both system structure and system operation, and affect the whole system cost and performance (Ahkioon, 2007). As such, manufacturing attributes must be incorporated to address these structural (e.g. number of machines, machine availability, capacity) and operational (e.g. production planning aspects) issues, allowing the cell designer to evaluate cell design using cost-oriented or performance-oriented objectives.

While cellular manufacturing is a popular research area, there is a singular absence of articles that deal with the human element in cellular manufacturing. There are a variety of reasons for this, including that these issues are typically difficult to quantify. It has been well documented that there is an absence of research in the area of worker placement based on both their technical and human skills. Considering human issues is one of the main points in cellular manufacturing since ignoring this factor can considerably reduce benefits of the utility of the cell manufacturing. Bidanda *et al*. (2005) state that it is important for the successful implementation of cellular manufacturing, to focus both on technical issues (cell formation and design) and human issues. Balakrishnan and Cheng (2007) claimed that in spite of the fact that several research papers have highlighted the importance of interactions between human resources management and operations management and the need to incorporate organizational behavior issues in operations management in recent years, there has not been much research on organizational behavior issues in cellular manufacturing.

Therefore, with regards to CM modeling, the following research objectives have been set and met in this thesis:

1. Identify the important manufacturing attributes that make the system more realistic and more effective.
2. Develop a comprehensive mathematical model which integrates worker assignments as well as all of our manufacturing attributes.
3. Develop efficient and exact procedures for solving the proposed integrated model.
4. Use IBM ILOG CPLEX OPTIMIZATION STUDIO 12.2/OPL to solve the proposed integrated model and evaluate its ability by solving various CM problems.

### 1.4. Research Approach

With regards to the development of integrated CM models, a number of steps are taken in order to select the important manufacturing aspects to be incorporated and to implement some possible solution approaches:

1. Through an extensive literature review of existing models and the manufacturing aspects which had been considered in each model, focusing on the previous works which considered the human issues in its work, the important manufacturing attributes then selected to build a comprehensive model.

2. A mathematical model which integrates all of the manufacturing attributes has been formulated.

3. A linearization has been made on the existing mathematical model and then it converted into a format that can be recognized and solved by CPLEX.

4. Data set of previous work used to formulate several CM problems with various sizes to evaluate the ability of CPLEX software.

### 1.5. Outline of Thesis

This thesis is organized in five chapters. Chapter 2 presents a literature review with regards to CM systems design methods, including the CM solution procedures and modeling approaches. Chapter 3 presents a comprehensive mathematical CM model that integrates the important manufacturing attributes that have been identified in chapter 2. The properties of the model are discussed followed by the implementation of some linearization procedures. In chapter 4 the linearized model is solved using CPLEX optimization studio, various numerical examples followed by a detailed discussion of the computational results. Chapter 5 presents the summary, conclusions and future research directions. This chapter also highlights the research contributions brought to both CM modeling and solution methodologies. Future research directions are also discussed.

# Chapter 2

# Literature review

## 2.1 Introduction

The literature on the design of cellular manufacturing systems is quite extensive. Comprehensive reviews and taxonomies of cellular manufacturing systems and classifications can be found [Greene and Sadowski, 1984; Wemmerlov and Hyer, 1986; Kusiak, 1987; Singh, 1993; Vakharia and Slim, 1994; Joines *et al*. 1996; Selim *et al.* 1998]. The reminder of this chapter is divided into two main sections. First section presents a review of the literature pertaining to the classification and the solution methods proposed for the Cell Formation (CF) problem. Figure 2-1 shows Classification of CF methods. The second section presents a review for the recently published work, taking into consideration the manufacturing attributes to be used during the Cellular Manufacturing System design.

### 3.2. Taxonomy of CM Design Methods

At the highest level, methods for part family/machine cell formation can be classified as design-oriented or production-oriented. Design-oriented approaches group parts into families based on similar design features while production –oriented techniques aggregate parts requiring similar processing. Classification and coding schemes are design-oriented tools that can be used to important GT applications. Analysis of codes facilitates the rationalization of the design process, rapid prototyping, the development of new parts, and to a certain extent can be used for machine cell formation. Since part codes are assigned based upon physical geometry, parts having similar design features have similar codes providing a weak connection between part features and machine grouping. This makes the application of classification and coding to machine cell formation very limited. This can be seen by the fact that the large number of CM designed methods proposed during the late decades are not based on classification and coding. They are production-oriented approaches (Defersha, 2006). The production-oriented approaches can be further classified into: Descriptive Procedures, Cluster Analysis, Graph partitioning, Artificial Intelligence, Mathematical Programming, and Metaheuristic Approach.

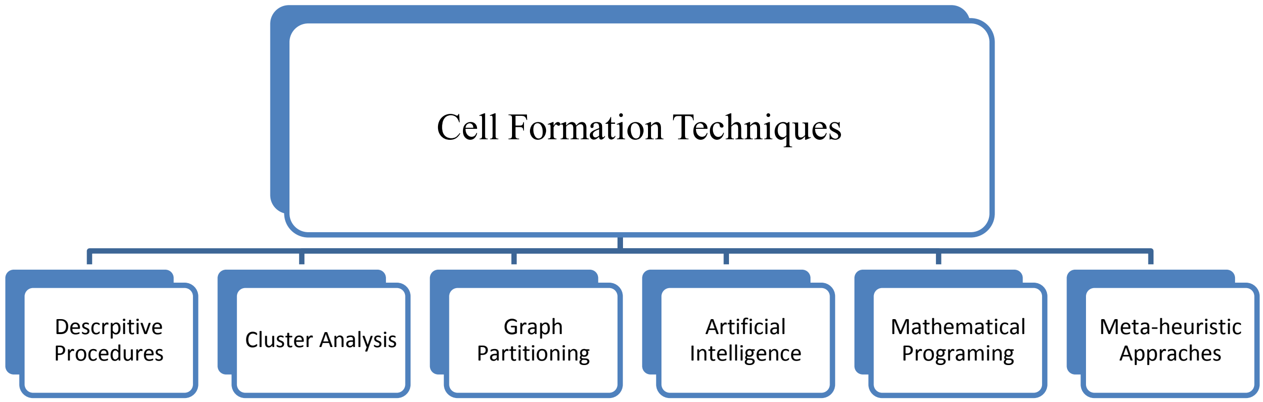



Figure 2-1: Classification of CF methods

### 2.2.1. Descriptive Procedures

In general, descriptive procedures can be classified into three major classes. The first class, which is referred to as part families identification (PFI), begins the cell formation process by identifying the families of parts first and then allocates machines to the families. The second class, which is referred to as machine groups identification (MGI), follows the reversal of the first class' steps. The third class of the descriptive procedures, which is referred to as part families/machine grouping (PF/MG), identifies the part families and machine groups simultaneously (Selim *et al.* 1998).

PFI methods identify part families, and after that machines are allocated to those parts families. This category can be sub-classified into both informal systems, and formal coding and classification system. An example of informal system is the visual inspection method, in which part families are formed based on the experience of experts. In a part coding method, parts are coded in relation to shapes, sizes, features, etc. ,and based on them part families are formed. A code is a string of characters that stores information about a part and is used to either group similar parts or to separate dissimilar parts. It is used in three coding systems: monocode (hierarchical code), polycode (attribute code) and mixed code. Using polycodes, distance measures (Minkowski, weighted Minkowski and Hamming distance measures) can be found between each one of the parts according to some selected manufacturing attribute (Ah kioon, 2007). MGI-related descriptive procedures consider the cell formation problem as having two- phases. In the first one, machines are grouped based on part routings. In the second stage, parts are allocated to machine groups. PF/MG methods identify part families and machine groups simultaneously. Some of these methods are (1) production flow analysis (PFA) that analyzes the information given in route cards to form cells (Burbidge 1963), (2) nuclear synthesis in which manufacturing cells are created around “key machines” and (3) component flow analysis (CFA) that is similar to PFA except CFA does not divide the problem at the outset (Elessaway, 1972).

### 2.2.2. Cluster Analysis Procedures.

Cluster analysis is composed of many diverse techniques for recognizing structure in a complex data set. The main objective of this statistical tool is to group either objects or entities or their attributes into clusters such that individual elements within a cluster have a high degree of "natural association" among themselves and that there is very little "natural association" between clusters. Clustering procedures can be classified as: 1) array-based clustering techniques, 2) hierarchical clustering techniques, and 3) non-hierarchical clustering techniques (Selim *et al.* 1998).

- **Array based clustering**

Array based clustering is one of the simplest classes of production-oriented cell formation method. This class of algorithms utilizes the machine-part incidence matrix. The latter has zero and one entries, where a “1” entry in row i and column j ($a_{ij}$=1) of the matrix means that part j requires machine i for one of its operations, whilst a “0” entry means that it does not need. Rows and columns are permutated to form a set of blocks with high densities of 1s along the diagonal, see figure (2-2, 2-3). Any tightly clustered block represents the candidate part families and machine cells, which formed simultaneously (Albadawi, 2003).

Several array-based clustering algorithms have been proposed: Bond Energy Analysis (BEA) by McCormick *et al*. (1972),which maximize the total ‘ bond energy’ of the machine-part incidence matrix, Rank Order Clustering (ROC) by King (1980a, 1980b), which rearranges the machine-part incidence matrix based on the 'binary rank orders' of its rows and columns, ROC2 by King and Nakornchai (1982), Modified Rank Order Clustering (MODROC) by Chandrasekharan and Rajagopalan (1986a), Direct Clustering Algorithm (DCA) by Chan and Milner (1982), which form part and machine families by rearranging the rows and columns of the incidence matrix, based on the number of non-zero elements in each, Cluster Identification by Kusiak and Chow (1987), and the Hamiltonian Path Heuristic by Askin *et al*. (1991).

| | | Products | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| Machines | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 |
| | 2 | 1 | 0 | 0 | 0 | 0 | 0 | 1 |
| | 3 | 0 | 0 | 1 | 1 | 0 | 1 | 0 |
| | 4 | 0 | 0 | 1 | 1 | 0 | 1 | 0 |
| | 5 | 1 | 0 | 0 | 0 | 0 | 0 | 1 |
| | 6 | 0 | 0 | 1 | 1 | 0 | 1 | 0 |
| | 7 | 0 | 1 | 0 | 0 | 1 | 0 | 0 |

Figure 2-2 Machine-Part Matrix

| | | Products | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 7 | 3 | 4 | 6 | 2 | 5 |
| Machines | 2 | 1 | 1 | | | | | |
| | 5 | 1 | 1 | | | | | |
| | 3 | | | 1 | 1 | 1 | | |
| | 4 | | | 1 | 1 | 1 | | |
| | 6 | | | 1 | 1 | 1 | | |
| | 1 | | | | | | 1 | 1 |
| | 7 | | | | | | 1 | 1 |

Figure 2-3 Parts-Machines Families

The array based clustering techniques used in the design of manufacturing cells are both efficient and simple to apply to the part-machine matrix. However, this technique ignores operation sequence. If a part needs more than one operation, the part-machine matrix cannot use to identify all the operations, the only information that the matrix can help with it is which machine type each part needs. Ignoring the machine capacity limitations is another disadvantages of array-based clustering techniques, the latter assume that each machine type has enough capacity to process all parts require this machine. Also this technique does not take into account production requirements, machine costs, part production costs; maximum cell size and it usually require visual inspection of the output to determine the composition of the manufacturing cells. This is unpractical for problems of real-life size where large numbers of columns and rows need to be represented and visualized (Ah kioon, 2007).

- **Hierarchical Clustering**

Hierarchical clustering techniques operate on an input data set described in terms of a similarity or distance function and produce a hierarchy or partitions. At each similarity level in the hierarchy, there can be a different number of clusters with different number of members. Unlike the array-based techniques, hierarchical clustering methods do not form machine cells and part families simultaneously. These methods can be described as either divisive or agglomerative. Divisive algorithms start with all data (machine or parts) in a single group and create a series of partitions until each machine (part) is in a singleton cluster.  On the contrary, agglomerative technique start with a singleton clusters and proceed to merge them into larger partitions until a partition containing the whole set is obtained (Albadawi, 2003). Hierarchal clustering may be represented by a two dimensional diagram known as dendogarm will illustrates the fusion or divisions made at each successive stage of analysis. An example of such a dendogram is given in figure 2-4. The cell designer must choose a similarity level or threshold in order to define the number of clusters. As the threshold increases, the number of cells increases while the size of each cell decreases.

The most widely used technique is Single Linkage Clustering (SLC) algorithm by McAuley (1972), which defines the similarity between two machines in terms of the number of parts that visit both machines and the number of visiting either machine. McAuley (1972) then aggregated machines with high similarity into manufacturing cells. Jaccard's similarity coefficient is the most commonly used one, defined as the ratio of the number of parts processed on both machines (*m* and *n*) to the sum of the total number of parts processed on machines *m* and *n*. The value of the Jaccard's coefficient ranges from 0.0 (maximum dissimilarity when the two machines do not process the same part types) to 1.0 (maximum similarity) (Ahkioon, 2007).

Other manufacturing features such as part volume, part operation sequence, tooling requirements, setup features, production volume and lead time can be considered while computing the similarity measure.

The defining feature of SLC is that distance between clusters is defined as the distance between the closest pair of objects where the pair of objects is constructed by taking one element from each of the two clusters. The major drawback of SLC is the "chaining" problem, which may be caused by two clusters joining together. The two machine cells may join together just because two of their members are similar, but the other members may remain far apart in terms of similarity. In other words, two clusters can be grouped based merely upon a single bond between one machine in each cluster. The main advantage of SLC is the simplicity and less computational requirement (Albadawi, 2003).

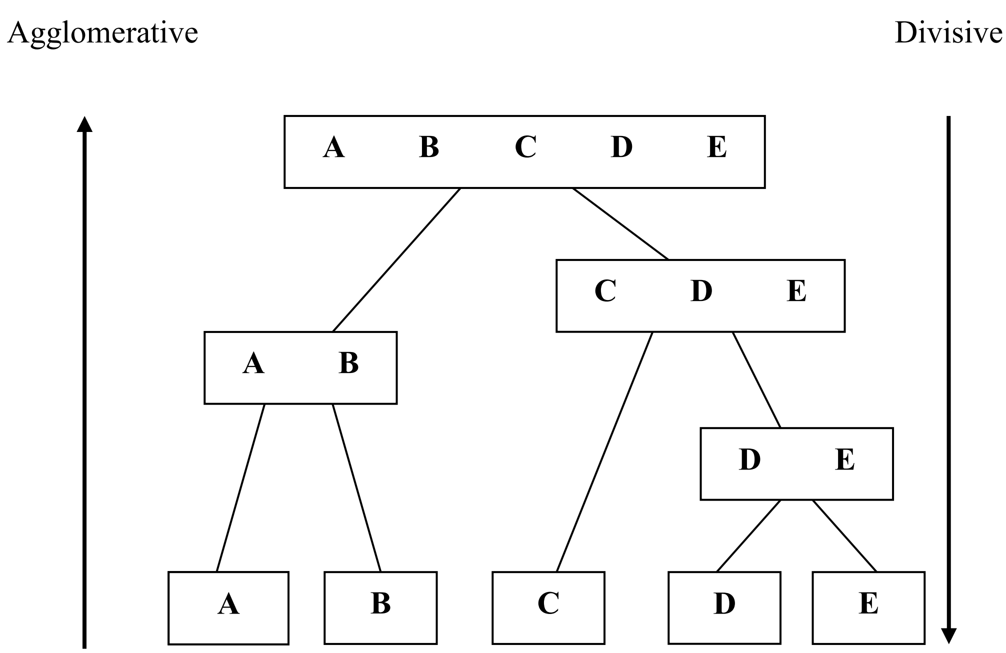



Figure 2-4: A dendogram showing the hierarchical classifications

Complete Linkage Clustering algorithm (CLC) is considered to be the other extreme of SLC in that it is the least likely to cause chaining, CLC reduces the chaining problem by selecting the minimum similarity coefficient as the in-between cluster relationship instead of maximum. To help reduce the chaining problem, (Seifoddini and Wolfe, 1986) applied the Average Linkage Clustering algorithm (ALC) where clustering occurs by considering the average of all links within cluster. When clusters *v* and *t* are merged, the sum of the pairwise similarity between the two clusters is (Albadawi, 2003):

$$S_{tv} = \frac{\sum_{m \in t} \sum_{n \in v} S_{ij}}{N_t \times N_v}$$

Where the double summation are the sum of pairwise similarity between all machines of the two groups, and $N_t$, $N_v$ are the number of machines in groups *t* and *v* respectively. However, ALC produces results that lie between the extremes of SLC and CLC, especially with regards to the machine chaining problem. Although the algorithms provide different sets of groups, they do not give the best way to group machines (e.g. machine chaining problem, no insight for the treatment of bottleneck machines). Furthermore, the part families have yet to be formed and get assigned to the machine groups. One of the limitations of SLC and CLC is that the similarity coefficient used in these methods does not give importance to the parts that do not need processing by the machines pairs. The (Linear Cell Clustering) LCC method overcomes this problem. It clusters machines based on the use of commonality score not only considers the parts that require both machines for processing, but also parts, which do not require both machines. The commonality score is presented as below (Albadawi, 2003):

$$C_{mn} = \sum_{p=0}^{P} \gamma(a_{pm}, a_{pn})$$

Where:

$$\gamma(a_{pm}, a_{pn}) = \begin{cases} (p-1), & \text{if } a_{pm} = a_{pn} = 1 \\ 1, & \text{if } a_{pm} = a_{pn} = 0 \\ 0, & \text{if } a_{pm} \neq a_{pn} \end{cases}$$

*p, q* are indexes for parts and *m, n* are indexes for machines.

- **Non-Hierarchical Clustering**

In comparison to the hierarchical techniques, the non-hierarchical procedures allow objects to change group membership during the cell formation process. Hierarchical Clustering methods are iterative methods and they begin with either an initial partition of the data set or the choice of a few seed points. In either case, one has to decide the number of clusters in advance. Arbitrariness in the choice of seed points (or initial partition of data) could lead to unsatisfactory results (Ah kioon, 2007). Non-hierarchical procedures have been developed by Lemoine and Mutel, (1983), Chandrasekharan and Rajagopalan, (1986b), and Srinivasan and Narendran, (1991).

#### 3.2.3. Graph Theoretic Approaches

Graph theoretic approaches can be used to structure the cell formation problem in a number of forms through a number of methods including Graph Partitioning Algorithms, Bipartite Graphs, Minimum Spanning Tree, and Network Flow.

- **Graph Partitioning Algorithms**

Graph partitioning methods treat the machines and/or parts as vertices and the processing of parts as arcs connecting these nodes. These models aim at obtaining disconnected subgraphs from a machine-machine or machine-part graph to identify manufacturing cells (Selim *et al*. 1998). Rajagoplan and Batra (1975) suggest the use of Jaccard's similarity coefficients and graph theory to form machine groups. Each vertex in the graph represents a machine type and the edge connecting vertices j and k is introduced in the graph only if the "similarity" between the machine types is greater than a prespecified threshold value. After allowable edges have been introduced, cliques are formed. These cliques are then merged to create cells so that intercell moves are minimized. An upper limit on cell size constraints the number of machines in each partition. During the process high and balanced machine utilization are strived for and machine loads are used to determine the number of machines of a given type needed for each cell (Selim et al., 1998). A cost-based mathematical formulation have been proposed by Askin and Chiu (1990) and a heuristics graph portioning solution approach. They adapted the Kernighan and Lin graph partitioning method and applied a two-phase portioning algorithm. In the first phase parts will be assigned to a specific machines and then machines will be grouped into cells in the second phase. Faber and Carter (1986) use a graph theoretic algorithm which converts the machine similarity matrix into a cluster network. This is used to group the machines and parts into cells. The cluster network is partitioned into cells by solving a minimum cost flow problem (Ah kioon 2007).

- **Bipartite Graphs**

King and Nakornchai (1982) suggested the use of a bipartite graph. The processing requirements of components on machines can be represented in graph-theoretic terminology as a bipartite graph *G(V*ms *V" A)* where *V*m and Vc are the two sets of vertices of the graph which correspond respectively to the machine and components. *A* is a set of arcs of the graph such that:

- If an arc exists between machine vertex i and component vertex *j (aij*= I) component *j* requires processing on machine *i.*
- If an arc does not exist between machine vertex *i* and component vertex *j (aij=O)* then component j does not require processing on machine i.

Each vertex of the graph can be viewed as a compound element if so desired and components, which require exactly the same set of machines, may be depicted as one vertex. Similarly, machines of the same type can, if required, be represented as one vertex. Such devices can be used to reduce the overall size of the graph.

The processing requirements of the components on the machines are also specified by the incidence matrix representation of the bipartite graph. It is easy to see that in this form the problem of allocating machines to groups and components to associated families reduces to that of finding, by appropriately rearranging the order of rows and columns, a block diagonal form of the $aij$= 1 entries in the incidence matrix.

- **Network Flow**

Vohar *et al*., (1990) proposed a network-based algorithm. The algorithm operates with the objective of identifying cells that yield a minimum interaction. Wu and Salvendy (1993) developed a network model to partition the machine-machine graph into cells by considering operation sequences. Lee and Garcia Diaz (1996) represented the clustering problem as a capacitated circulation network that measures the functional similarity between machines. Bertsekas and Tseng (1988) proposed a new class of algorithms for linear cost network flow problems with and without gains. These algorithms are based on iterative improvement of a dual cost and operate in a manner that is reminiscent of coordinate ascent and Gauss-Seidel relaxation methods. Nsakanda *et al*. (2006) integrated several other manufacturing issues to the cell formation problem. A model was mathematically formulated and solved using a hybrid genetic approach. The solution methodology involves partially solving the main model by applying mutation operators that determine the values for the decision variables related to the machine assignment to cells. The partially solved model is further modified by relaxing the machine capacity constraints. It is then observed that the fully modified model has a min-cost flow structure that readily lends itself to a Dantzig-Wolfe decomposition approach (Ah kioon, 2007).

### 2.2.4. Artificial Intelligence-based Approaches

Researchers have increasingly applied artificial intelligence (AI) techniques to the cellular manufacturing system design problem. The techniques developed include syntactic pattern recognition, expert system/knowledge base, fuzzy mathematics, artificial neural networks.

- **Syntactic Pattern Recognition**

Syntactic pattern recognition borrows most of its analytical methods from formal language theory. In syntactic pattern recognition, complex patterns are represented in terms of simple subpatterns and relations among subpatterns. This is analogous to natural language. Syntactic pattern recognition approach is developed for formation of machine cells by classification of machining sequences. There are four steps in this approach: (1) primitive selection, (2) cluster analysis, (3) grammar inference, and (4) syntactic recognition. Wu *et al*. (1986) applied syntactic pattern recognition approach to cell manufacturing design, using the machine sequence data of the parts to be produced.

- **Expert System**

Elmaghraby and Gu (1989) presented an approach for using domain specific knowledge rules and a prototype feature based modeling system to automate the process of identifying parts attributes and assigning the parts to the most appropriate manufacturing cell. The expert assignment system is based on the geometric features of parts, characteristics of formed manufacturing cells, parts functional characteristics and attributes, as well as domain specific manufacturing knowledge. Kusiak (1988) developed a pattern recognition based parts grouping which is similar to the grouping in GT. The basic difference between these two approaches is in the degree of automation. Luong *et al*., (2002) developed a knowledge-based system that attempts to make recommendations of system feasibility, cell formation techniques and cell types during the conceptual design of CM. The recommendation of system feasibility is based on the production quantity and product variety ratio.

- **Fuzzy Logic**

Most clustering methods assume that part families are mutually exclusive and collectively exhaustive. While some parts definitely belong to certain part families, it is not always clear which family is appropriate. Xu and Wang (1989) applied fuzzy mathematics to the cell formation problem where part features are transformed by membership functions into fuzzy numbers. The membership function of each feature is designed such that the resulting fuzzy number is able to differentiate parts according to the feature's processing needs. The fuzzy numbers are then used to construct a similarity coefficient matrix. A threshold value is used to specify the minimum value of similarity coefficient for a part to be in the same family. Chu and Hayya (1991) applied a fuzzy c-means clustering algorithm to production data. The fuzzy c-means clustering can be classified as a non-hierarchical method and suffers from the same problems associated with those methods. The number of part families, c, must be specified a priori. The authors stated that if c is underestimated, the result is far from optimal. Also, a poor stopping criterion leads to inferior clusters. However, the technique is unaffected by exceptional elements. The workload among machine cells can be balanced better by using a reallocation scheme that utilizes the degree of membership a part has in particular family. Chu and Hayya (1991) compared the fuzzy approach to the optimal 0-1 integer-programming model and a heuristic approach. The fuzzy approach was clearly better than the integer programming (IP) approach in both execution time and the quality of the solution. It was not as efficient as the heuristic but provided more information than is available from a "crisp" definition of families and cells (Albadawi, 2003).

Further work reporting the use of fuzzy mathematics in CM design can be found in Josien and Liao (2002), Lozano *et al*. (2002). Gungor and Arikan (2000) used fuzzy set theory for CM design through an algorithm that treats design and manufacturing attributes and operation sequences as input parameters when formulating the cell formation problem. Membership functions are used to fuzzy if such parameters so that they can be used together with some IF-THEN decision rules with a view to determining the part relationships s fuzzy sets. The defuzzification step follows where crisp values for the part relationships are obtained. A traditional cell formation procedure, e.g. Single Linkage Clustering (SLC), can thus be applied by using the defuzzified part relationships chart as input (Ah kioon, 2007).

- **Neural Networks**

Artificial Neural Networks (ANN) have been applied successfully to many manufacturing areas. Several researchers have applied a supervised learning approach to the classification and coding problem based on the back-propagation learning algorithm.

This method can also be applied to a production-oriented method to determine the machine cells and part families. Unsupervised learning techniques are better suited for the general clustering problem. It is not necessary to specify a priori the number of clusters or the representative members of these clusters. Once the part families and machine cells are determined, a supervised model can be trained to assign new parts to the existing cells (Albadawi, 2003). By taking a design-oriented approach Kaparthi and Suresh (1992) have applied artificial neural networks for classification and coding of rotational parts, using a three-digit part description whilst Liao and Lee (1994) have developed an automated GT coding and part-based computer-aided design (CAD) system. Malave and Ramachandran (1991) applied a modified version of the Hebbian learning rule to the cell formation problem. This technique belongs to the supervised learning category but is also a production-oriented method for forming part families and machine cells. Unsupervised learning approaches have also been applied to the cell formation problem and the methods include Adaptive Resonance Theory (ART) and its numerous variants, fuzzy ART, competitive learning (Chu, 1993; Venugopal and Narendran, 1992a) and Kohenen nets (Venugopal and Narendran, 1992a). Several researchers used the neural network classifier based on an unsupervised learning model by Carpenter and Grossberg (1987) called adaptive resonance theory (ART1) and its variants. Unsupervised learning techniques such as ART Cluster the input vectors into separate groups based upon similarities (Kusiak and Chung, 1991; Dagli and Sen, 1992; Kaparthi and Suresh, 1992; Rao and Gu, 1992, 1994; Liao and Chen, 1993; Chen and Cheng, 1995). The artificial neural network technique executed quickly and obtained good clusters. The real advantage is its ability to solve large data sets (10,000 parts and

100 machine types). ART and its variants can be classified as non-hierarchical methods (Ah kioon, 2007). Another variant of ART called fuzzy ART, implements fuzzy logic into ART's pattern recognition and enhances generalization. It also handles both analogue and binary inputs while assimilating and utilizing new learning laws (Suresh and Kaparthi, 1994; Burke and Kamal, 1992).

### 2.2.5. Mathematical Programming Method

Mathematical programming approaches are widely employed in the design of cellular manufacturing systems. These techniques can be classified as linear programming (LP), linear and quadratic programming (LQP), dynamic programming (DP) and goal programming (GP). They offer distinct advantages over other cell formation techniques as they can easily incorporate a number of design logics in their objectives and constraint functions. These formulations also suffer from critical limitation of being computationally intractable for realistically sized problem (Defersha, 2006).

Kusiak (1987) proposed the p-median model to identify part families, this was the first model to form part families using mathematical programming. The p-median model is used to cluster $n$ parts (machines) into $p$ part families (machine cells). Constraints specify that each part can belong to only one part family and the required number of part families is $p$. A part can only be assigned to a part family that has been formed. Similarity between two parts is defined as the number of machines the two parts have in common. This procedure identifies only the part families, and an additional procedure is needed to identify the machine groups (Albadawi, 2003). Subsequently, several authors further modified the generalized p-median model and reported successful applications (Ribeiro and Pradin, 1993; Viswanathan, 1996; Lee and Garcia-Diaz, 1996; Wang and Roze, 1997; Deutsch *et al*., 1998).

However, only small-scale problems were solved. Medium-sized problems required prohibitive computational time while there has been little reported about large-scale problems that represent real-life industrial instances. Also, off-the-shelf optimization software do not have enough solving capabilities to solve the cell formation problem since the latter is NP-hard (Ahkioon, 2007). To avoid the problem of having to determine the optimal value of *f*, Srinivasan *et al*. (1990) proposed an assignment model for the part families and machine grouping problem. They provided a sequential procedure to identify machine groups followed by identification of part families. The objective of assignment model is to maximize the similarity. This approach is reported to be superior both in terms of quality of solution and computational time in comparison with the p-median model. Shtub (1989) show that the group formation problem and its extension, the generalized group formation problem, are equivalent to the Generalized Assignment Problem (GAP). In the Generalized Assignment Problem II tasks have to be assigned to *m* agents, so that each task is assigned to exactly one agent and the total resources available for each agent are not exceeded. Purcheck (1974; 1975) was among the first researchers to apply linear programming to group technology. A mathematical classification has been developed and tested which overcomes the shortcomings of conventional methods of workpiece classification and workflow analysis. The Cranfield method facilitates the construction of a combinatorial Programming model. A hand-method of solution has been developed which may be used to program a computer. This has been achieved since cluster analysis represents a linear programming problem where the objective is to maximize the total sum of similarities between each pair of individuals (parts or machines) or to minimize the distances between each pair (Ah kioon, 2007).

The discussion so far on CM design methods considers indirect measures, for example similarity/dissimilarity, bond energy, ranking, distance, when solving the cell formation problem to obtain a block diagonal form. Part families and machine cells are identified while minimizing the number of exceptional elements and voids. However, one needs to better consider the costs related to voids and exceptional elements, as such costs vary for different part/machine combinations. The procedures so far also decouple the cell formation process and any cell evaluation procedure (Ah kioon, 2007). Boctor (1991) developed a CM model which simultaneously assigns machines and parts to cells. The model objective function minimizes the number of exceptional elements. Choobineh (1988) developed a linear programming model that uses a similarity measure based on part operations and sequence, taking into account machine cost and capacity but ignoring the presence of alternate process routings. Adil *et al*. (1993) proposed a nonlinear mathematical model to identify part families and machine groups simultaneously without manual intervention. The objective of the model is to explicitly minimize the weighted sum exceptional elements and voids. These parts can be considered to have potential for subcontracting or developing alternative process plans before allocating them to cells. By changing weights for voids and exceptional elements the user has the flexibility to form large loose cells, or small tight cells to suite the situation. Ballakur and Steudel (1987) presented a heuristic problem. The distinguishing feature of this heuristic is its consideration of several practical criteria such ***w*** within-cell machine utilization, work load fractions, maximum number of machines that are assigned to a cell, and the percentage of operations of parts completed within a single cell. Heragu and Chen (1998) presented a mathematical model for Cellular Manufacturing System (CMS) design which incorporates three critical aspects - resource utilization, alternate routings, and practical constraints; Benders' decomposition algorithm also presented. Song and Hitomi (1996) presented a flexible cellular layout design. The method integrates production planning and cellular layout in a long-run planning horizon. The integrated planning model is formulated as a Mixed-Integer Problem (MIP), which contains two types of integer programming problems: determining (1) the production quantity for each product and (2) the timing of adjusting for the cellular layout in a finite planning horizon with dynamic demand situation. This decision problem is solved so as to minimize the sum of inventory-holding costs, group-setup costs, material-handling costs and layout-adjusting costs subject to the capacity constraint and the demand requirement. The Benders decomposition is used to solve the MIP. Rajamani *et al.* (1996) develop a mixed integer program for the design of cellular manufacturing systems. They assumed that there are alternate process plans for each part and that each operation in these plans can be performed on alternate machines. The objective of the model is to minimize the sum of investment, processing and material handling costs. Processing times, capacities of machines and cell size restrictions are considered in the process. Part families, machine groups and part plans are identified concurrently.

Goal programming (GP) has been applied mostly for multi-criteria CM design. Sankaran (1990) presented a mathematical model of goal programming that addresses the issue of developing alternate solutions with respect to conflicting objectives and preferential ordering of different goals. Shafer and Rogers (1991) developed a cell formation procedure that directly addressed these design objectives. I) reduce setup times, 2) produce parts cell complete, i.e., minimize intercellular movements of parts, 3) minimize investment in new equipment, and 4) maintain acceptable machine utilization levels. To achieve this, three goal programming models were developed corresponding to three unique situations: (1) setting up an entirely new system and purchasing all new equipment, (2) reorganizing the system using only existing equipment, and (3) reorganizing the system using existing equipment and some new equipment. A heuristic solution procedure was presented. The heuristic solution procedure involved partitioning the goal programming formulations into two subproblems and solving them in successive stages.

However, because of the way the CM models are formulated, certain limitations apply to the mathematical programming approaches. First, because of the resulting nonlinear form of the objective function, most approaches do not concurrently group machines into cells and parts into families. Second, the number of machine cells must be specified a priori, affecting the grouping process and potentially obscuring natural cell formations in the data. Third, since the variables are constrained to integer values, most of these models are computationally intractable for realistically sized problem. It has been shown that large scale problems typically require that the model be subject to model-specific linearization procedures and/or be solved using approximate methods such as Lagrangian relaxation with subgradient optimization, simulated annealing, genetic algorithms, Tabu search or a hybrid of any of these methods. Therefore, the major drawback of mathematical programming approaches in CM design is the adverse computational time and effort required to solve real-life sized problems (Albadawi, 2003).

### 2.2.6. Meta-heuristic Approaches

A heuristic method is a procedure that is likely to discover a very good feasible solution, but not necessarily an optimal solution, for the specific problem being considered. No guarantee can be given about the quality of the solution obtained, but a well-designed heuristic method usually can provide a solution that is at least nearly optimal (or conclude that no such solutions exist). The procedure also should be sufficiently efficient to deal very large problems. The procedure often is a full-fledged iterative algorithm, where each iteration involves conducting a search for a new solution that might be better than the best solution found previously. When the algorithm is terminated after a reasonable time, the solution it provides is the best one that was found during any iteration. Heuristic methods often are based on relatively simple common-sense ideas for how to search for a good solution. These ideas need to be carefully tailored to fit the specific problem of interest. Thus, heuristic methods tend to be ad hoc in nature. That is each method usually is designed to fit a specific problem type rather than a variety of applications (Fredrick and Gerald, 2010).

For many years, this meant that an operation research team would need to start from scratch to develop a heuristic method to fit the problem at hand, whenever an algorithm for finding an optimal solution was not available. This all has changed in relatively recent years with the development of powerful metaheuristic. A metahuristic is a general solution method that provides both a general structure and strategy guidelines for developing a specific heuristic method to fit a particular kind of problem. Methaheuristics have become one of the most important techniques in the toolkit of operation research practitioners (Fredrick and Gerald, 2010).

The popularity of meta-heuristics is further explained by the fact that they have been successfully used to solve a wide range of optimization problems, especially combinatorial problems, whilst yielding an approximate solution in an acceptable computational time (Ah kioon, 2007). Jones *et al*. (2002) reviewed 115 articles concerned with the theory and application of meta-heuristics. They concluded that theoretical papers account for only 20.9% of the articles concerned. This healthy ratio indicates that these techniques have a lot of real-world applications rather than having just theoretical value. 70% of the work surveyed utilize Genetic Algorithm (GA) as the primary meta-heuristic, 24 % use Simulated Annealing (SA) whilst only 6% draw on Tabu Search (TS). TS is more frequently used in conjunction with either GA or SA as a secondary meta-heuristic refinement in order to strengthen the avoidance of convergence at local optima (enhancing global optimization). A possible disadvantage is that there are a larger number of parameters to be set by the modeler in meta-heuristics. The solution is sensitive to these parameters; so a number of executions of the meta-heuristics (with different parameter settings) might be required before a good solution is produced. In other words, meta-heuristics can be considered to be “poor black boxes”; they become more difficult to apply when only a single run is allowed due to time or other pressures. It has to be also noted that these meta-heuristics might be sensitive to the initial solution (size and diversity of the initial population), the ‘groupability’ of the input machine-part matrix and the number of cells specified (Ah kioon, 2007). The meta-heuristics that have been extensively adapted to solve the CM design problem are, namely, genetic algorithm (Venugopal and Narendran 1992b; Gupta *et al*. 1995; Joines *et al*. 1996; Nsakanda *et al*. 2006), simulated annealing (Venugopal and Narendran 1992c; Chen *et al*. 1995; Mungwattana 2000) and tabu search (Logendran *et al*. 1994; Dake *et al*. 1995; Vakharia and Chang 1997; Lozano *et al*. 1999).

### 2.3. Manufacturing Attributes considered in CM Design

Lokesh and Jain (2010) presented an algorithm with important production data for single period. Lokesh and Jain (2010) also presented an algorithm with important production data for single period. As reported by several other researchers like Rheault *et al*., (1995), Chen (1998), Cao and Chen (2004), Defershah and Chen (2006a, 2006b, 2007, 2008), etc., Lokesh Kumar and Jain (2009, 2010) also reaffirmed the need of CMS relocation with change in product mix and demand. In most of the published articles, the cell formation problem has been considered under statistic conditions, in which cells are formed for a single time period with constant demand and product mix.

Today, the dynamic business environment needs shorter time periods with variable demand and product mix from period to period. Consequently, the best cell formation for one period may not be efficient for subsequent periods. A promising technique to overcome this problem is dynamic relocation. Therefore, there is increasing thrust for research to develop models and solution procedures for dynamic cell relocations over multiple times periods (Saxena and Jain, 2011).

A number of factors are typically included in solving manufacturing cell formation and part-family identification problems. A list of some of these attributes is given in table 2-1 (Saxena and Jain, 2011).

**Table 2-1 : List of Manufacturing Attributes**

| | |
|---|---|
| • **Alternative routing**<br>➢ **Selecting the best route**<br>➢ **Allowing alternative routing coexist** | • Demand fluctuation<br>➢ Deterministic<br>➢ Probabilistic |
| • **Dynamic cell relocation** | • Workload balancing<br>➢ Intercell workload<br>➢ Intracell workload |
| • **Types of tools required by a part** | • Types of tools available on a machine |
| • **Machine proximity constraint**<br>➢ **Separation constraint**<br>➢ **Collection constraint** | • Sequence of operation<br>➢ Used as input for determine magnitude of material flow<br>➢ Used as similarity measure between parts |
| • **Setup cost/time**<br>➢ **Setup cost**<br>➢ **Setup time** | • Cell/part-family size constraint<br>➢ Cell size constraint<br>➢ Part-family size constraint |
| • **Movement of parts(material handling cost)**<br>➢ **Intercell movement**<br>➢ **Intracell movement** | • Facility layout<br>➢ Intercell layout<br>➢ Intracell layout |

| | |
|---|---|
| • **Operator allocation** | • Machine capacity |
| • **Identical machines**<br>➢ **Within a cell**<br>➢ **In the entire system** | • Machine investment cost |
| • **Subcontracting cost** | • Tool consumption cost |
| • **Unit operation time** | • Machine operation cost |
| • **Lot splitting** | • Transfer batch size<br>➢ Intercell movement<br>➢ Intracell movement |
| • **Part holding** | • Breakdown effect to incorporate |
| • **Reliability modeling**<br>➢ **Machine repair cost**<br>➢ **Maintenance overhead cost**<br>➢ **Production time increase on machine due to machine downtime** | • Human Issues<br>➢ Salary cost<br>➢ Hiring cost<br>➢ Firing cost |
| • **Multiperiod planning** | • Machine relocation cost |
| • **Process batch size** | • Internal production overhead cost |

- **Intracell movements and intercell movements**

Many researchers included intercell movement in their model such as Defersha and Chen (2006a, 2006b, 2007, 2008), Cao and Chen (2004), Naskanda *et al*. (2006), Ahkioon *et al*., (2009a, 2009b), Safaei and Saidi-Mehrabad (2006), and Safaei *et al*., (2008). The impact of considering the cost of intracellular movement as a function of cell size was shown by Nsakanda *et al*., (2006) to be critical for quality of solution, highlighting the importance of this dimension in cell formation problem.

The sum of intercell and intracellular movement cost has been defined as one of the most effective in the performance evaluation of CMS since it directly affects various operational issues. In addition, these costs allow the consideration at the cell design level of the trade-off between the material movement and operational control costs on one hand and the number and sizes of cells on other hand (Saxena and Jain, 2011).. It also presents the trade-off between intercell cost and intercell movement cost (Nsakanda *et al.,* 2006). Intracell movements are included in their model by Nsakanda *et al.,* (2006), Ahkioon *et al*. (2009a, 2009b), Safaei and Saidi-Mehrabad (2006), and Safaei *et al*. (2008).

- **Process batch size, transfer batch size for the intracellular, and intercellular movements**

Alhourani and Seifoddini (2007) in their paper emphasized that a major portion of consumer goods is manufactured in batch-type production systems. According to one recent study Alhourani and Seifoddini (2007), about 75% of all manufacturing units are engaged in batch production of a large variety of parts in small batches.

In real world production systems, the parts to be produced do not move individually between machines; instead, they move in the form of batches. Therefore, it is misleading to consider the intracellular and intercellular movements of individual parts instead of the intracellular and intercellular movements of batches, Alhourani and Seifoddini (2007). Therefore, process Lokesh and Jain (2010) batch size and transfer batch sizes for the intracellular and intercellular movements should be included in DCMS model. Between 20% and 50% costs within manufacturing are related to material handling. Effective and innovative facility planning can reduce material handling costs by 10-30% (Tompkins *et al*. 2003). Very few batch sizes for intracellular movement and intercellular movement costs in their model.

- **Alternative routings**

A vast majority of the models assume a single process routing. Several authors have argued that by taking the flexibility offered by the multiple process routes (or routings) into account at design phase, several benefits can be realized such as allowing for a smaller number of machines, higher machine utilization, a reduced interdependence between cells, and improved system throughput Kusiak (1987). The presence of alternative routing is typical in many discrete, multi-batch, small lot size production environments. Defersha and Chen (2006) considered alternative routing feature. They also studied influence of this feature in cell formation model to conclude its importance for inclusion in cell formatin. Alternative routing is considered by Defersha and Chen (2006a, 2006b, 2007, 2008), Ahkioon *et al*. (2009a, 2009b), and Nsakanda *et al*. (2006).

- **Multiple copies of identical machines**

With multi-functional machines and multiple copies of each machine type allowed in the system, alternative routings give more flexibility in deciding upon cell formation (Lokesh and Jain 2010). Defersha and Chen (2006a, 2006b, 2007, 2008), Ahkioon *et al*. (2009a, 2009b), considered multiple copies of identical machine feature.

- **Dynamic cellular relocation of cells**

Due to Lokesh and Jain (2010) product mix and demand variation in a period in the multiperiod planning horizon, cell relocation is a promising strategy to make a manufacturing system efficient. With increased demand for flexibility, this strategy becomes more prominent in designing manufacturing cells (Chen 1998). Further, Lokesh and Jain (2010), Defersha and Chen (2006) presented a model with dynamic relocation of cell consideration. They studied the influence of dynamic relocation of cell feature to conclude importance of this feature for inclusion in cell formation problem. Dynamic relocation of cell attribute is also included in their models by Defersha and Chen (2006b, 2007, and 2008), Ahkioon *et al*. (2009a, 2009b), Wicks and Reasor (1999), Safaei and Saidi-Mehrabad (2006), and Safaei *et al*. (2008).

- **Machine procurement**

In multiperiod planning horizon, machine procurement feature improves manufacturing flexibility to respond to variations in part mix and demands through machine purchases to increase the internal production capacity (Lokesh and Jain 2010). This feature is included in their models by Defersha and Chen (2006b, 2007, and 2008), Ahkioon *et al*., (2009a, 2009b), Safaei and Saidi-Mehrabad (2006), Safaei *et al*., (2008), etc. Ahkioon *et al*. (2009a, 2009b) also studied the impact of this feature in cell formation model and concluded that the importance of this feature be included in the cell formation models.

- **Lot splitting**

Lot splitting is a process used primarily in batch manufacturing scheduling for dividing large orders into smaller batches providing the opportunity for simultaneous processing of orders to more than one work center (i.e., onto two machines within the same cell or even in different cells) (Saxena and Jain, 2011). This may result in better due date performance and in reduced flow time (Lokesh and Jain 2010). Defersha and Chen (2006a) included lot splitting in their model for improved machine utilization, reduced intercell movement, decreased operation cost, reduced machine investment, and evenly distributed workload They also studied the impact of lot splitting in their work to recommend its inclusion in cell formation models. Lot splitting is used by Defersha and Chen (2006a, 2006b, 2007, and 2008) and Ahkioon *et al.,* (2009a, 2009b).

- **Workload balancing**

Work load balancing feature results a smooth running of the system and better performance in terms of throughput, make span, flow tome, and tardiness (Lokesh and Jain 2010). It also decreases work-in-process inventory, improves material flow through system, and prevents heavy utilizations of some cells and lower utilization of other cells (Baykasoglu *et al,* 2001). Defersha and Chen (2006) included this featured in their work to conclude importance of this feature for inclusion in cell formation models.

- **Machine proximity and separation requirements**

Some machines must be separated from each other while others must be kept together. A number of authors included these feature in CMS design phase (Defersha and Chen (2006a, 2006b, 2007, 2008), Heragu and Chen (1998), Plaquin and Pierreval (2000), Sofianopoulou (1999).

- **Outsourcing**

Finished part outsourcing is an important production planning feature. This feature improves manufacturing flexibility to respond product mix and demand variation. Due to limited machine capacity or high cost of capacity addition, outsourcing can be used to procure some of the required parts to meet the market demands (Lokesh and Jain 2010). This feature is included in the models of Defersha and Chen (2006a, 2006b, 2007, 2008), Nasakanda *et al*. (2006), Ahkioon *et al*. (2009a, 2009b). Ahkioon *et al*. (2009a) also studied the impact of this feature in cell formation model and concluded that the importance of this feature be included in the model.

- **Part inventory held**

Finished part inventory held is also an important option of production planning. This feature also enhances manufacturing flexibility to respond product mix and demand variations. Depending on the demand and total cost of meeting that demand, the system could produce some surplus parts in a time period which can be used to provide part or all the demand for the same part in the future planning periods (Lokesh and Jain 2010). This feature is included in the models of Cao and Chen (2004), Defersha and Chen (2006a, 2006b, 2007, 2008), and Ahkioon *et al*. (2009a, 2009b). Ahkioon *et al*. (2009a, 2009b) also studied the impact of this feature in cell formation model and concluded that the importance of this feature be included in the model.

- **Breakdown effect to model reliability**

Among the factors influencing the performance of CMS is the reliability of the machines in manufacturing cells. An important aspect of CM systems that can be improved is the effect of machine breakdowns. Traditional CMS design models create CM systems that are vulnerable to disruption in the part routings. Machines are key elements of manufacturing systems. Generally, it is not possible to handle their breakdowns as quickly as production requirements. Traditionally, cell formation and work allocation are done with the assumption of 100% reliability of machines. In practice, machines fail during operations. Machines failure creates the greatest impact on due dates and other performance criteria, even if there is an existence of alternative routes of the parts to alternative workstation (Saxena and Jain, 2011).

Machine reliability lives consideration may help in realistic selection of process routing for parts in case of CF problems with alternative process routings. Avery small amount of research has considered machine breakdown or reliability or breakdown effects at the design stage of cells, it will enhance the solution by selection of process plans with lower machine failure leading to reduced overall cost of the CMS (Lokesh and Jain 2010).
The reliability of manufacturing systems, in general, is defined as the probability of a system or systems that will perform a required function for a given period of time using understated operating conditions (Lokesh and Jain 2010). Jabal Ameli *et al*. (2007, 2008) in their paper proposed that the reliability effect may be modeled as machine repair costs and production time delay costs.

- **Human Issues**

To get a full comprehensive model, the consideration of human issues should take into consideration in the model as well as technical issues (cell formation and design), since ignoring human issues will reduce the benefits of the proposed model and its implementation. Unfortunately, human issues are typically not examined as rigorously as often as technical issues. Nembhard (2001) discussed a heuristic worker-task assignment based on individual worker learning rates is examined for two tasks, one with a long production run, the other with a short production run. Norman *et al*. (2002) developed a mixed integer programming model for worker assignment in manufacturing cells that considers both human and technical skills and their impact on system performance, their model considers the case where there are different workers skill levels for each skill. Bidanda *et al*., (2005) presented an overview and evaluation of the diverse range of human issues involved in cellular manufacturing based on an extensive literature review. Further, a survey to determine the importance of eight different human issues in cellular manufacturing was administered to a sample of academics, managers, and workers involved in cellular design and implementation results are presented and discussed. Wirojanagud *et al*. (2007) used General Cognitive Ability (GCA) as the measure for individual differences, they developed a mixed integer programming model to determine the amount of hiring, firing, and cross-training for each GCA level to minimize total costs, which include training costs, salary costs, firing costs and missed production costs over multiple time periods. Aryanezhad *et al*. (2009) developed a nonlinear integer programming model to deal with a simultaneous dynamic cell formation and worker assignment problem (SDCWP). Part routing flexibility and machine flexibility and also promotion of workers from one skill level to another are considered.

However, the model ignores machine procurement, internal part production, machine operating, intracell movement and outsourcing. Mahdavi *et al*. (2010) presented the latest model in CMS design that aims at incorporating various aspects of technical issues in addition to consideration of human issues. They take into consideration multi-period production planning, dynamic system relocation, duplicate machines, machine capacity, available time of workers, and worker assignment. They have developed an integer non-linear mathematical programming model and have followed some linearization steps in order to obtain an integer linear problem and solve two examples. Their model is also a well-integrated model but it does not take into consideration certain issues that are addressed: machine procurement cost, internal part production cost, machine operating cost, and outsourcing cost instead of backorder cost.

### 2.4. Findings of the literature review

In this chapter, a review of recent literature on CM models that integrate various production aspects is presented, allowing the identification of several important manufacturing attributes. The design of CM systems is a multi-criteria and multi-step process. Before implementing a CM system, a company needs to invest adequate effort during the planning and design phase because the benefits of CM are only possible by sufficiently incorporating the structural and operational features of a manufacturing plant within the CM design decisions. Therefore, integrated models can be used by designers to evaluate cellular layouts considering various aspects of the manufacturing operations. The models developed in this research are briefly presented in this section so as to demonstrate the manufacturing attributes that are covered herein. Such attributes are used to represent the important structural and operational aspects that the cell designer has to take into consideration when forming machine cells and part families. As already mentioned, the design of a cellular manufacturing system consists of three main stages (Dimopoulos and Zalzala 1998). This research deals with the first phase of the CM design problem, namely, the cell formation problem. Wu and Salvendy (1993) draw attention upon the fact that the design of CM systems must address the need for many important production factors to be considered when the cells are created. Table 2-2 shows a survey of 16 recently published articles together with the manufacturing attributes (referenced by the caption) that are incorporated within each one of the developed models. The models developed in this research are also presented in table 2-2, showing that the proposed models in this research cover an extensive amount of the manufacturing attributes that are important in CM design and integrate more of these than previous models. A review of a few key models is now presented in more detail to not only describe the manufacturing criteria that were considered but to also discuss the solution approaches used.

Most of the researchers had minimization of cost objective function with a sum of the various cost terms combinations. For instance, Cao and Chen (2004) used the objective function in their model to minimize the sum of intercell material handling cost, setup cost, and product inventory cost. Nsakanda *et al*., (2006) used the objective function in their model to minimize the sum of intercell material handling cost, intracell material handling cost, and outsourcing cost. Safaei and Saidi-Mehrabad (2006) and Safaei *et al*., (2008) used the objective function in their model to minimize the sum of intercell material handling cost, intracell material handling cost, constant and variable production cost, relocation cost, and machine procurement cost. Defersha and Chen (2006a, 2006b, 2007, and 2008) used the objective function to minimize the sum of intercell material handling cost, intracell material handling cost, setup cost, machine procurement cost, and machine maintenance and overhead cost.

Ahkioon *et al*., (2009a) used the objective function in their model to minimize the sum of intercell material handling cost, intracell material handling cost, internal part production cost, outsourcing cost, inventory holding cost, relocation cost, machine maintenance, and overhead cost. Ahkioon *et al*., (2009b) used the objective function in their model to minimize the sum of intercell material handling cost, intracell material handling cost, internal part production cost, outsourcing cost, inventory holding cost, relocation cost, machine procurement cost, and machine maintenance, and overhead cost. Mahdavi *et al*., (2010) used the objective function in their model to minimize the sum of intercell material handling cost, backorder cost, inventory holding cost, relocation cost, and machine maintenance and overhead cost, workers hiring, firing, and salary cost.

It is obvious that minimization of some of various cost criteria as objective function is used by various authors to identify machine cell (i.e., machine similarities) and part families (i.e., part similarities). It is also obvious that most authors did not take into consideration the human issues (workers cost and workers assignments).

In the existing research works, each researcher/research group included few design attributes of their interests individually or simultaneously, and excluding the most of the design attributes in their models. CM design is currently being researched with emphasis on development of more integrated models by including various issues. The proposed model in this research deals with multi-period planning where the part demand and production requirements vary from one period to the next. The CM model is designed so as to achieve an agile cell configuration, that is, machine relocation can occur to change the overall CM layout as well as workers. At the same time, various features about the machines are integrated namely: machines can have identical copies, have limited capacities, multifunctional, can be procured and can be relocated. Machine operating, maintenance and overhead costs, and overhead costs are minimized in the objective function. Other costs that are minimized include both intercellular and material handling, internal part production, subcontracting and inventory holding. The proposed model also considers the human issues: worker available time, cell size limits of workers, salary cost, hiring cost, firing cost.

**Table 2-2 : Review of manufacturing attributes used in CM design**

| Models/Manufacturing Attributes | 1 | | 2 | 3 | 4 | 5 | | 6 | 7 | | 8 | | | | | | 9 | | 10 | 11 | 12 | 13 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | a | b | | | | a | b | | a | b | a | b | c | d | e | f | a | b | | | | a | b | c | d | e |
| Proposed model | X | | X | X | X | | X | X | | X | X | X | X | X | X | X | | X | | | X | X | X | X | X | X |
| Saxena and Jain (2011) | X | X | X | X | X | | X | X | | X | X | X | X | X | X | X | | X | X | X | X | | | | | |
| Mahdavi *et al.* (2010) | X | | | | X | | X | X | | X | X | X | | X | X | X | | X | | | X | X | X | X | X | X |
| Ahkioon *et al.* (2009a) | X | X | X | X | X | | X | X | | X | X | X | X | X | X | | | X | | X | X | | | | | |
| Ahkioon *et al.* (2009b) | X | X | X | X | X | | X | X | | X | X | X | X | X | X | X | | X | X | X | X | | | | | |
| Aryanezhad *et al.* (2009) | X | | | | | | X | X | | X | X | X | X | | X | X | | X | | | X | X | X | X | X | X |
| Caux *et al.* (2000) | X | | | | | | | | | | X | X | X | | | | X | | | X | X | | | | | |
| Chen (2001) | X | | | | X | | X | | | | | | X | | | | | | | | | | | | | |
| Cao and Chen (2005) | X | | | | | X | | | | | X | X | X | | | | | | | | X | | | | | |
| Chen and Cao (2004) | X | | | | X | | X | | | | X | X | X | | | | | | | | X | | | | | |
| Das *et al.* (2006) | X | | | | | | X | X | | | | X | X | | | | | | | X | X | | | | | |
| Defersha and Chen (2006) | X | | | X | | | X | X | | X | X | X | X | X | X | X | X | | | X | X | | | | | |
| Jayaswal and Adil(2004) | X | | | | | | | | | | X | X | X | | | | X | | | X | | | | | | |
| Gupta *et al.* (1996) | X | X | | | | | | | | | | X | | | | | | | | | | | | | | |
| Mungwattana (2000) | X | | | | X | X | X | X | | X | X | X | X | | X | | X | | | X | X | | | | | |
| Nsakanda *et al.* (2006) | X | X | | X | | | | | | | X | X | | | | | X | | | X | X | | | | | |
| Safaei *et al.* (2007) | X | X | | | | | X | X | | X | X | X | X | X | X | | X | | | X | X | | | | | |

**Caption to Table 2-2: Important design attributes for CMS design**

| | | | |
|---|---|---|---|
| 1a. Intercellular material handling cost<br>1b. Intracellular material handling cost | 4. Inventory holding in production planning | 7a. Robust cell configuration<br>7b. Agile cell configuration | 10. Formation of part *contingency* routings. |
| 2. Part internal production cost | 5a. Stochastic demand requirements<br>5b. Deterministic demand requirements | 8a. Machines with multiple copies; 8b. Machine with limited capacities; 8c. Machine operating cost; 8d. Machine maintenance and overhead cost; 8e. Machine relocation and cost;<br>8f. Machine procurement | 11. Part operation sequence and processing times |
| 3. Subcontracting cost | 6. Multi-period planning | 9. Alternate routings: a. Chosen from user-specified routings; b. Chosen from all possible options based on operation and machine type | 12. Cell size limits of machines – upper and lower bound |
| 13a. Worker available time 13b. Cell size limits of workers – upper bound 13c. Salary cost 13d. Hiring cost 14e. Firing cost | | | |

# Chapter 3

## Integrated Model with Production Planning, Dynamic System Relocation and Human Issues Considerations

### 3.1. Introduction

The design of Cellular Manufacturing System (CMS) involves many structural and operational issues. One of the first important design steps is the formation of part families and machine cells. The effectiveness of this design step heavily depends on the proper consideration of the relevant aspects. To this end, a model that incorporates various pragmatic issues is essential. In this chapter, a comprehensive mathematical model for the design of cellular manufacturing systems is proposed. The Model incorporates dynamic system relocation (machine relocation as well as workers), machine procurement and production planning with the options of internal production of parts, inventory holding, and subcontracting. The CM model is first formulated as a non-linear Mixed Integer Programming (MIP) model. Some linearization procedures are then proposed and implemented on the model, resulting in a linear mixed integer formulation of the model. The linearized Model is solved through small, medium and large problem instances, using IBM ILOG CPLEX Optimization Studio 12.2/OPL. The computational results are discussed.

### 3.2. Model assumptions

The CM model has been developed under the following assumptions:

- The demand for each part type in each period is known and deterministic.
- Each machine type has a limited capacity expressed in hours during each time period.
- Relocation involves the addition and removal of machines to any cell and relocation from one cell to another between periods; also, it involves the addition and removal of worker to any cell and relocation from one cell to another between periods.
- Maintenance and overhead costs of each machine type are known. These costs are considered for each machine in each cell and period no matters that the machine is active or idle.
- Salary of each worker type is known. This cost is considered for each worker in each cell and period no matter that the worker is active or idle.
- The available time for each worker is known.
- The number of cells is known and constant during all periods.
- Only one worker is allotted for processing each part on each corresponding machine.
- The demand for each part in each period can be satisfied by production, inventory from the last periods and/or purchasing.

## 3.3. The proposed mathematical model

In this section, we present the problem definition, the mathematical model, and the explanations of the objective function and the constraints.

### 3.3.1. Problem definition

The proposed model is formulated as a single objective nonlinear mixed integer programming which is converted to a linear one. The objective function consists of two separate components. The first part of the objective function is related to machine-based costs such as production cost, intercell material handling cost, machine costs in the planning horizon. The second part is related to human issues and consists of hiring cost, firing cost, and salary cost

Classical cell formation problem commonly represented in a matrix called the part-machine matrix with 0 or 1 entry. A 1 indicates that part P requires machine m for an operation, and 0 indicates otherwise. As an example figure (3.1) shows the part-machine matrix for a small problem of seven parts and seven machines. Within a manufacturing environment there are machine types which have different operational capabilities, limited capacities and multiple copies. There are also different part types, each of which requires a certain sequence of specific operations and processing capacity to complete production.

| | | Products | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 |
| | 2 | 1 | 0 | 0 | 0 | 0 | 0 | 1 |
| | 3 | 0 | 0 | 1 | 1 | 0 | 1 | 0 |
| Machines | 4 | 0 | 0 | 1 | 1 | 0 | 1 | 0 |
| | 5 | 1 | 0 | 0 | 0 | 0 | 0 | 1 |
| | 6 | 0 | 0 | 1 | 1 | 0 | 1 | 0 |
| | 7 | 0 | 1 | 0 | 0 | 1 | 0 | 0 |

Figure 3-1 Machine-Part Matrix

The overall strategy of forming a CM layout; is to group parts that require similar operations into the same cell whilst assigning machines to these cells so that they are capable of performing these operations. In other words, the part-machine matrix is rearranged to a new matrix such that each part family is completely processed within a cell of machines and each part in part family processed by every machine in the corresponding machine group. For example, the rearrangement of the matrix in figure (3.1) is shown in figure (3.2), where three different machine cells are indicated within blocks. Cell 1 consists of machines 2 and 5; cell 2 consists of machines 3, 4 and 6, while cell 3 consists of machines 1 and 7. Obviously, three part families are formed, parts 1 and 7 constitute the first family, parts 3, 4 and 6 constitute the second family, and the rest of the parts constitute the third family. However, in real life the nature of data sets are such that a perfect decomposition is hardly ever obtained. In this situation the goal is to obtain a near perfect decomposition considering the following objectives while partitioning the matrix:

1. To have a minimum number of zeros inside the diagonal block (Voids).
2. To have a minimum number of ones outside the diagonal blocks (Exceptional).

| | | Products | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 7 | 3 | 4 | 6 | 2 | 5 |
| Machines | 2 | 1 | 1 | | | | | |
| | 5 | 1 | 1 | | | | | |
| | 3 | | | 1 | 1 | 1 | | |
| | 4 | | | 1 | 1 | 1 | | |
| | 6 | | | 1 | 1 | 1 | | |
| | 1 | | | | | | 1 | 1 |
| | 7 | | | | | | 1 | 1 |

Figure 3-2 Parts-Machines Families

Figure (3.3) shows a representation of a solution to the classical CFP where four machines have been grouped into two cells, e.g. machines 2 and 4 are in cell I, and where five part types are grouped into two part families in such a way that each of these part families are assigned to a cell containing the machines required for the operations. Part type 1 and 3 (belonging to part family I) are thus assigned to machine cell I as they require machines 2 and 4 for processing.

The 'X', termed an exceptional element, created when part requires processing on machine that is not available in the allocated cell of the part, when part needs visit a different cell for its processing the intercell material handling cost increase. This also requires more coordinating effort between cells; machine cell I does not contain machine type 1 required for an operation on part 3. So the latter has to be transferred to machine cell II as the latter contains a copy of machine type 1. The 'O' represents a void, a void indicates that a machine assigned to a cell is not required for the processing of a part in the cell. When a part passes a machine without being processed on the machine, it contributes to an additional intra-cell material handling cost. This leads to large, inefficient cells; machine type 3 is only required to process parts 2 and 4 in cell II and is not needed for part type 5. It must be noted that this is a very simple situation as machine capacities, availabilities, multiple routings and other manufacturing aspects are ignored.
Relocation is not restricted on machines, it is applied for workers; to get a full comprehensive model the consideration of human issues should take into consideration as well as technical issues (cell formation and design), since ignoring human issues will reduce the benefit of the proposed model. Since workers have different available time, different skills, and different ability to work on different machines; a relocation for the workers is important, it means group the workers who have the ability and the skills to

work with the machines that exist in that cell, also, when a relocation happened to parts and machines, then it should also be applied for the workers. Hiring and firing for the workers in each time period for each cell should be considered.

| | | Products | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 3 | 2 | 4 | 5 |
| Machines | 2 | 1 | 1 | | | |
| | 4 | 1 | 1 | | | |
| | 1 | | **X** | 1 | 1 | 1 |
| | 3 | | | 1 | 1 | **O** |

Figure 3-3 Voids and Exceptional

The optimal configuration for the classical cell formation problem is the one that minimizes the total cost of material handling in terms of intercellular (from cell to cell) and intracellular (within the same cell). With regards to the multi-period production planning problem, it is assumed that the demands for parts vary in a deterministic way. This allows the model to consider producing more in a period so that inventory can be used in future periods or to subcontract parts when internal production is not feasible either due to insufficient machine capacity or uneconomical repercussions. Simultaneously, the CM environment can respond by undergoing system relocation where machines are relocated from one cell to another and/or where new process routings are selected for the part types. Additionally, machines can be procured to increase the internal production capacity. Finally, minimizing the salary, hiring, and firing worker's cost while consideration of the workers relocation to give the best production output. The notations used for the model are presented followed by the objective function, constraints and model properties.

- Sets:

*p= {1, 2, 3… P}* Index set of part types.

*m= {1, 2, 3... M}* Index set of machine types.

*c= {1, 2, 3… C}* Index set of cells.

*t= {1, 2, 3… T}* Index set of time periods.

*w= {1, 2, 3… W}* Index set of worker types.

- Model Parameters:

$D_{pt}$ Demand for part type $p$ in time period $t$

$V_p^{inter}$ Intercell movement cost of part type $p$

$\mu_{mpw}$ = 1, if machine type *m* is able to process part type *p* with worker *w*,

= 0, otherwise.

$\lambda_{pm}$ = 1, if part type *p* needs machine type *m,*

= 0, otherwise.

| | |
|---|---|
| $U_p$ | Outsourcing cost per unit of part type *p* in period *t*. |
| $t_{pmw}$ | Processing time part type $p$ on machine type $m$ with worker type $w$ |
| $T_{mt}$ | Time capacity of one machine of type $m$ for one time period $t$ |
| $LL_c$ | Minimum number of machines limit in cell $c$ |
| $UL_c$ | Maximum number of machines limit in cell $c$ |
| $LW_c$ | Minimum size of cell $c$ in terms of the number of workers |
| $R_m^+$ | Relocation cost of installing one machine of type $m$ |
| $R_m^-$ | Relocation cost of removing one machine of type $m$ |
| $L^p$ | a large positive number |
| $H_{pt}$ | Part holding cost per part type $p$ per time period $t$ |
| $A_m$ | Quantity of machine type $m$ available at time period $t=1$ |
| $A_w$ | Number of worker type $w$ available |
| $RW_{wt}$ | Available time for worker type $w$ at time period $t$ |
| $S_{wt}$ | Salary cost of worker type $w$ within period $t$ |
| $HI_{wt}$ | Hiring cost of worker type $w$ within period $t$ |
| $F_{wt}$ | Firing cost of worker type $w$ within period $t$ |
| $OV_m$ | Machine maintenance overhead cost of machine type $m$ per unit time in time period $t$ |
| $OP_m$ | Procurement cost per machine type m |
| $Ɣ_m$ | Operating cost per unit time per machine type m |
| $£_p$ | Internal production cost per part type p |

- Model Decisions Variables:

$N_{mct}$ Number of type $m$ machines to present at cell $c$ at beginning of time period $t$

$Y^{+}_{mct}$ Number of type $m$ machines added in cell $c$ at beginning of time period $t$

$Y^{-}_{mct}$ Number of type $m$ machines removed from cell $c$ at beginning of time period $t$

$BN_{mt}$ Number of machines of type m procured at time t

$A^{*}_{mt}$ Quantity of machine type m available at time period t after accounting for machines that have been procured

$Q_{pt}$ Number of part inventory of type $p$ kept in time period $t$ and carried over to period *(t+1)*

$\beta_{pt}$ Production volume of part type p to be produced in time period t

$O_{pt}$ Number of parts to be outsourced at time period t.

$L^{+}_{wct}$ Number of workers of type $w$ added to cell $c$ during period $t$

$L^{-}_{wct}$ Number of workers of type $w$ removed from cell $c$ during period $t$

$N_{wct}$ Number of workers of type $w$ allotted to cell c in period $t$

$v_{pct}$ = 1, if part type p is processed in cell c in period t.

= 0, otherwise.

$z_{pmwct}$ = 1, if part type p is to be processed on machine type m with worker w in cell c in period t.

= 0, otherwise.

### 3.3.2. Objective function and constraints

The objective function and constraints of our model is as follows:

Minimize

$$\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M} N_{mct}.OV_m \tag{1.1}$$

$$+\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M} R_m^{+}.Y_{mct}^{+} \tag{1.2}$$

$$+\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M} R_m^{-}.Y_{mct}^{-} \tag{1.3}$$

$$+\sum_{t=1}^{T}\sum_{p=1}^{P} Q_{pt}.H_{pt} \tag{1.4}$$

$$+\sum_{t=1}^{T}\sum_{p=1}^{P} O_{pt}.U_p \tag{1.5}$$

$$+\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{w=1}^{W} S_{wt}.N_{wct} \tag{1.6}$$

$$+\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{w=1}^{W} HI_{wt}.L_{wct}^{+} \tag{1.7}$$

$$+\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{w=1}^{W} F_{wt}.L_{wct}^{-} \tag{1.8}$$

$$+\sum_{t=1}^{T}\sum_{p=1}^{P}\left[\left(\sum_{c=1}^{C} v_{pct}\right)-1\right].V_p^{inter}.\beta_{pt} \tag{1.9}$$

$$+\sum_{t=1}^{T}\sum_{m=1}^{M} BN_{mt}.OP_m \tag{1.10}$$

$$+\sum_{t=1}^{T}\sum_{p=1}^{P} \beta_{pt}.£_p \tag{1.11}$$

$$+\sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{c=1}^{C} z_{pmwct} * \beta_{pt} * t_{pmw} * \text{Ɣ}_m \tag{1.12}$$

The objective function has several terms. The first term (1.1) represents machines maintenance overhead cost. The second term (1.2) represents relocation cost of machines installation. The third term (1.3) represents relocation cost of machines removal. The fourth term (1.4) represents part holding cost. The fifth term (1.5) represents outsourcing cost. The sixth term (1.6) represents the salary worker cost. Term (1.7) represents the hiring worker cost. Term (1.8) represents the firing worker cost. The ninth term (1.9) represents part intercellular movement cost. Tenth term (1.10) represents machine procurement cost. Term (1.11) represents the internal production cost. Term (1.12) represents machine operating cost.

**Subject to**

$$\beta_{pt} + Q_{p(t-1)} - Q_{pt} + O_{pt} = D_{pt}\,; \forall(p,t) \tag{2}$$

constraints (2) shows that demand of part type $p$, in each time period $t$ is satisfied through internal part production $\beta_{pt}$, and/or part inventory carried over from previous period $Q_{p(t-1)}$, and/or by outsourcing option $O_{pt}$, subtracting the inventory volume which will be kept to satisfy the demand for the coming period $Q_{pt}$.

$$v_{pct} = \min\left(1, \sum_{m=1}^{M}\sum_{w=1}^{W} z_{pmwct}\right) \; ; \; \forall(p,c,t) \tag{3}$$

Equation (3) is to determine whether part type p is processed within cell c in period t.

$$\sum_{c=1}^{C} z_{pmwct} \leq \mu_{mpw} \; ; \; \forall(p,m,w,t) \tag{4}$$

$$\sum_{c=1}^{C}\sum_{w=1}^{W} z_{pmwct} = \lambda_{pm}; \forall(p,m,t) \tag{5}$$

Constraints (4) and (5) are to make sure that only one worker is assigned for each part on each machine type.

$$N_{mct} = N_{mc(t-1)} + Y_{mct}^{+} - Y_{mct}^{-}; \; \forall(m,c,t) \tag{6}$$

Constraint(6) is to ensure that the number of machines type m in current period $N_{mct}$ is equal to the number of machines in the previous period $N_{mc(t-1)}$, adding the number of machines moved in $Y_{mct}^{+}$ and subtracting the number of machines moved out of that cell $Y_{mct}^{-}$.

$$LB_c \leq \sum_{m=1}^{M} N_{mct} \leq UB_c; \; \forall(c,t) \tag{7}$$

By constraint (7), lower and upper bounds on sizes of cell in terms of the number of machines are enforced.

$$\sum_{w=1}^{W} N_{wct} \geq L_{wc},\ \forall(c,t) \tag{8}$$

Constraint (8) ensures that the minimum number of workers will be assigned to cell k in each period.

The cell size constraint is a customer defined, by making the lower bound of these constraints equal to zero; there is a probability of forming a cells with no machines or workers exist in it, so it is required to put the lower bound greater than zero.

$$\sum_{m=1}^{M}\sum_{p=1}^{P} z_{pmwct}.\,t_{pmw}.\,\beta_{pt} \leq N_{wct}.\,RW_{wt} \quad ,\forall(w,c,t) \tag{9}$$

$$\sum_{w=1}^{W}\sum_{p=1}^{P} z_{pmwct}.\,t_{pmw}.\,\beta_{pt} \leq N_{mct}.\,T_{mt} \quad ,\forall(w,c,t) \tag{10}$$

Constraints (9) and (10) ensure that the available time for workers and capacity of machines are not exceeded, respectively.

$$N_{wc(t-1)} + L_{wct}^{+} - L_{wct}^{-} = NW_{wct} \ ,\forall(w,c,t) \tag{11}$$

Equation (11) balances the number of workers between consecutive time periods. Where the number of worker of type *w* in cell *c* at time *t* ($NW_{wct}$) is equal to the number of worker in the previous period $N_{wc(t-1)}$, plus the number moved to that cell $L_{wct}^{+}$, minus the number moved out $L_{wct}^{-}$.

$$\sum_{c=1}^{C} N_{wct} \leq AW_{w} \ ,\forall(w,t) \tag{12}$$

Constraint (12) guarantees that the total number of workers of each type assigned to different cells in each period will not exceed total available number of workers of that type.

$$\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{w=1}^{W} z_{pmwct} \leq \beta_{pt}.L^{p}; \forall(p,t) \tag{13}$$

Constraint (13) ensures that If $\beta_{pt} = 0$, no machines, worker and cell should be considered.

$$A^{*}_{m(t=1)} = A_{m(t=1)} + BN_{m(t=1)}, \forall(m) \tag{14}$$

Constraint (14) relates to the machine availability constraint for period 1, taking into consideration the extra machines introduced through the machine procurement option. In period 1, the total number of machine of each type available is equal to the machine availability (before procurement) plus the number of machines procured in the same period 1. Therefore, if $A_{m(t=1)} = 0$, there are no machines present in the system initially, meaning that a CM system is being designed and implemented from no existing manufacturing layout. If $A_{m(t=1)} > 0$, there are machines already available in the system, meaning that the existing manufacturing layout is being reconfigured to form a CM layout.

$$A^{*}_{m(t+1)} = A^{*}_{mt} + BN_{m(t+1)}, \forall(m) \tag{15}$$

Constraint (15) relates to the machine availability constraint for the subsequent time periods. It takes into consideration the extra machines introduced through the machine procurement option in the period under consideration as well as those procured in all of the previous periods.

$$\sum_{c=1}^{C} N_{mct} \leq A^{*}_{mt}; \forall(m,t) \tag{16}$$

Constraint (16) ensures that the total number of machines in each cell will not exceed the number of available machines.

$$N_{mct}; Y_{mct}^{+}; Y_{mct}^{-} \geq 0 \text{ and integer } \forall(m, c, t)$$
$$L_{wct}^{+}; L_{wct}^{-}; N_{wct} \geq 0 \text{ and integer } \forall(w, c, t)$$
$$Q_{pt}; \beta_{pt}; O_{pt} \geq 0 \text{ and integer } \forall(p, t)$$
$$BN_{mt}; A_{mt}^{*} \geq 0 \text{ and integer } \forall(m, t)$$
$$v_{pct} \in \{0, 1\} \; \forall(p, c, t) \tag{17}$$
$$z_{pmwct} \in \{0, 1\} \; \forall(p, m, w, c, t)$$

Constraint (17) is the logical binary and non-negativity integer requirements on the decision variable.

### 3.4. Linearization of the model

This section presents the linearization procedures, the linearized model, and the number of variables and constraints.

#### 3.4.1. Linearization Procedures

Objective function is a nonlinear integer equation due to nonlinear terms (1.9) and (1.12) in the objective function and also constraints (3), (9) and (10). To transform these terms to linear terms, the following new variables are defined Mahdavi *et al*. (2010):

$$\boldsymbol{F_{pct}} = \boldsymbol{v_{pct}} * \boldsymbol{\beta_{pt}}$$

$$\boldsymbol{J_{pmwct}} = \boldsymbol{z_{pmwct}} * \boldsymbol{\beta_{pt}}$$

By considering these equations, following constraints must be added to the model:

$$F_{pct} \geq \beta_{pt} - L^p\left(1 - v_{pct}\right) \forall (p, c, t) \qquad (18)$$

$$F_{pct} \leq \beta_{pt} + L^p\left(1 - v_{pct}\right) \forall (p, c, t) \qquad (19)$$

$$J_{pmwct} \geq \beta_{pt} - L^p\left(1 - z_{pmwct}\right) \forall (p, m, w, c, t) \qquad (20)$$

$$J_{pmwct} \leq \beta_{pt} + L^p\left(1 - z_{pmwct}\right) \forall (p, m, w, c, t) \qquad (21)$$

$$F_{pct} \geq 0 \; and \; is \; integer \quad \forall (p, c, t) \qquad (22)$$

$$J_{pmwct} \geq 0 \; and \; is \; integer \quad \forall (p, m, w, c, t) \qquad (23)$$

Also to linearize the proposed model, constraint (3) should be replaced by these two constraints:

$$\sum_{m=1}^{M} \sum_{w=1}^{W} z_{pmwct} \leq L^p * \boldsymbol{v_{pct}}, \forall (p, c, t) \qquad (24)$$

$$\sum_{m=1}^{M} \sum_{w=1}^{W} z_{pmwct} \geq \boldsymbol{v_{pct}}, \forall (p, c, t) \qquad (25)$$

### 3.4.2. The linearized model

Therefore, the proposed linear mathematical programming model is as follows:

Min = Eq. (1.1) to Eq. (1.8)

$$+\sum_{t=1}^{T}\sum_{p=1}^{P}\left[\left(\sum_{c=1}^{C} F_{pct}\right)-\beta_{pt}\right].V_p^{inter}$$

+ Eq. (1.10) + Eq. (1.11)

$$+\sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{c=1}^{C} J_{pmwct} * t_{pmw} * \gamma_m$$

St.:

Constraints (2), (4) - (8), (11) - (25) and the new version of constraints (9) and (10) are:

$$\sum_{m=1}^{M}\sum_{p=1}^{P} J_{pmwct} * t_{pmw} \le N_{wct} * RW_{wt}, \forall(w,c,t) \qquad (26)$$

$$\sum_{w=1}^{W}\sum_{p=1}^{P} J_{pmwct} * t_{pmw} \le N_{mct} * T_{mt}, \forall(m,c,t) \qquad (27)$$

To set the value of the beginning inventory and the number of workers in the period time (0) since a CM system is being designed and implemented from no existing manufacturing layout, constraints (28) and (29), should be added to the model constraints:

$Q_{p(t=0)} = 0\ ;\ \forall(p)$ (28) $\sum_{c=1}^{C} N_{wc(t=0)} = 0\ ;\ \forall(w)$ (29)

### 3.5. Number of variables and constraints

Table (3-1) and (3-2) show the numbers of variables and the number of constraints in the linearized model, respectively.

Table 3-1 : Number of Variables

| Variables | Count | Variables | Count | Variables | Count |
|---|---|---|---|---|---|
| $\mathbf{N_{mct}}$ | M×C×T | $Q_{pt}$ | P×T | $N_{wct}$ | W×C×T |
| $\mathbf{Y^{+}_{mct}}$ | M×C×T | $\beta_{pt}$ | P×T | $v_{pct}$ | P×C×T |
| $\mathbf{Y^{-}_{mct}}$ | M×C×T | $O_{pt}$ | P×T | $z_{pmwct}$ | P×M×W×C×T |
| $\mathbf{BN_{mt}}$ | M×T | $L^{+}_{wct}$ | W×C×T | $F_{pct}$ | P×C×T |
| $\mathbf{A^{*}_{mt}}$ | M×T | $L^{-}_{wct}$ | W×C×T | $J_{pmwct}$ | P×M×W×C×T |

Total = 3(M×C×T) + 2(M×T) + 3(P×T) + 3(W×C×T) + 2(P×C×T) + 2(P×M×W×C×T)

Table 3-2 : Number of Constraints

| Constraint | Count | Constraint | Count | Constraint | Count |
|---|---|---|---|---|---|
| 2 | P×T | 13 | P×T | 21 | P×M×W×C×T |
| 4 | P×M×W×T | 14 | M | 24 | P×C×T |
| 5 | P×M×T | 15 | M×T | 25 | P×C×T |
| 6 | M×C×T | 16 | M×T | 26 | W×C×T |
| 7 | 2×(C×T) | 18 | P×C×T | 27 | M×C×T |
| 11 | W×C×T | 19 | P×C×T | 28 | P |
| 12 | W×T | 20 | P×M×W×C×T | 29 | W |
| 22 | P×C×T | 23 | P×M×W×C×T | | |

Constraint 17 : 3× (M×C×T) + 3×(W×C×T) + 3×(P×T) + 2×(M×T) + (P×C×T) + (P×M×W×C×T)

Total = 5(P×C×T) + 3(P×M×W×C×T) + 2(M×T) + 2(M×C×T) + 2(W×C×T) + M + P + W + 2(C×T) + 2(P×T) + (P×M×W×T) + (P×M×T) + 3(M×C×T) + 3(W×C×T) + 3(P×T) + 2(M×T) + (P×C×T) + (P×M×W×C×T)

### 3.6. Computational results and discussion

The objective of this section is to run and test the comprehensive model developed. This section presents the use of 8 numerical examples extracted from existing CM literature to solve the proposed CM model. Mahdavi *et al*. (2010) presented a real-life data size, which had been collected from a company running CMS environment. Since their model is different from our proposed model, we added some additional cost parameters for the features not addressed in their data sets and model (e.g. Machine procurement cost). The unknown cost parameters, which proved more difficult to get, were extracted by cross-referencing between the data sets containing them and then incorporated within the other data sets that are missing this information. Therefore, all of the data sets used in each solved numerical example contain values within the same range in terms of unit costs.

The models were solved using IBM ILOG CPLEX Optimization Studio 12.2/OPL and run with Intel core 5 and 6 GB RAM workstation. Each one of the numerical examples used is solved as an integrated model and the solving ability of CPLEX is being tested as the problem size increases (number of variables and constraints). We compare the computational time taken and optimality gap (difference between current feasible solution and best bound on optimal solution) with respect to the various problem sizes.

The results are presented in table 3-3, where elapsed time and optimality gap are shown for each problem instance. Also shown are the number of time periods for which the design is performed, the number of cells *c* used in each problem, number of parts, number of machines and the number of workers.

It is evident that the required computational times increase as the problem sizes are increased. All of the small-scale problems (problems 1 to 3) were successfully solved in less than 10 seconds with the highest number of variables and constraints encountered being 605 and 683 respectively. The medium-sized problems (problems 4 to 6) required more computational times but were solved within 778.84 seconds. The largest number of variables and constraints in these medium-sized problems were 829 and 1013 respectively. Therefore, the small to medium-scale problems (1 to 6) were solved within reasonable computational times. Problems 7 and 8 are considered to be large-scale ones with the highest number of variables and constraints being 881 and 1030 respectively. Both of these two problems scenarios proved to be too difficult for the CPLEX/ OPL to solve since no optimal solution was obtained after 3 hours of computation. In fact, CPLEX stopped solving both problems (7 and 8) even before the time limit due to insufficient memory. This clearly indicates that the CPLEX/OPL is unable to produce good quality solutions in reasonable computational times for large-scale problems of the CMS model.

Table 3-3 Summary of computational results from selected data sets

| Problem scenario | Classification | No of part types | No of time periods | No of Machines | No of Workers | No of cells | No of variables | No of constraints | Time elapsed (seconds) | Optimality Gap (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Small-Scale | 1 | 2 | 6 | 2 | 2 | 260 | 265 | 0.95 | 0.00 |
| 2 | Small- Scale | 1 | 5 | 6 | 2 | 2 | 561 | 649 | 07.4 | 0.00 |
| 3 | Small- Scale | 4 | 2 | 3 | 4 | 2 | 605 | 683 | 3.62 | 0.00 |
| 4 | Medium-Scale | 4 | 2 | 3 | 3 | 3 | 653 | 758 | 98.17 | 0.00 |
| 5 | Medium-Scale | 4 | 2 | 3 | 4 | 3 | 818 | 941 | 648.46 | 0.00 |
| 6 | Medium-Scale | 4 | 3 | 3 | 4 | 2 | 829 | 1013 | 778.84 | 0.01 |
| 7 | Large- Scale | 2 | 3 | 4 | 2 | 3 | 857 | 917 | 1041.53 | 3.48 |
| 8 | Large- Scale | 2 | 5 | 6 | 2 | 2 | 881 | 1030 | 2249.1 | 12.38 |

# Chapter 4

# Numerical Examples and Discussion

## 4.1 Introduction

In this chapter two comprehensive examples are introduced. At the beginning of each example a fully input data are presented, as shown in figure 4-1, these input data can be divided into three main categories: a) Machine information; b) Products information; and c) Workers information, a classification of these input data are shown below. The results of solving the proposed model are then discussed. It is clearly shown the production planning for each time period; the quantity of internal production, the quantity to be held as inventory, and the quantity to be outsourced for each part type, also the results of parts, machines and workers assignments for each cell in each time period as well as the cost of production and relocation. An explanatory scheme shows the design of our system for the first period, actions to be taken during relocation, and the system design after relocation. These actions consist of: a) Hiring workers; b) Firing workers; c) Machines relocation; and d) Parts relocations.

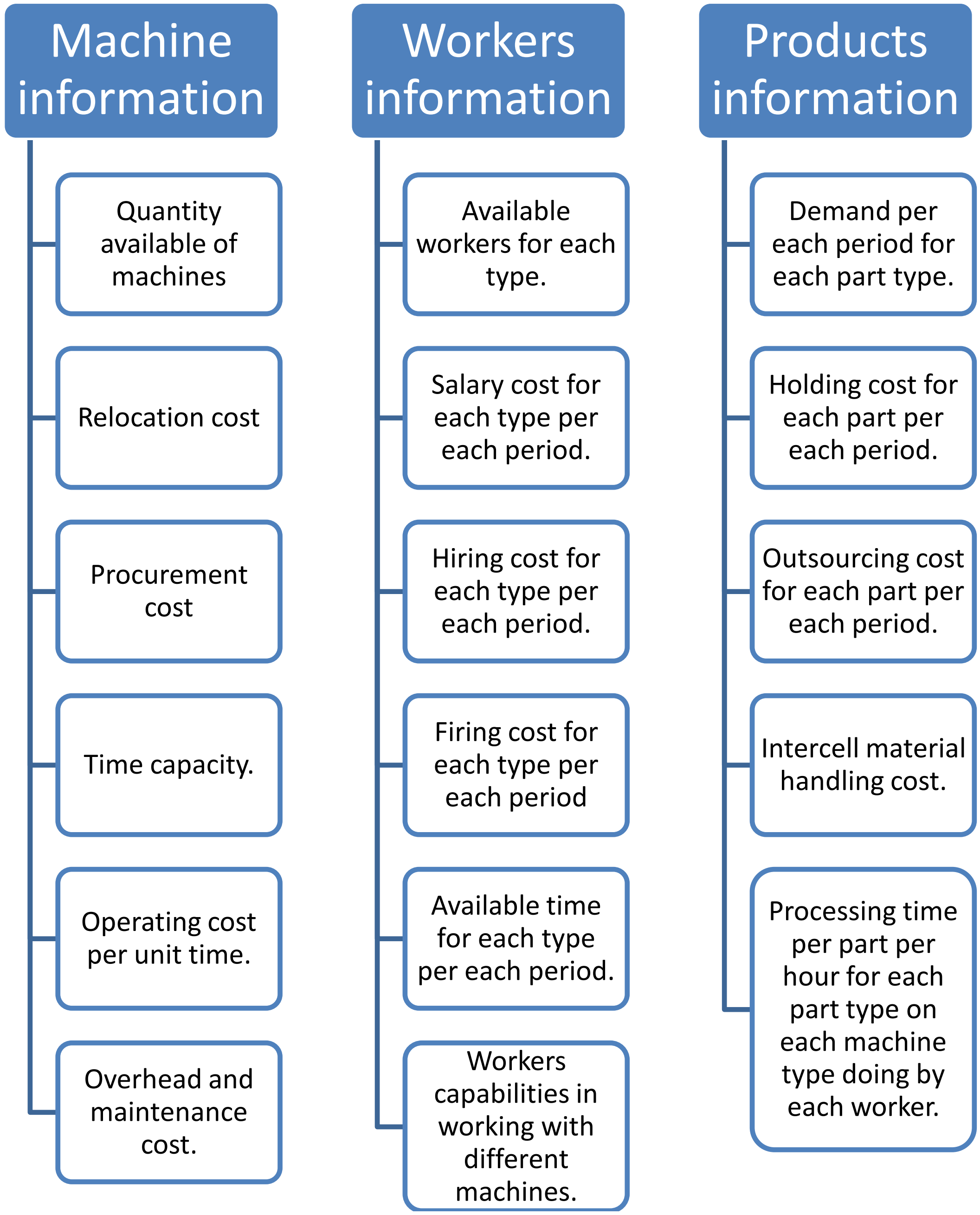



Figure 4-1: Input Data Classifications

## 4.2 Example 1

This example is a small- scale problem, includes two cells, three machines, four parts, two periods, and four workers. As shown in table 3-3 the number of variables for such system is 605 and the number of constraints is 683. The related information is given in tables 4-1, 4-2, 4-3, and 4-4.

Table (4-1) shows the machine information: quantity available of machine, relocation cost, procurement cost, time capacity, operating cost per unit time and overhead and maintenance cost, and in this example we assume that the number of available machines for all types is equal to zero, in other words we need to establish a new company to show the benefits of the new factor (Machine Procurement Cost). Table (4-2) shows the processing time per part per hour for each part type on each machine type doing by each worker. For example, part type 3 must be processed on machine type 1 with processing time 0.02h by worker 1 or with processing time 0.03h by worker 2. The data set related to the machine-part and machine workers incidence matrices are shown in tables (4-3) and (4-4), respectively. For instance, as seen in table (4-3), machine types 2 and 3 are required for part type 4. Also table (4-3) shows input data: demand per each period for each part type, holding cost for each part per each period, outsourcing cost for each part per each period and intercell material handling cost. Table (4-4) shows the workers input data: available workers for each type, salary cost for each type per each period, hiring cost for each type per each period, firing cost for each type per each period and available time for each type per each period. Also it shows workers capabilities in working with different machines. For example, worker 3 is able to work with machines type 2 and 3. Moreover, the number of cells to be formed is two and the minimum and maximum cell sizes for each cell sizes for each cell are 1 and 4, respectively. The minimum size of each cell in terms of the number of workers is assumed to be one.

The results are shown in tables (4-5), (4-6), and (4-7). Tables (4-5) and (4-6) show the optimal production plan and the objective function value respectively. Table (4-7) shows the part families, machine groups, and worker assignments.

As we mentioned above, in this example we need to build a new company that does not have any old machines, so that we need to buy new machines, thus we need to buy at the beginning of the first period two machines of type 1 and 2, and three machines of type 3, the total cost of buying these machines is found in table 6 (Procurement cost = $29,000). In table (4-6) we see that the demand of part type 1 in the first period is zero but we need to produce some quantity which will be held to the next period to satisfy a portion of demand in the coming periods. We can also note that the demand for part type 4 in the first period is 1700 but the production is 1500 and the shortage quantity (200 units) will be satisfied by outsourcing.

Part type 4 will be processed in cell 2 during the first period, this will done by machines type 2 and 3 by workers type 1 and 4. In the second period it will be processed in cell 1 by the same machines and the same worker types. Moreover part type 2 will be processed in cell 1 during the first and second period by machines type 1 and 2 by workers type 1, 2 and 4.

Table (4-7) shows the distribution of the machines between cells in the first period and their relocation in the second period; one machine of both type 2 and 3, and 2 machines of type 1 are assigned to the first cell during the first period, and the remaining are assigned to the second cell (two machines of type 3, and one machine of type 2), the relocation in the second period consist of moving one machine type 1 from the first cell as well as one machine of type 3 from the second cell, also, it consist of installing one machine of type 1 in the second cell. Table (4-7) also shows the distribution for the workers in the two periods, cell 1 needs in the first period two workers of type 1 and one worker of both types 2 and 4, in the second period one worker of type 1 will be fired, on other hand, cell 2 needs in the first period one worker of type 4 and two workers of type 3, in the second period one worker of type 2 will be hired and on worker of type 4 will be fired.

System design for this example and the allocation of workers, machines, and parts are shown in figure (4-2). The system relocation actions are also shown in this figure. System design after relocation shown in figure (4-3) (system design for period 2), in the second period we have two fired workers and one unused machine; machine of type 3, in this case we can hold the machine to be used in the coming period, or we can sell it.

Table 4-1: Machine Information

| Machine Type | Machine Information | | | | | | |
|---|---|---|---|---|---|---|---|
| | $A_m$ | $OV_m$ | $R_m^+$ | $R_m^-$ | $T_{m1}$ | $T_{m2}$ | $\text{Ɣ}_m$ | $OP_m$ |
| 1 | 0 | 400 | 550 | 140 | 30 | 30 | 15 | 3000 |
| 2 | 0 | 410 | 530 | 130 | 30 | 30 | 13 | 4000 |
| 3 | 0 | 430 | 560 | 150 | 30 | 40 | 14 | 5000 |

Table 4-2: The Processing Time

| | Part1 | | | | Part2 | | | | Part3 | | | | Part4 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | W1 | W2 | W3 | W4 | W1 | W2 | W3 | W4 | W1 | W2 | W3 | W4 | W1 | W2 | W3 | W4 |
| M1 | 0.04 | 0.02 | | | 0.04 | 0.01 | | | 0.02 | 0.03 | | | | | | |
| M2 | | | 0.02 | 0.03 | | | 0.04 | 0.03 | | | | | | | 0.03 | 0.02 |
| M3 | 0.01 | | 0.02 | | | | | | 0.01 | | 0.02 | | 0.03 | | 0.04 | |

Table 4-3: The input data of machine-part incidence matrix

| | | Machine Type | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | $D_{p1}$ | $D_{p2}$ | $\pounds_p$ | $H_{p1}$ | $H_{p2}$ | $U_{p1}$ | $U_{p2}$ | $V_p^{inter}$ |
| Part Type | 1 | 1 | 1 | 1 | 0 | 1550 | 20 | 4 | 4 | 80 | 80 | 11 |
| | 2 | 1 | 1 | 0 | 900 | 600 | 21 | 6 | 6 | 82 | 82 | 9 |
| | 3 | 1 | 0 | 1 | 1700 | 500 | 23 | 8 | 8 | 90 | 90 | 8 |
| | 4 | 0 | 1 | 1 | 1700 | 300 | 24 | 10 | 10 | 100 | 100 | 10 |

Table 4-4: The input data of machine-worker incidence matrix

| | | Machine Type | | | Worker Information | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | $A_w$ | $S_{w1}$ | $S_{w2}$ | $HI_{w1}$ | $HI_{w2}$ | $F_{w2}$ | $RW_{w1}$ | $RW_{w2}$ |
| Worker Type | 1 | 1 | 0 | 1 | 2 | 470 | 490 | 270 | 285 | 145 | 30 | 30 |
| | 2 | 1 | 0 | 0 | 2 | 460 | 485 | 260 | 290 | 145 | 30 | 30 |
| | 3 | 0 | 1 | 1 | 2 | 455 | 475 | 200 | 250 | 155 | 30 | 30 |
| | 4 | 0 | 1 | 0 | 2 | 450 | 480 | 265 | 280 | 140 | 30 | 30 |

Table 4-5: Optimal Production Plan

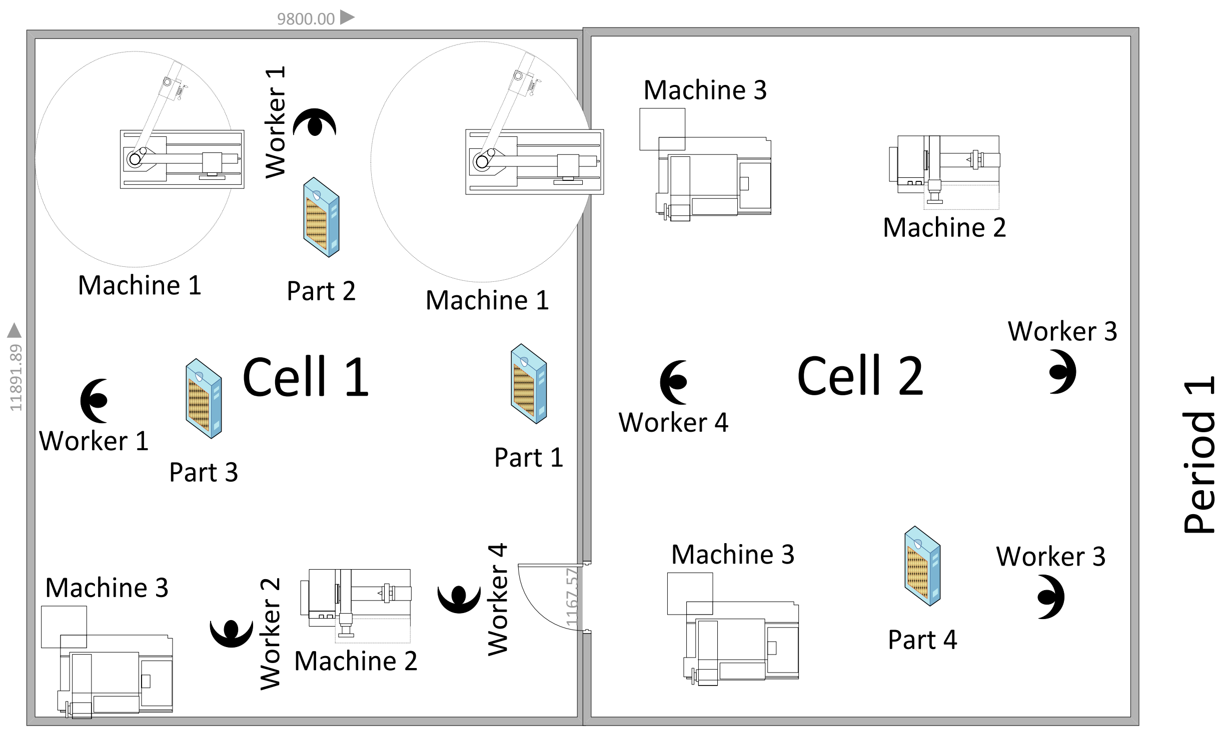
| | Period1 | | | | Period2 | | | |
|---|---|---|---|---|---|---|---|---|
| | Part1 | Part2 | Part3 | Part4 | Part1 | Part2 | Part3 | Part4 |
| Outsourcing | | | | 200 | | | | |
| Holding | 50 | | | | | | | |
| Productions | 50 | 900 | 1700 | 1500 | 1500 | 600 | 500 | 300 |
| Demand | 0 | 900 | 1700 | 1700 | 1550 | 600 | 500 | 300 |

Table 4-6: Objective Function value and its components

| Total | Outsourcing | Holding | Inter-cell movement | Maintenance and overhead | Machine Procurement | Production cost | Operating cost | Machine relocation | Salary | Hiring | Firing |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 224662 | 20000 | 200 | 0 | 5390 | 29000 | 156300 | 2852 | 840 | 6100 | 3695 | 285 |

Table 4-7: The result of parts, machines and Workers Assignments

| | Parts assigned to | | Machines in | | Workers assigned to | |
|---|---|---|---|---|---|---|
| | Cell1 | Cell2 | Cell1 | Cell2 | Cell1 | Cell2 |
| Period1 | 1,2,3 | 4 | 1,1,2,3 | 2,3,3 | 1,1,2,4 | 3,3,4 |
| Period2 | 2,3,4 | 1 | 1,2,3 | 1,2,3 | 1,2,4 | 2,3,3 |



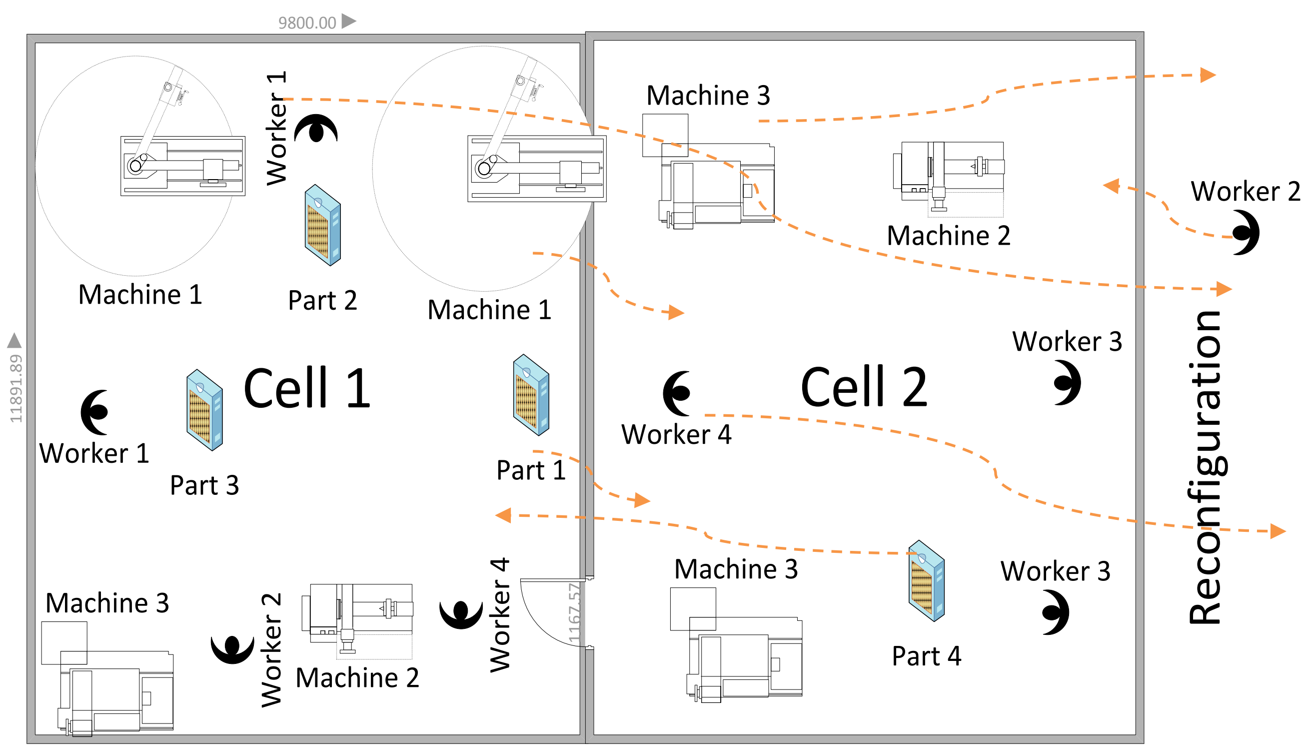




Figure 4-2: Example 1 System Design in period 1 and Relocation.

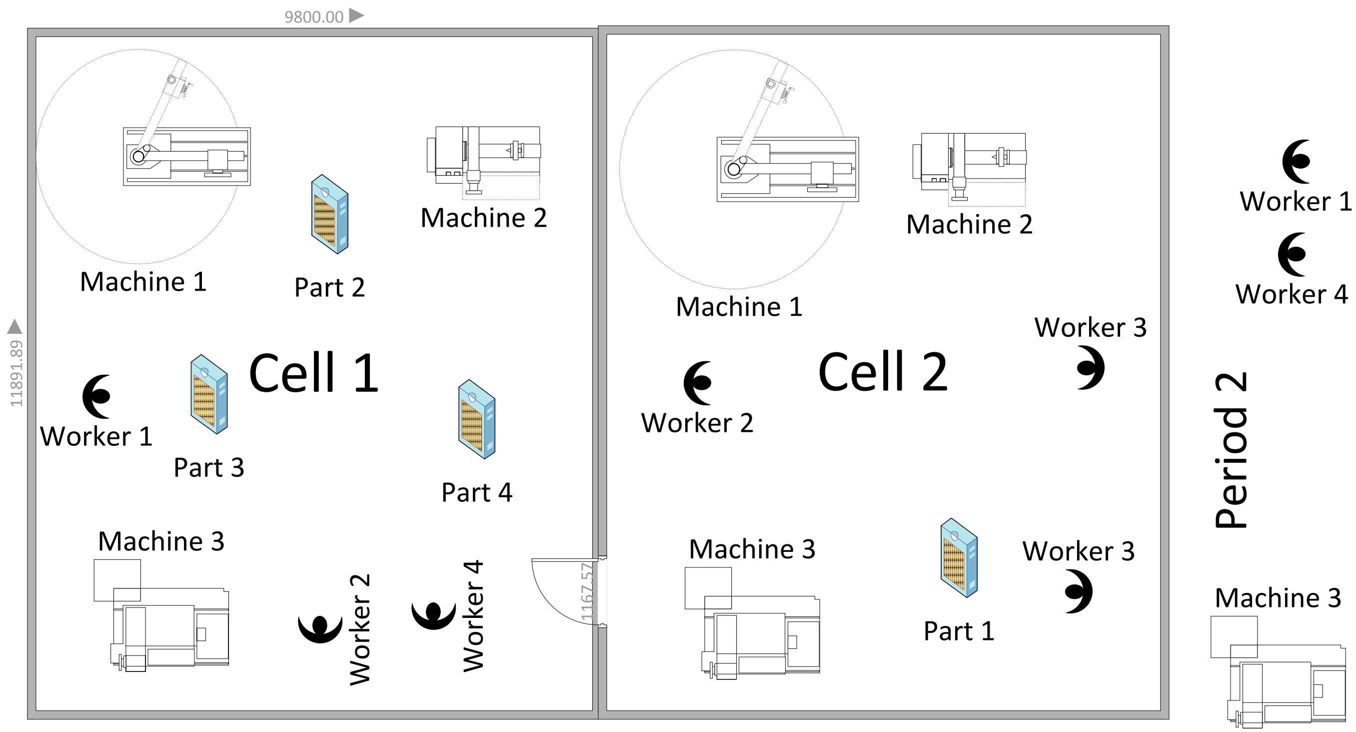



Figure 4-3: Example 1 System Design in period 2.

From the above example, the benefit of introducing the human issues in the proposed model can be seen clearly; the main actions during the relocation of the system above is firing two workers, one worker of type 1 and one worker of type 4, and hiring of one worker of type 2, by this action a salary of one worker will be saved, therefore, the demands in the second period of all parts type will be satisfied by six workers instead of seven workers in the first period. It is shown also that the demand in the second period will be satisfied by six machines instead of seven machines, since that one machine of type 3 is no longer needed, on the other hand, this machine can be held to the next period in case if it is needed or it can be sold.

## 4.3 Example 2

This example is a Medium-scale problem, includes two cells, three machines, four parts, three periods and four workers. As shown in table 3-4 the number of variables for such system is 829 and the number of constraints is 1013. Machine Information, processing input data of machine-worker incidence matrix, time input data of machine-part incidence matrix, are given in tables (4-8), (4-9), (4-10) and (4-11), respectively. Moreover, the number of cells to be formed is two and the minimum and maximum cell sizes for each cell sizes for each cell are 1 and 5, respectively. The minimum size of each cell in terms of the number of workers is assumed to be one.

The results have been shown in tables (4-12), (4-13), and (4-14). Tables (4-12) and (4-13) show the optimal production plan and the objective function value respectively. Table (4-14) shows the part families, machine groups, and worker assignments.

We need to buy a new machines, thus we need to buy at the beginning of the first period two machines of each type, the total cost of buying these machines is found in table (4-13) (Procurement cost = 24000). Also, we can see from table (4-12) that not outsourcing part will be, we can match this by the zero cost of outsourcing in table (4-13), we can conclude that the demand of all parts in each period will satisfy by internal production and inventory.

In table (4-13) we can see that the intercell cost is equal to zero, which means that each part will be produced completely in its own cell, in other world all operations that the part needed will be done in one cell (no moving between cells will occur).

System design for this example and the allocation of workers, machines, and parts are shown in figure (4-4). In addition, the system relocation actions are shown in this figure. System design after relocation shown in figure (4-5) (system design for period 2), as it is three period problems a second relocation should be done, this clearly shown in figure (4-5).

After the second relocation the system design for the third period has been achieved and this can be seen by figure (4-6). It is clearly seen from figure (4-4) that no changes will be done on the system design between period 1 and period 2, which means that this system design is the optimal configuration for period 1 and period 2. After the second relocation has been made a system design for the third period then achieved see figure (4-6). Obviously, all the products will produce in the first cell; cell 2 will not be used for the third period production, and there are one machine and worker assigned to this cell, just to satisfy the conditions that expressed in the model's constraints, specifically constraints number (7) and (8).

Constraint (7) $\{LB_c \leq \sum_{m=1}^{M} N_{mct} \leq UB_c;\ \forall(c,t)\}$, enforce the number of machines assigned to each cell in each period to be not less than the lower limit (in this example it is 1) and not more than the upper limit (in this example it is 5).

Constraint (8) $\{\sum_{w=1}^{W} N_{wct} \geq L_{wc},\ \forall(c,t)\}$, enforce the number of workers assigned to each cell in each period to be not less than the lower limit (in this example it is 1). So these constraints don't take into account whether the cell will be used for production during a specific period or not.

Table 4-8: Machine Information

| Machine Type | Machine Information | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $A_m$ | $OV_m$ | $R_m^+$ | $R_m^-$ | $T_{m1}$ | $T_{m2}$ | $T_{m3}$ | $\gamma_m$ | $OP_m$ |
| 1 | 0 | 520 | 600 | 100 | 40 | 40 | 40 | 18 | 3000 |
| 2 | 0 | 510 | 650 | 150 | 40 | 40 | 40 | 16 | 4000 |
| 3 | 0 | 550 | 660 | 200 | 40 | 40 | 40 | 14 | 5000 |

Table 4-9: The Processing Time

| | Part1 | | | | Part2 | | | | Part3 | | | | Part4 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | W1 | W2 | W3 | W4 | W1 | W2 | W3 | W4 | W1 | W2 | W3 | W4 | W1 | W2 | W3 | W4 |
| M1 | 0.04 | 0.02 | | | 0.04 | 0.01 | | | 0.02 | 0.03 | | | | | | |
| M2 | | | 0.02 | 0.03 | | | 0.04 | 0.03 | | | | | | | 0.03 | 0.02 |
| M3 | 0.01 | | 0.02 | | | | | | 0.01 | | 0.02 | | 0.03 | | 0.04 | |

Table 4-10: The input data of machine-worker incidence matrix

| | | Machine Type | | | Worker Information | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | $A_w$ | $S_{w1}$ | $S_{w2}$ | $S_{w3}$ | $HI_{w1}$ | $HI_{w2}$ | $HI_{w3}$ | $F_{w2}$ | $F_{w3}$ | $RW_{w1}$ | $RW_{w2}$ | $RW_{w3}$ |
| Worker Type | 1 | 1 | 0 | 1 | 2 | 400 | 450 | 450 | 230 | 285 | 285 | 110 | 145 | 40 | 40 | 40 |
| | 2 | 1 | 0 | 0 | 2 | 420 | 465 | 465 | 220 | 290 | 290 | 120 | 145 | 40 | 40 | 40 |
| | 3 | 0 | 1 | 1 | 2 | 415 | 475 | 475 | 200 | 250 | 250 | 115 | 155 | 40 | 40 | 40 |
| | 4 | 0 | 1 | 0 | 2 | 430 | 480 | 480 | 245 | 280 | 280 | 120 | 140 | 40 | 40 | 40 |

Table 4-11: Optimal Production Plan

| | Period 1 | | | | Period 2 | | | | Period 3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | P1 | P2 | P3 | P4 | P1 | P2 | P3 | P4 | P1 | P2 | P3 | P4 |
| Outsourcing | | | | | | | | | | | | |
| Holding | 4 | 12 | | 82 | | | | | | | | |
| Production | 4 | 612 | 1200 | 1282 | 1546 | 788 | 1000 | 818 | 500 | 1000 | 500 | 900 |
| Demand | 0 | 600 | 1200 | 1200 | 1550 | 800 | 1000 | 900 | 500 | 1000 | 500 | 900 |

Table 4-12: Objective Function value and its components

| Total | Outsourcing | Holding | Inter-cell movement | Maintenance and overhead | Machine Procurement | Production cost | Operating cost | Machine relocation | Salary | Hiring | Firing |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 291523 | 0 | 356 | 0 | 5770 | 24000 | 225500 | 28172 | 200 | 6255 | 1125 | 145 |

Table 4-13: The result of parts, machines and Workers Assignments

| | Parts assigned to | | Machines in | | Workers assigned to | |
|---|---|---|---|---|---|---|
| | Cell1 | Cell2 | Cell1 | Cell2 | Cell1 | Cell2 |
| Period1 | 1,2,4 | 3 | 1,2,2,3 | 1,3 | 1,2,3,4 | 1 |
| Period2 | 1,2,4 | 3 | 1,2,2,3 | 1,3 | 1,2,3,4 | 1 |
| Period3 | 1,2,3,4 | | 1,2,2,3 | 1 | 1,2,3,4 | 1 |

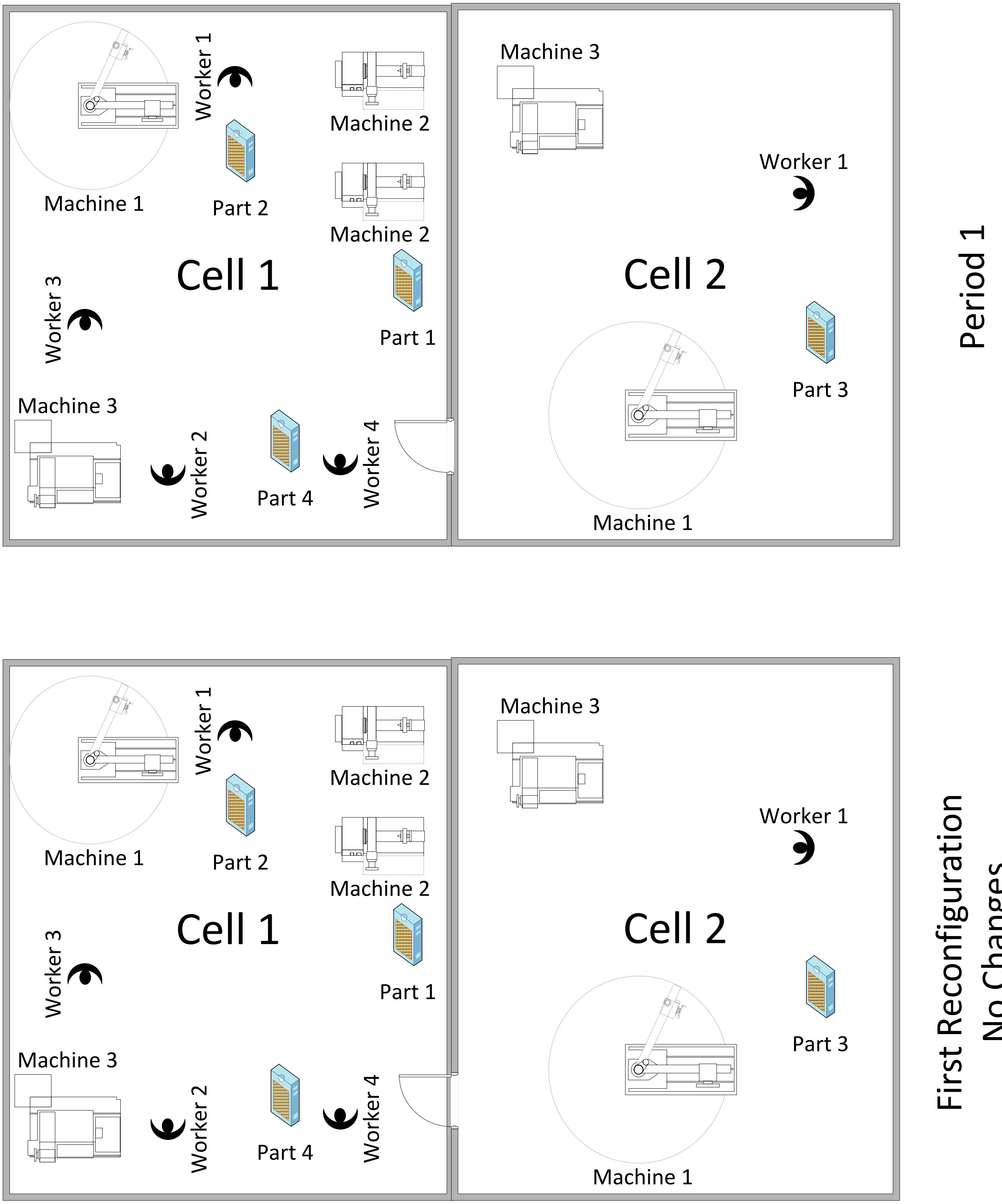



Figure 4-4: Example 2 System Design in period 1 and First Relocation.

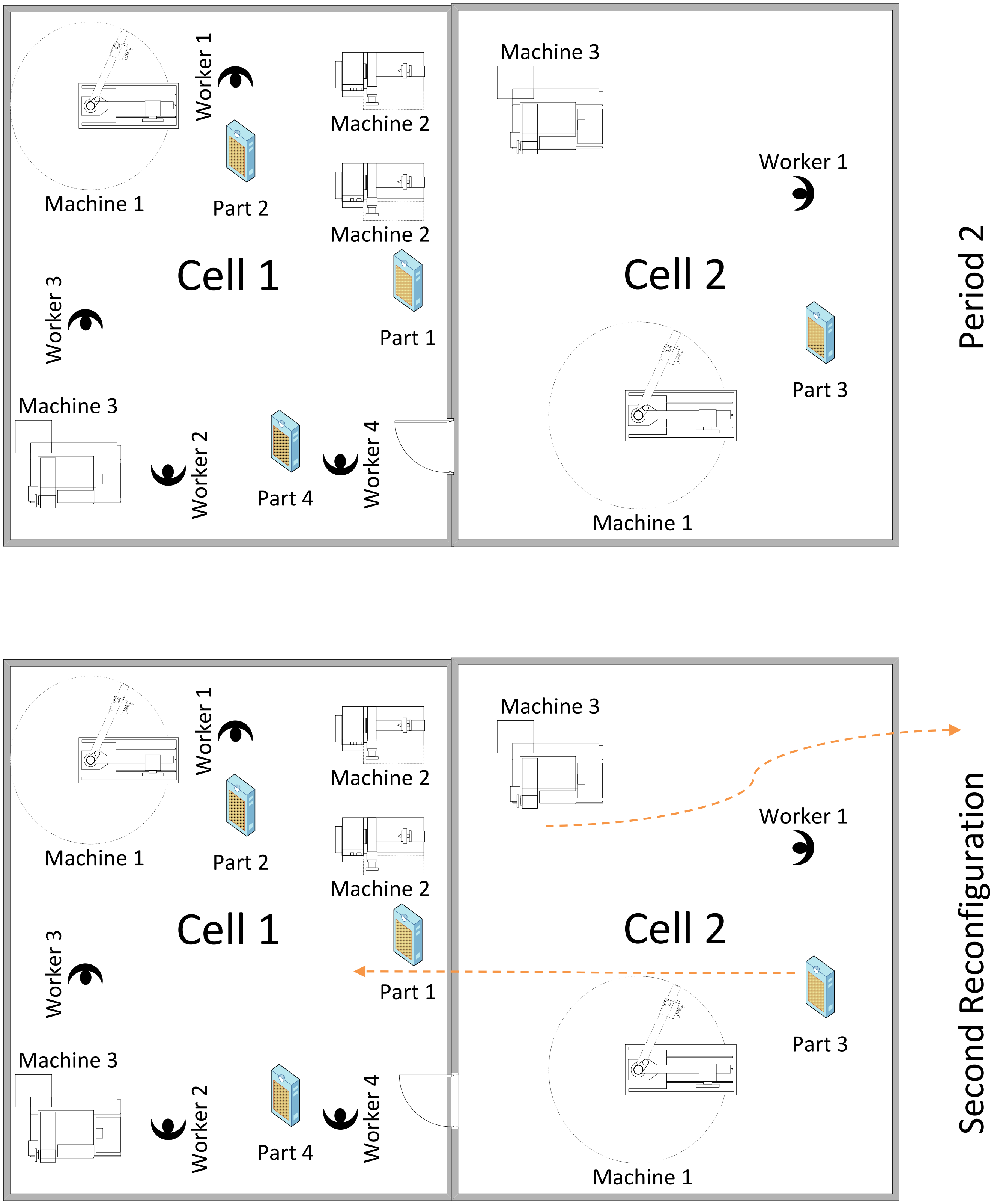



Figure 4-5: Example 2 System Design in period 2 and Second Relocation.

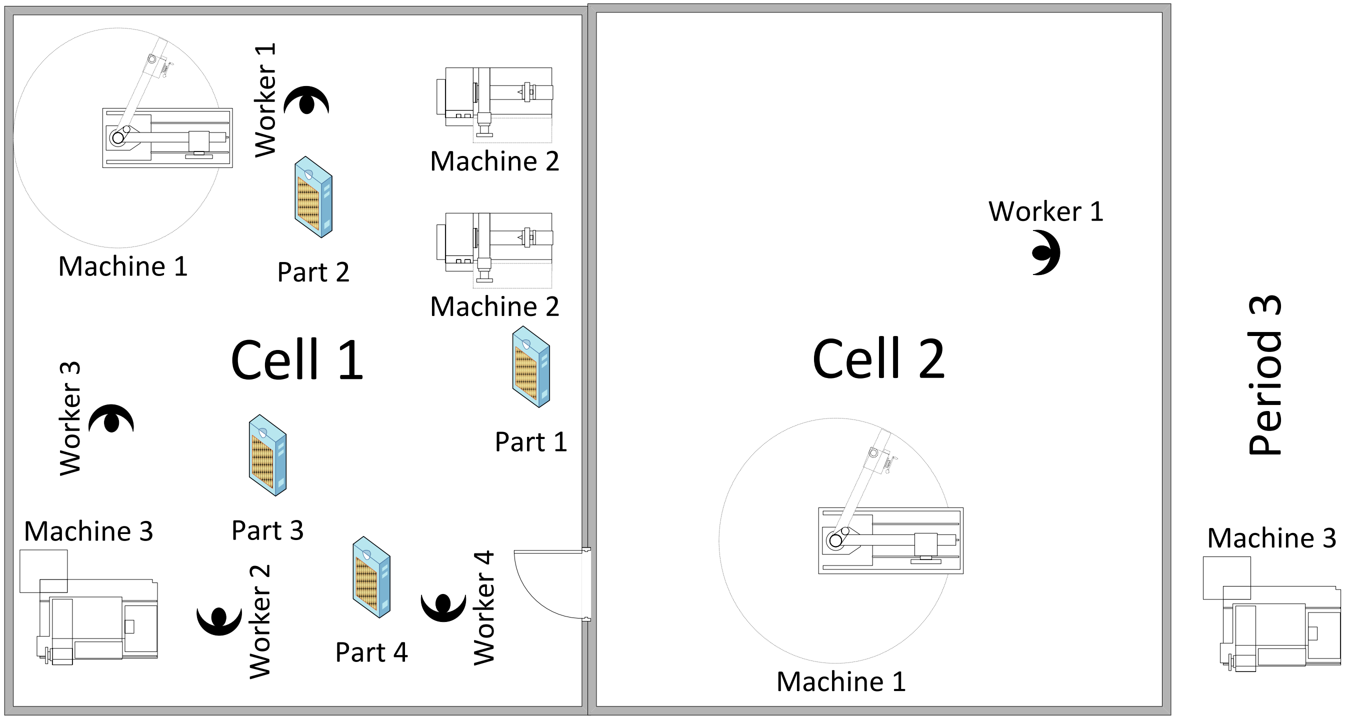



Figure 4-6: Example 2 System Design in period 3.

It is clearly shown from the above example that the demand in the third period will be satisfied by using of one cell, four workers, and four machines. Instead of two cells, five workers, and six machines in the previous two periods (period one and two). In other words, the system in the third period no longer needs the second cell, one worker of type one, and two machines of both types one and three. So, all of these are cost savings.

It is clearly seen from the above two examples that the human issues consideration (worker assignments) are one of the most important factors that should be considered when designing a Cellular Manufacturing System (CMS), considering this factor gives a comprehensive review of the system, good tracking, and since there is a variety in the demand and the variety in the products, the system does not need the same team of workers in each period, so, a relocation of the workers should be taken into consideration as well as the machines and products; ignoring this factor can considerably reduce benefits of the cellular manufacturing.

# Chapter 5

# Summary, Conclusions and Future Research

## 5.1. Introduction

In the past few decades, there has been an increasing worldwide awareness towards productivity improvements. A new style of operation and new environment in the workplace conductive to improvement in such factors as flexibility, efficiency, management-worker relation, team work and job satisfaction are becoming important for survival in the international market. CMS has emerged as one of the promising strategies to address such requirements. The contributions of this research lie: (1) The development of comprehensive mathematical models that integrate several important manufacturing aspects; (2) The development and implementation of efficient solution procedures to solve the proposed models.

## 5.2 Contributions of this study

In order to achieve the cellular manufacturing system's benefits which represented in chapter 1, when designing such a system, a number of manufacturing aspects should be taken into consideration. In chapter 2, the literature review of the previous works shows the important manufacturing attributes to be defined. The proposed model presented in this thesis is a comprehensive model which integrates the important manufacturing attributes:

- Intercellular material handling cost.
- Part internal production cost.
- Subcontracting cost.
- Inventory holding cost.
- Deterministic demand.
- Multi period planning.
- Cellular manufacturing configurations.
- Machine characteristics:
    i. Machine with multiple copies.
    ii. Machine with limited capacity.
    iii. Machine operating cost.
    iv. Machine maintenance and overhead cost.
    v. Machine relocation cost.
    vi. Machine procurement.
- Cell size limits in terms of upper and lower bounds.
- Human issues:
    i. Workers salary cost.
    ii. Workers hiring.
    iii. Workers firing.
    iv. Cell size limit in terms of lower limit of workers.
    v. Workers available time.

From the literature review, it is found even that cellular manufacturing is a popular research area; there is a singular absence of articles that deal with the human element in cellular manufacturing. Considering human issues is one of the main points in cellular manufacturing since ignoring this factor can considerably reduce benefits of the utility of the cell manufacturing. Also from the literature review, it is found that recent research on CM modeling tends to include only some of the above identified manufacturing attributes. Indeed as Ahkioon (2007) noted, a recurring theme is a piecemeal approach when formulating CMS models, as many of the existing models include only a limited subset of these manufacturing attributes. As such, this present research takes a holistic approach in CM design by integrating the identified important manufacturing aspects within a proposed CM model focusing on human issues consideration, thus bringing several important extensions to previous models.

In chapter 3, a comprehensive mathematical model is presented and solved using an exact solution procedure. Numerical examples consisting of small to medium sized problems are solved, showing that the proposed model allows better decision-making in CM design, especially in terms of multi-period planning, production planning and dynamic system relocation. The CMS solutions generated through the proposed model allow the cell designer to determine for a multi-period horizon:

- Worker assignments; the allocation of each worker to a specific cell, hiring workers, and firing workers in each time period.
- The machine to cell composition in each time period and machine relocation.

- Optimal values for internal part production, inventory holding and outsourcing.
- The number of machines to be procured.

In chapter 4, two comprehensive examples with full input data and results analysis are presented; also, an explanatory scheme shows the design of our system for the first period, actions to be taken during relocation, and the system design after relocation. These actions consist of: a) Hiring workers; b) Firing workers; c) Machines relocation; and d) Parts relocations.

## 5.3. Future Research

### 5.3.1. Multiple Criteria Decision Making for CMS Design

The objectives sought in the proposed model are cost-oriented, with a number of different costs being considered. Performance-oriented objectives in CM design form part of future research work that are beyond the scope of this thesis, given the limited time frame. As such, these possible CM system criteria and objectives include performance measures that cannot be expressed in monetary terms and are as follows:

- Maintaining acceptable within-cell machine utilization levels
- Minimizing setup times
- Minimizing work-in-progress
- Maximizing the CM system reliability

CM models that address such multiple design criteria can be formulated as a multi-objective decision making (MODM) problem, which can be solved either via a constraint or weighted method. Goal programming is another approach that can be used for solving cellular manufacturing MODM problems.

A closer look at and a thorough analysis of overhead costs can give better performance of CMS design, overhead is an accounting term that refers to all ongoing business expenses not including or related to direct labor, direct materials or third-party expenses that are billed directly to customers. Overhead must be paid for on an ongoing basis, regardless of whether a company is doing a high or low volume of business. It is important not just for budgeting purposes, but for determining how much a company must charge for its products or services to make a profit.

### 5.3.2. Further CM Design Phases

This research deals only with the first phase of CM design, namely the cell formation problem. Additional research can be conducted for the two next phases in CM design. Further CM design work can center on phase 2, which deals with the layout of the cells and equipment within the manufacturing facility (facility layout problem), typical decision in this phase include: a) Equipment layout; b) Design/ selection material handling equipment; c) Assessment of operators training requirement; d) Machine loading and scheduling; e) Quality control and inspection policies, and phase 3, dealing with the layout of machines within the cells.

### 5.3.3. Development of further efficient solution procedures

By using CPLEX small to medium-sized problems could be solved within up to 1 hour of computational time. The large-scale problems proved to be more difficult to solve using the proposed exact solution approach with the proposed model as no optimal solution was obtained after up to 6 hours of computation. However, the solutions from this integrated model show that additional CM structural and operational design decisions that were not considered in previous research can be addressed with the proposed model. The next step in research is the investigation of the use of meta-heuristics, especially Tabu Search, Simulated Annealing and Genetic Algorithm, to solve problems of larger scale for this integrated CM model.

## Bibliography


[1] Adil, G.K., Rajamani, D., and Strong, D., 1993. A mathematical model for cell formation considering investment and operational costs. *European Journal of Operational Research*, 69, 330-341.

[2] Ahkioon, S. 2007. Comprehensive models and solution procedures for integrated cellular manufacturing systems design. *PhD thesis*, Concordia University, Montreal, Quebec.

[3] Ahkioon S, Bulgak AA, Bektas T, 2009a. Cellular manufacturing system design with routing flexibility, machine procurement, production planning & dynamic system reconfiguration. *International Journal of Production Research. 47/(6):1573-1600.*

[4] Ahkioon S, Bulgak AA, Bektas T, 2009b. Integrated manufacturing system design with production planning & dynamic system reconfiguration. . *European Journal of Operational Research*,192:414-428.

[5] Albadawi, Z. 2003. A mathematical approach for designing cell formation in cellular manufacturing systems. *M.A.Sc thesis*. Concordia University, Montreal, Quebec.

[6] Alhourani F, Seifoddoni H, 2007. Machine cell formation for production management in cellular manufacturing systems. *International Journal of Production Research.* 45(4)913-934.

[7] Aryanezhad, M. Deljoo, V. Al-e-hashem, S., 2009. Dynamic cell formation and the worker assignment problem: a new model. *International Journal of Advanced Manufacturing Technology. 41:329–342.*

[8] Askin, R. G. and Chiu, K. S., 1990. A graph partitioning procedure for machine assignment and cell formation in group technology. *International Journal of Production Economics*, 28, 1555–1572.

[9] Askin, R.G., Creswell, J.B., Goldberg, J.B. and Vakharia, A.J., 1991. A Hamiltonian path approach to reordering the part-machine matrix for cellular manufacturing. *International Journal of Production Research*, 29, 1081 – 1100.

[10] Balakrishnan, J., Cheng C.H., 2007. Multi-period planning and uncertainty issues in cellular manufacturing: A review and future directions. *European Journal of Operational Research*, 177, 281-309.

[11] Ballakur, A., 1985. An Investigation of Part Family/Machine Group Formation in Designing a Cellular Manufacturing System. *PhD thesis*, University of Wisconsin, Madison, WI.

[12] Ballakur, A., and Steudel, H.J., 1987. A within-cell utilization based heuristic for designing cellular manufacturing systems. *International Journal of Production Research*, 25, 639-665.

[13] Baykasoglu A, Gindy NNZ,Cobb RC, 2001. Capability based formulation and solution of multiple objective cell formation problems using simulated annealing. *Integer Manufacturing System, 12:258-274.*

[14] Bertsekas, D., and Tseng, P., 1988. Relaxation methods for minimum cost ordinary and generalized network flow problems. *Operations Research*. 36, 93-114.

[15] Bidanda, B. Ariyawongrat, P. Needy, K. Norman, B. Tharmmaphornphilas, W., 2005. Human related issues in manufacturing cell design, implementation, and operation: a review and survey. *Computers and Industrial Engineering.* 48, 507–523.

[16] Boctor, F., 1991. A linear formulation of the machine-part cell formation problem. *International Journal of Production Research*. 29, 343–356.

[17] Brandon, J.A., 1996. Cellular Manufacturing: Integrating Technology and Management. *Research Studies Press Ltd*., 61-79.

[18] Burbidge, J.L., 1963. Production Flow Analysis. *The Production Engineer*, 42, 742.

[19] Burke, L.I., and Kamal, S., 1992. Fuzzy art and cellular manufacturing. In *Artificial Neural Networks in Engineering*, 779 – 784.

[20] Cao, D., and Chen, M., 2004. Using penalty function and Tabu search to solve cell formation problems with fixed cell cost, *Computers and Operations Research*, 31, 21-37.

[21] Cao, D., and Chen, M., 2005. A robust cell formation approach for varying product demands. *International Journal of Production Research*, 49, 1587–1605

[22] Carpenter, G. A. and Grossberg, S., 1987. A massive parallel architecture for a self-organizing neural pattern recognition machine. *Computer Vision, Graphics and Image Processing*, 37, 54–115.

[23] Caux, C., Bruniaux, R., and Pierreval, H., 2000. Cell formation with alternative process plans and machine capacity constraints: A new combined approach. *International Journal of Production Economics*, 64, 279-284.

[24] Chan, H. and Milner, D., 1982. Direct clustering algorithm for group formation in cellular manufacturing. *Journal of Manufacturing Systems*, 1, 65–74.

[25] Chandrasekharan, M. P. and Rajagopalan, R., 1986a. MODROC: an extension of rank order clustering for Group Technology. *International Journal of Production Research*, 24, 1221-1233.

[26] Chandrasekharan, M. P. and Rajagopalan, R., 1986b. An Ideal Seed Nonhierarchical Clustering algorithm for cellular manufacturing. *International Journal of Production Research*, 24, 451–464.

[27] Chen, M., 1998. A mathematical programming model for system reconfiguration in a dynamic cellular manufacturing environment. *Annals of Operations Research* 74, 109 – 128

[28] Chen, M., 2001. A model for integrated production planning in cellular manufacturing systems. *Integrated Manufacturing Systems*, 12, 275-284.

[29] Chen, M. and Cao, D., 2004. Coordinating production planning in cellular manufacturing environment using Tabu search. *Computers and Industrial Engineering*, 46, 571–588.

[30] Chen, S. J. and Cheng, C. S., 1995. A neural network-based cell formation algorithm in cellular manufacturing. *International Journal of Production Research*, 32, 293–318.

[31] Chen, C.L., Cotruvo, N., and Baek, W., 1995. A simulated annealing solution to the cell formation problem. *International Journal of Production Research*, 33, 2601–2614.

[32] Choobineh, F., 1988 A framework for the design of cellular manufacturing systems. *International Journal of Production Research*, 26, 1161–1172.

[33] Chu, C.H., 1993. Manufacturing cell formation by competitive learning. *International Journal of Production Research*, 31, 829-843.

[34] Chu, C.H. and Hayya, J.C., 1991. A fuzzy clustering approach to manufacturing cell formation. *International Journal of Production Research*, 29, 1475 – 1487.

[35] Dagli, C. H. and Sen, C. F., 1992. Art1 neural network approach to large scale group technology problem. ASME Press, New York, 4, 787–792.

[36] Dake, S., Lin, L. and Batta, R., 1995. Cell formation using tabu search. Computers and Industrial Engineering, 28(3), 485 – 494.

[37] Das, K., Lashkaria, R.S. and Sengupta, S., 2007. Reliability consideration in the design and analysis of cellular manufacturing systems. *International Journal of Production Economics,* 105, 243-262.

[38] Defersha, F. and Chen, M., 2006. A comprehensive mathematical model for the design of cellular manufacturing systems. *International Journal of Production Economics*, 103, 767 – 783.

[39] Defersha, F. and Chen, M., 2006. Machine cell formation using a mathematical model and a genetic-algorithm-based heuristic. *International Journal of Production Research.* 44(12):2421-2444

[40] Defersha, F. and Chen, M., 2007. A parallel genetic algorithm for dynamic cell formation in cellular manufacturing systems. *International Journal of Production Research.* 46:6389-6413

[41] Defersha, F. and Chen, M., 2008. A parallel multiple Markov chain simulated annealing for multi period manufacturing cell formation. *International Journal of Advance Manufacturing Technology. 37:140-156*

[42] Deutsch, S. J., Freeman, S. F., and Helander, M., 1998. Manufacturing cell formation using an improved p-median model. *Computers and Industrial Engineering*, 34, 135–146.

[43] Dimpoulos, C. and Zalzala, A.M.S., 1998. Evolutionary programming for designing manufacturing cells. Proceedings from the 1998 *IEEE International Conference on Evolutionary Computing, Piscataway NJ IEEE*, pages 148- 153.

[44] El-Essawy, I.F.K. and Torrance, J., 1972. Component flow analysis – an effective approach to production systems' design. *Production Engineer*, 51, 165.

[45] Elmaghraby, H.A, and Gu, P., 1989. Feature based expert parts assignment in cellular manufacturing. *Journal of Manufacturing Systems*, 8, 139-152.

[46] Faber, Z. and Carter, M. W., 1986. A new graph theory approach for forming machine cells in cellular production systems. *In Flexible Manufacturing Systems: Methods and Studies*, ed. A. Kusiak. North-Holland, New York, 301–318.

[47] Fredrick S. Hillier and Gerald J. Lieberman (2010), Introduction to Operation Research (Ninth Edition).

[48] Greene, T. and Sadowski, R., 1984. A review of cellular manufacturing assumptions, advantages and design techniques. *Journal of Operations Management*, 4, 85 – 97.

[49] Gungor, Z. and Arikan, F., 2000. Application of fuzzy decision making in part-machine grouping. *International Journal of Production Economics*, 63, 181–193.

[50] Gupta, Y., Gupta, M., Kumar, A. and Sundram, C., 1995. Minimizing total intercell and intracell moves in cellular manufacturing: a genetic algorithm approach. *International Journal of Computer Integrated Manufacturing*, 8, 92 - 101.

[51] Gupta, Y., Gupta, M., Kumar, A. and Sundaram, C., 1996. A genetic algorithm-based approach to cell composition and layout design problems. *International Journal of Production Research*, 34, 447–482.

[52] Heragu, S.S. and Chen J.S., 1998. Optimal solution of cellular manufacturing system design: Bender's decomposition approach. *European Journal of Operational Research*, 107, 175-192.

[53] IBM ILOG OPL V6.3. International Business Corporation 1987, 2009.

[54] Jabal Ameli MS, Arkat J, 2007. Cell formation with alternative process routings and machine reliability consideration. *International Journal of Advance Manufacturing Technology*. 35:761-768.

[55] Jayaswal, S. and Adil, G.K., 2004. Efficient algorithm for cell formation with sequence data, machine replications and alternative process routings. *International Journal of Production Research*, 42, 2419 - 2433.

[56] Joines, J.A, Culbreth, C.T. and King, R.E., 1996. Manufacturing cell design: an integer programming model employing genetic algorithms. *IIE Transactions*, 28, 69 – 85.

[57] Jones, D.F., Mirrazavi, S.K., and Tamiz, M., 2002. Multi-objective meta-heuristics: An overview of the current state-of-the-art. *European Journal of Operational Research*, 137, 1-9.

[58] Josien, K. and Liao, T. W. R., 2002. Simultaneous grouping of parts and machines with an integrated fuzzy clustering method. *Fuzzy Sets and Systems*, 126, 1–21.

[59] Kaparthi, S. and Suresh, N., 1992. Machine-component cell formation in group technology: a neural network approach. *International Journal of Production Research*, 30, 1353–1367.

[60] King, J.R., 1980a. Machine-component grouping in production flow analysis: an approach using a rank order clustering algorithm. *International Journal of Production Research*, 18, 213–232.

[61] King, J.R., 1980b. Machine-component group formation in Group Technology. *OMEGA: The International Journal of Management Science*, 8, 193-199.

[62] King, J. and Nakornchai, V., 1982. Machine-Component Group Formation in Group Technology: Review and Extension. *International Journal of Production Research*, 20, 117 – 133.

[63] Kusiak, A., 1987. The generalized group technology concept. *International Journal of Production Research*, 25, 561 – 569.

[64] Kusiak, A., 1988. Exgt-s: A knowledge based system for group technology. *International Journal of Production Research*, 26, 887–904.

[65] Kusiak, A. and Chow, W., 1987. Efficient solving of the group technology. Problem. *Journal of Manufacturing Systems*, 6, 117-124.

[66] Kusiak, A. and Chung, Y., 1991. Using neural networks to form machine cells. *Manufacturing Review*, 4, 293–301.

[67] Lee, H. and Garcia-Diaz, A., 1996. Network flow procedures for the analysis of cellular manufacturing systems. *IIE Transactions*, 28, 333–345.

[68] Lemoine, Y. and Mutel, B., 1983. Automatic recognition of production cells and part families. In *Advances in CAD/ CAM*, Ellis, T. M. R., and Semenkov, O. I., (Eds). North-Holland, Amsterdam, pp. 239–248.

[69] Liao, T.W., and Chen, L.J., 1993. An evaluation of ART1 neural models for group technology part family machine cell forming. *Journal of Manufacturing Systems*, 12, 282-290.

[70] Liao, T. W. and Lee, K. S., 1994. Integration of a feature-based cad system and an ART1 neural model for GT coding and part family forming. *Computers and Industrial Engineering*, 26, 93–104.

[71] Logendran, R., Ramakrishna, P. and Srikandarajah, C., 1994. Tabu Search-Based Heuristics for Cellular Manufacturing Systems in the Presence of Alternative Process Plans". *International Journal of Production Research*, 32, 273 - 297.

[72] Lokesh K, Jain PK, 2009. Part-machine group formation with ordinal-ratio level data and production volume. *International Journal of Simulation Model* 8(2):90-101.

[73] Lokesh K, Jain PK, 2010. Concurrently part-machine group formation with important production data. *International Journal of Simulation Model* .9(1):5-16.

[74] Lokesh K, Jain PK, 2010. Dynamic cellular manufacturing systems design- a comprehensive model & HHGA. *Advances in production engineering & management journal.* 5(3):151-162.

[75] Lozano S., Adenso-Diaz, B. and Onieva, L., 1999. A one-step Tabu search algorithm for manufacturing cell design. *OR: the Journal of the Operational Research Society*, 50, 509 – 516.

[76] Lozano S., Dobado, D., Larraneta, J., and Onieva, L., 2002. Modified fuzzy c-means algorithm for cellular manufacturing. *Fuzzy Sets and Systems*, 126, 23-32.

[77] Luong, L., He, J., Abhary, K., and Qiu, L., 2002. A decision support system for cellular manufacturing system design. *Computers and Industrial Engineering*, 42, 457–470.

[78] Mahdavi, I. Aalaei, A. Paydar, M. Solimanpur, M., 2010. Designing a mathematical model for dynamic cellular manufacturing systems considering production planning and worker assignment. *Computers and Mathematics with applications.* 60, 1014- 1025.

[79] Malave, C.O., and Ramachandran, S., 1991. A neural network-based design of cellular manufacturing systems. *Journal of Intelligent Manufacturing*, 2, 305–314.

[80] McAuley, J., 1972. Machine grouping for efficient production. *Production Engineering*, 51, 53–57.

[81] Mungwattana, A., 2000. Design of Cellular Manufacturing Systems for dynamic and uncertain production requirements with presence of routing flexibility. PhD thesis submitted to the Faculty of the Virginia Polytechnic Institute and State University, Blackburg, VA.

[82] Nembhard, D., 2001. Heuristic approach for assigning workers to tasks based on individual learning rates. *International Journal of Production Research. 1955-1968.*

[83] Norman, B. T harmmaphornphilas, W. Needy, K. Bidanda , B.Warner, R., 2002. Worker assignment in cellular manufacturing considering technical and human skills. *International Journal of Production Research. 1479- 1492*

[84] Nsakanda, A.L., Diaby, M. and Price, W.L., 2006. Hybrid genetic approach for solving large-scale capacitated cell formation problems with multiple routings. *European Journal of Operational Research*, 171, 1051 – 1070.

[85] Plaquin MF, Pierreval H, 2000. Cell formation using evolutionary algorithm with certain constraints. *International Journal of Advance Economy. 64:267-278.*

[86] Purcheck, G., 1974. A mathematical classification as a basis for the design of group technology production cells. *Production Engineer*, 54, 35–48.

[87] Purcheck, G., 1975. A linear programming method for the combinatorial grouping of an incomplete power set. *Journal of Cybernetics*, 5, 51–76.

[88] Rajamani, D., Singh, N. and Aneja,Y. P., 1996. Design of cellular manufacturing systems. *International Journal of Production Research*, 34, 1917 - 1928.

[89] Rao, H.A, and Gu, P., 1992. Design of a cellular manufacturing system: a neural network approach. *International Journal of Systems Automation: Research and Applications,* 2, 407-424.

[90] Rao, H.A, and Gu, P., 1994. Expert self-organizing neural network for the design of cellular manufacturing systems. *Journal of Manufacturing Systems*, 13, 346-358.

[91] Rheault M Drolet J, Abdulnour G, 1995. Physically reconfigurable virtual cells: a dynamic model for a highly dynamic environment. *Comput Ind Eng 29(1-4):221-225*

[92] Ribeiro, J. F. F. and Pradin, B., 1993. A methodology for cellular manufacturing design*. International Journal of Production Research*, 31, 235–250.

[93] Safaei, N., Saidi-Mehrabad, N, (2006) A new modelof dynamic cell formation by a neural approach. *International Journal of Advance Manufacturing Technology. 33:1001-1009.*

[94] Safaei, N., Saidi-Mehrabad, M., Jabal-Ameli, M.S., 2007. A Hybrid Simulated Annealing for Solving an Extended Model of Dynamic Cellular Manufacturing System, *European Journal of Operational Research*, (In press).

[95] Sankaran, S., 1990. Multiple objective decision making approach to cell formation: a goal programming model. *Mathematical Computer Modeling*, 13, 71-82.

[96] Selim, H.M., Askin, R.G. and Vakharia, A.J., 1998. Cell Formation in group technology: review, evaluation and direction for future research. *Computers and Industrial Engineering*, 34, 3-20.

[97] Saxena, L. Jain,P., 2011. Dynamic cellular manufacturing systems design – a comprehensive model. *The International Journal of Advanced Manufacturing Technology 53:11 – 34.*

[98] Shafer, S.M., and Rogers, D.F., 1991. A goal programming approach to cell formation problems. *Journal of Operations Management*, 10, 28-43.

[99] Shtub, A., 1989. Modeling group technology cell formation as a generalized assignment problem. *International Journal of Production Research*, 27, 775– 782.

[100] Singh, N. and Rajamani D., 1996. Cellular Manufacturing Systems: design, planning and control. *Chapman and Hall*,

[101] Singh, N., 1993. Design of cellular manufacturing systems: an invited review. *European Journal of Operational Research*, 69, 281- 511.

[102] Song, S. and Hitomi, K., 1996. Integrating the production planning and cellular layout for flexible cellular manufacturing. *Production Planning and Control*, 7, 585-593.

[103] Srinivasan, G., Narendran, T., and Mahadevan, B., 1990. An assignment model for the part family problem in group technology. *International Journal of Production Research*, 28, 145–152.

[104] Srinivasan, G., and Narendran, T., 1991. GRAFICS – a nonhierarchical clustering algorithm for group technology. *International Journal of Production Research*, 29, 463-478.

[105] Suresh, N. C. and Kaparthi, S., 1994. Performance of fuzzy art neural network for group technology cell formation. *International Journal of Production Research*, 32, 1693–1713.

[106] Vakharia, A.J., and Chang, Y., 1997. Cell formation in group technology: A combinatorial search approach. *International Journal of Production Research*, 35, 2025 – 2043.

[107] Vakharia, A. J. and Slim, H., 1994. Group Technology. In R.C. Dorf and A. Kusiak (Eds). *The Handbook of Design, Manufacturing, and Automation*. Wiley, New York, pp. 435–460.

[108] Venugopal, A., and Narendran, T. T., 1992a. A neural network approach for designing cellular manufacturing systems. *Advances in Modeling and Analysis*, 32, 13–26.

[109] Venugopal, V. and Narendran, T., 1992b. A genetic algorithm approach to the machine-component grouping problem with multiple objectives. *Computers and Industrial Engineering*, 22, 469-480.

[110] Venugopal, V. and Narendran, T., 1992c. Cell formation in manufacturing Systems through simulated annealing: An experimental evaluation. *European Journal of Operational Research*, 63, 409 – 422.

[111] Viswanathan, S., 1996. A new approach for solving the p-median problem in group technology. *International Journal of Production Research*, 34, 2691–700.

[112] Wang, J. and Roze, C., 1997. Formation of machine cells and part families in cellular manufacturing: an experimental study. *Journal of Operations Management*, 35, 1259–1286.

[113] Wemmerlov, U. and Hyer, N., 1986. Procedures for part family/machine group identification problem in cellular manufacturing. *Journal of Operations Management,* 6, 125-145.

[114] Wirojanagud,P. Gel, E. Fowler, J. Cardy, R. (2007). Modeling Inherent Worker Differences for Workforce Planning. *International Journal of Production Research. 525-553(29).*

[115] Wu, N. and Salvendy, G., 1993. A modified network approach for the design of cellular manufacturing systems. *International Journal of Production Research*, 35(1), 29-49.

[116] Wu, H., Venugopal, R., and Barash, M., 1986. Design of a cellular manufacturing system: A syntactic pattern recognition approach. *Journal of Manufacturing Systems*, 5, 81–88.

[117] Xu, H., and Wang, H.P., 1989. Part family formation for GT applications based on fuzzy mathematics. *International Journal of Production Research*, 27, 2053-2062.