Application of Artificial Intelligence (AI) Methods for Designing and Analysis of Reconfigurable Cellular Manufacturing System (RCMS)

Bo Xing, Fulufhelo V. Nelwamondo, Kimberly Battle, Wenjing Gao and Tshilidzi Marwala

Abstract—**This work focuses on the design and control of a novel hybrid manufacturing system: Reconfigurable Cellular Manufacturing System (RCMS) by using Artificial Intelligence (AI) approach. It is hybrid as it combines the advantages of Cellular Manufacturing System (CMS) and Reconfigurable Manufacturing System (RMS). In addition to inheriting desirable properties from CMS and RMS, RCMS provides additional benefits including flexibility and the ability to respond to changing products, product mix and market conditions during its useful life, avoiding premature obsolescence of the manufacturing system. The emphasis of this research is the formation of Reconfigurable Manufacturing Cell (RMC) which is the dynamic and logical clustering of some manufacturing resources, driven by specific customer orders, aiming at optimally fulfilling customers' orders along with other RMCs in the RCMS.**

Key words— **RCMS, RMC, AI, ANN**

I. Introduction

With the growing trend towards great product variety and fluctuating market demands, an important problem confronted by today's manufacturing companies is to balance the need for higher product variety with the request for more production resources. In order to satisfy customer's demands in today's market, industry and academe have invested considerable effort to make manufacturing systems more efficient and competitive. Traditionally, once a manufacturing system is adopted by a manufacturer, the operation model of the manufacturer will remain the same over the time. However, in the face of facing a changing product mix environment, a manufacturer needs an adaptable manufacturing system to gain the best performance possible.

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According to *Linck* [1], a manufacturing system can be defined as follows: Manufacturing system consists of people, machines, tools, material and information, which are related to each other to produce a value-added product. If manufacturing systems are classified according to the arrangement of machines and departments in a plant, manufacturing systems in industry fall into four major categories: job shop, mass production, batch production, and traditional cellular manufacturing [2].

A. Job Shop

The main characteristic of a job shop is that it produces a wide variety of products in relatively small volume [3]. Machines with the same functions are arranged together to form a department in a plant, as shown in Figure 1 a). A part being processed will jump from one department to another based on the part's operational sequence. Because a job shop type factory is designed to produce a variety of different products, it must have relatively high flexibility. In general, a job shop is very adaptive to a dynamic environment in which the product types and desired volumes change frequently. However, the main disadvantage of this type of layout is the lower productivity which is caused by the frequency of machine set-ups and excessive material handling between departments in a job shop. In addition, high expense may be associated with the large variety of tools and fixtures.

B. Mass Production

The mass production system is also called Dedicated Manufacturing System (DMS), which produces few products in large volumes [3]. To produce a large volume of a product type, the machines needed for production are arranged sequentially and organized together to form a dedicated production line, as shown in Figure 1 b). In most cases, the machines in a production line need to be set up only once. The flow in a DMS is much smoother than that of any other manufacturing system; as a result, the mass production system has the highest productivity. However, a mass production system is relatively inflexible because a production line is employed for only or very few product types. It is unsuitable for a manufacturing environment that experiences a changing

978-1-4244-3523-4/09/$25.00©2009 IEEE

product mix due to its least adaptability among all manufacturing systems.

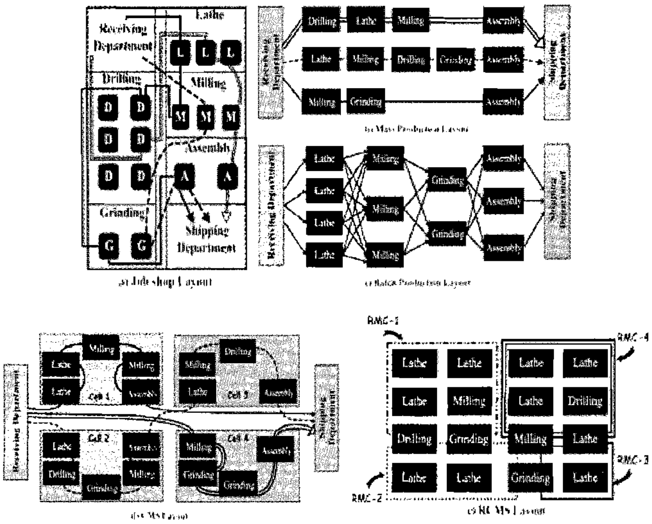

Fig. 1. Different Types of Manufacturing Layouts.

C. Batch Production

The batch production system lies between the job shop and mass production [3]. The main characteristic of a batch production system is that it produces a range of product, each one in medium volume. The layout of a batch production system is functionally similar to that of a job shop, as shown in Fig. 1 c). Because products are processed in batches, some of the recurring fixed costs between individual batches can be shared. In general, the batch production system is the most suitable one for a company that produces and markets mature products with stable periodic demands. However, because products are produced in batches, a single product may occupy a machine for a considerable time, which might necessitate long delays in working on other products. Moreover, a batch production system is unsuitable for a changing product mix environment because its products and the relative sizes of batches to be produced during a period are generally known ahead of time.

D. Cellular Manufacturing System (CMS)

Cellular manufacturing is an application of the group technology philosophy to designing manufacturing systems [4]. According to the literature, the main characteristic of CMS is that it groups together the machine cells which are dedicated to the processing of a set of part families [5]. The typical layout of a traditional CMS is shown in Figure 1 d). Jobs in the same part family could share the same setup, or a common setup could be designed for the whole part family. With the common setup, accomplishing each job in a part family needs only a minor setup, so that the set-up time for producing the whole part family is reduced significantly. Because the manufacturing cells are formed and organized according to part families, a CMS is more flexible than a mass production system. Although CMS can offer us numerous benefits such as reduction in setup time, reduction in material handling cost and time, and reduction in tooling cost, there are still some disadvantages of CMS that need to be addressed. As per the literature review, a few of these drawbacks are discussed as follows [6]:

a) *Increased capital investment*: Switching from DMS to CMS can require heavy investments in new machines and equipments. It may also require the older machines and equipment to be scrapped. In addition, equipment and machines that are shared by multiple parts may have to be duplicated and put in multiple cells, increasing capital investment.

b) *Lower machine utilization:* Since cells are dedicated to a particular part family, when those parts are low in demand, the corresponding machines end up being underutilized. Also, duplication of equipment could result in lower machine utilization. For older, fully depreciated equipment it may be easier to justify lower machine utilization, but with newer, expensive machine that might not be the case.

c) *Labor resistance:* In cellular manufacturing, since the cells have dedicated resources (machines, equipment, operators), these resources are not available for use by other products in the plant unless they are duplicated. This makes cells less capable of handling products that require process steps outside the capabilities of the machines, equipment, or skills of the operator. This decreases the flexibility of the cell.

d) *Inefficiencies in a dynamic/stochastic environment:* In a dynamic/stochastic product mix environment, the design for one set of conditions may not be the most efficient for the subsequent conditions, i.e. when one set of conditions is optimized and a layout for those conditions; it may not be the optimum design for other sets of conditions.

E. Reconfigurable Manufacturing System (RMS)

Under these circumstances, a new manufacturing system paradigm called Reconfigurable Manufacturing System (RMS) was proposed by Koren et al. [7] in 1999. It is defined as follows: A Reconfigurable Manufacturing System (RMS) is designed at the outset for rapid change in structure, as well as in hardware and software components, in order to quickly adjust production capacity and functionality within a part family in response to sudden changes in market or in regulatory requirements.

According to this definition, an RMS is expected not only to accommodate for the production of a variety of products, which are grouped into families, but also it must give a positive response to new products introduced within each family. The MS is then required to be reconfigurable in capacity for volume's changes and functionality for families' changes. As summarized in Table 1, an RMS is expected to have the following 5 key characteristics [8]:

TABLE I
KEY CHARACTERISTICS OF AN RMS

1. Modularity.	Design all system components, both software and hardware, to be *modular*.
2. Integrability	Design systems and components for both *ready integration* and future introduction of new technology.
3. Convertibility.	Allow *quick changeover* between existing products and quick system adaptability for future products.
4. Diagnosability	*Identify quickly the sources of quality and reliability problems* that occur in large systems.
5. Customization	Design the system capability and flexibility (hardware and controls) *to match the application* (product family)

As the main component of RMS is Reconfigurable Machine Tool (RMT), the advances in RMS will not occur without RMT which has modular structure to provide the necessary characteristics for quick reconfiguration. However, the lack of RMT's design methodology and the lack of interfaces are the major barriers that impede structure modularity. Reconfiguration seems increasingly difficult because hardware interfaces are much more difficult to realize due to its inherent technical complexity.

F. Reconfigurable Cellular Manufacturing System (RCMS)

So in order to fill the gap between RMS and CMS (as shown in Fig. 2.), a novel hybrid manufacturing system, Reconfigurable Cellular Manufacturing System (RCMS), is proposed in this research. RCMS lies between the CMS and RMS. It is very similar to a traditional CMS; machine cells and parts families are also applied in RCMS. Moreover, RCMS also consists of a set of manufacturing cells which are called Reconfigurable Manufacturing Cells (RMCs) in this research. Compared with traditional manufacturing cell, RMC will have the following three advantages which could make it distinguished:

a) *Machines are logically, not physically organized in an RMC:* Unlike a traditional manufacturing cell, which is a physical entity, an RMC is a logical entity. An RMC defines its groupings of machines in a computer, in other words, machines in an RMC are not physically moved but are conceptually grouped. Machines belonging to the same RMC during any period may not necessarily occupy the same geographic region of a shop floor.

b) RMC is reconfigurable: RMCs are formed in response to the product mix released for production during a production session. Once a batch of jobs is completed and another batch is released for production, a new set of RMCs may be reconfigured. Therefore, machine set that constitutes an RMC constantly changes as the product mix changes. Due to the reconfigurability of RMCs, RCMS is very suitable for a dynamic changing product mix environment.

c) *Machines can be shared by different RMCs:* The machine-sharing concept is applied among RMCs. In a RCMS, connections between machines are accomplished by a highly automated material handling system. As a result, it is not only unnecessary to change a factory's current layout, but a machine can serve more than one RMC.

An example of RCMS is shown in Figure 1 e). As it shown in the picture, RMC-1 consists of four types of machines, Lathe, Milling, Drilling, and Grinding. RMC-2 and RMC-1 share the same Drilling and Grinding machine. RMC-2, RMC-3, and RMC-4 share the same Milling machine. RMC-2 and RMC-3 share the same Milling and Grinding machine. Meanwhile, RMC-3 and RMC-4 share the same Milling and Lathe machine. By using machine-sharing method, an RMC can provide more flexibility than traditional manufacturing cells; this suggests that RCMS might have a bright future for bridging the gap between CMS and RMS. Although a great amount of efforts have been invested on the traditional cell formation problem, these methods can not be applied directly to RMC formation problem due to the introduction of machine-sharing concept. So there is a need to develop a new method which can be used for configuring RMCs.

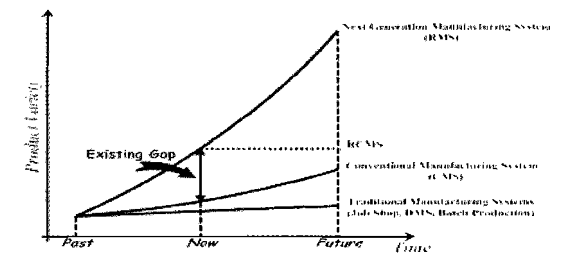

Fig. 2. Different Types of Manufacturing Layouts.

II. LITERATURE STUDY AND RELATED WORK

The cell formation (CF) problem is the main problem in designing a CMS. In this research, RCMS is very similar to CMS. So we will start our research with solving CF problems. CF is the problem of determining part families and machine cells. According to the literature, there are many approaches have been presented for solving CF problem. From production-oriented point of view, CF techniques can be classified into the following five categories: mathematical programming, manual techniques, graph theoretic, cluster analysis, and novel approaches.

A. Mathematical Programming

Several mathematical approaches have been used to identify part families and their corresponding manufacturing cells. Among them, the most basic and most popular are linear programming, non-linear programming, integer programming, and mixed integer programming [9]. These approaches off the distinct advantage of being able to incorporate ordered sequences of operations, alternative process plans, non-consecutive part operations on the same machine, setup and processing times, the use of multiple identical as well as outsourcing of parts. However, there are the following critical limitations impede mathematical programming method to be widely used in practice for solving CF problem [10]:

a) Most approaches do not concurrently group machines into cells and parts into families due to the resulting nonlinear form of the objective function;

b) With regard to number of decision variables and constraints, it is very time consuming to formulate and solve a mathematical model, even for a small size problem;

c) Mathematical programming is suitable only for a stable environment; once the mix of products is changed, a mathematical model needs to be reformulated. Furthermore, for a large-size problem, it is almost impossible to find an optimal solution within a reasonable time period, a phenomenon known as NP-complete.

B. Manual Techniques

Manual techniques require the analyst to make a series of judgments during the cell formation procedure such that part families and manufacturing cells are iteratively established by use of there manual approaches. Several manual techniques have been presented in the literature such as production flow analysis (PFA), in which the routing information of parts is used to simultaneously identify part families and their corresponding manufacturing cells [11] and component flow analysis (CFA), in which the parts are firstly sorted into groups based on their manufacturing requirement, and then the groups are manually analyzed to generate manufacturing cells. Finally, a detailed flow analysis is performed and appropriate adjustments are made to obtain an acceptable design [12]. Although according to literature, various manual procedures have been reported in case studies, there are two major disadvantages of manual techniques that should be addressed [10]:

a) Because these techniques are heavily dependent on human judgment, it is difficult to implement them on a computer;

b) The precise underlying use of manual techniques is that the various parts should be clearly defined, and this makes these techniques very difficult to apply.

C. Graph Theoretic

Several graph theoretic approaches for the CF problem such as network flow approach, bipartite graphs, and minimum spanning tree have been published in the literature. These methods treat the machines and/or parts as nodes, and the material flows as arcs. The intention of these approaches is to obtain disconnected sub-graphs from a machine-machine or machine-part graph, thereby identifying manufacturing cells. Rajagopalan and Batra were among the first to apply a purely graph theoretic approach to the cell formation problem [13]. The objective is to minimize the movements of parts between machine cells, using a measure called Jaccard's similarity coefficient [14], which is calculated for each machine pair. The same approach, with different similarity coefficients to design primary, secondary, and tertiary cells, was proposed by De Witte [15]. Other approaches in this category include network flow approach, proposed by Vohra et al. [16]; minimum spanning tree, presented by Ng [17]; and a heuristic graph partitioning approach, developed by Askin and Chiu [18]. However, the main drawbacks inherent to these approaches are the practical issues such as production volumes and alternate process plans are not addressed. Furthermore, the clique identification problem is a type of NP-complete problems.

D. Cluster Analysis

Cluster analysis assigns objects into clusters such that individual elements within a cluster have a high degree of relationship, while the relationship between clusters is very slight. A common feature of cluster analysis is that it sequentially rearranges columns and rows of the machine/part matrix based on an index, until diagonal blocks are generated [19]. In general, the methods in this category could be divided into three types: (1) array-based clustering techniques; (2) hierarchical clustering techniques; and (3) non-hierarchical clustering techniques [20].

Array-based clustering is one of the simplest classes of production-oriented cell formation methods. It operates on a 0-1 part/machine incidence array performing a series of column and row manipulations trying to produce small clustered blocks along the diagonal as shown in Figure 3. The part/machine incidence matrix, A, consists of elements aij=1 if part j requires processing on machine i, otherwise aij=0. Any tightly clustered blocks represent the candidate part families and machine cells, which are formed simultaneously.

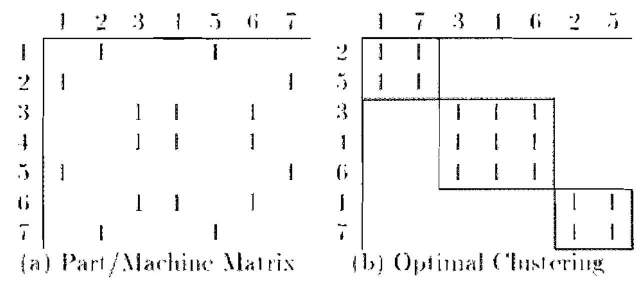

Fig. 3. Part/Machine Matrix and Optimal Clustering.

Although the array-based clustering techniques used in the design of manufacturing cells are both efficient and simple to apply to the part/machine matrix, there are still some drawbacks exist among these techniques as follows [21]:

a) Most array-based clustering techniques consider only binary routing information and do not take into account other types of manufacturing data such as the cost of machine, machine capacity, operational sequence, production volume of parts, and maximum cell size;

b) In most cases, bottleneck machine must be removed before any part/machine cluster block can be clearly identified;

c) To identify cluster blocks requires visual inspection, and that is difficult when a problem is large.

Unlike array-based techniques, hierarchical clustering methods do not produce machine cells and part families simultaneously. Instead, hierarchical clustering techniques operate on an input data set described in terms of a similarity/dissimilarity of distance function and then create a hierarchy of clusters or partitions [22]. Hierarchical clustering approaches consist of two steps. The first step is to calculate similarity/dissimilarity coefficients for every machine (part) pair. There are various coefficients available in the literature such as the Jaccard's similarity coefficient [14], Weighted similarity/dissimilarity coefficients [23], and operation-based similarity/dissimilarity coefficients [24]. The second step involves determining how to combine or merge the machine (part) pairs together. Several algorithms have been presented for this purpose such as single linkage clustering algorithm (SLINK) [14], average linkage clustering algorithm (ALINK) [25], weight average linkage clustering algorithm (WALCA) [26], complete linkage clustering algorithm (CLINK) [27], and linear cell clustering algorithm (LCC) [28]. Because of their flexibility to incorporate manufacturing data, the hierarchical clustering methods can be implemented easily and have advantages relative to array-based clustering. However, there are still several disadvantages exist in hierarchical clustering methods [29]:

a) The designer must decide on an appropriate similarity for groups. In small applications, this is not a problem since the designer can visually evaluate the dendrogram. However, as applications become too large for output for output in the form of a dendrogram, other methods for storing the hierarchy must be employed;

b) Most algorithms do not handle the duplication of bottleneck machines;

c) The problems of how to select the cluster criteria and the performance measure and how to determine the number of clusters remain unsolved.

Non-hierarchical clustering methods are iterative approaches. Basically, a non-hierarchical clustering approach operates on an input data set by pre-specifying the number of clusters to be formed using a similarity function. The input data set could be either an initial partition of the data set or the choice of a few seed points [20]. The major difference between hierarchical clustering and non-hierarchical clustering is that a similarity matrix does not need to be computed and stored in most non-hierarchical clustering algorithms [22]. However, the major drawback of non-hierarchical clustering is related to the selection of the seed. Arbitrariness in the choice of seed points could lead to unsatisfactory results [20].

E. Novel Approaches

This category consists of relatively new approaches to the CF problem. The major characteristics of these methods are the use of Artificial Intelligence (AI) and/or pattern recognition techniques, and search approaches to form machine cells or part families. From the computational point of view, CF problems have proven to be NP-complete and cannot be solved in polynomial time. Meanwhile, AI methods are tools to solve the complicated real-life problems within a reasonable time by generating high-quality solutions. So the application of AI approaches in CF area proves to be a very promising area. In general, the AI approaches can be classified into six types: expert system, fuzzy logic, simulated annealing (SA), tabu search (TS), genetic algorithms (GA), and artificial neural networks (ANN).

Knowledge-based rules and pattern recognition techniques are the two necessary components of expert systems. In 1986, Wu et al. [30] presented an algorithm for using syntactic pattern recognition for the CF problem. The advantages of syntactic pattern recognition include cell formation that takes into account material flow patterns, operation precedence relations, and non-uniform importance of machines. In 1988, Kusiak introduced a knowledge-based system that takes advantage of expert system techniques and optimization in which machine capacity, material-handling capabilities, technological requirement, and cell dimensions are considered in forming cells [31]. In another algorithm proposed in 1991 by Singh and Qi [32], the concept of multi-dimensional similarity coefficient using syntactic pattern recognition was introduced to form part families. Although there are several papers in the literature that were focused on knowledge-based expert systems, the main disadvantage of expert system is its less effective in facing the ever-changing, complex, and open system environment of today's manufacturing systems.

Although some objects obviously belong to certain clusters, in some other cases it is not clear which cluster is most appropriate. Fuzzy logic methods are used to deal with the issues of vagueness and uncertainty in the CF problem. Chu and Hayya [33] applied a fuzzy c-means clustering algorithm to production data. This approach 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 a particular family. However, if c is underestimated, the result is far from optimal. Also, a poor stopping criterion leads to inferior clusters. Furthermore, the fuzzy c-means clustering can be classified as a non-hierarchical method and suffers from the same problems associated with those methods.

Kirkpatrick et al. [34] initially presented the SA algorithm, which attempts to solve hard combinatorial optimization problems through controlled randomization. Since then this algorithm has been applied to many optimization problems in a variety of areas, including CF problems. The most important characteristic of this algorithm is that is mimics the process of cooling a physical system slowly in order to reach a state of globally minimum potential energy. The stochastic nature of the algorithm allows it to escape local minimum, explore the state space, and find optimal or near-optimal solutions.

TS is a stochastic neighbourhood search algorithm that was first suggested and applied by Glover [35]. The basic TS algorithm operates in the following way: it starts from a randomly selected or a known solution. From this solution, a set of neighbourhood solutions N is generated using the predefined movement strategies. The objective function is evaluated for each solution in set N, and the best neighbour solution replaces the current solution, even though the best neighbor solution may be worse than the current one. In this way, the algorithm makes it possible to escape from the local minima (or maxima) of the objective function. However, the major drawback of SA and TS methods is that users need to set some parameters before initiating the search.

GA mimics the evolutionary process by combining the survival of the fittest among solution structures with a structured, yet randomized, information exchange and creation of offspring [36]. GA solves linear and nonlinear problems by exploring all regions of the state space and exponentially exploiting promising areas through mutation, crossover, and selection operations [37]. Venugopal and Narendran [38] in 1992 proposed a GA-based approach to solve the CF problem. The objectives of the model are to minimize the inter-cell movements and the total within-cell load variation; limitations of machine capacities, production amounts, and processing times of parts are considered in the paper. In 1995, Gupta et al. [39] presented a similar GA to minimize a weighted total number of inter-cell and intra-cell movements. Later, their study was extended by adding one more objective that minimizes the total within-cell load variation [40]. There are two major differences between GA and traditional search algorithms. First, instead of improving a single solution, GA simultaneously examines and modifies a population that is a set of solutions. Second, GA is able to extract information from a population and then direct the search; by so doing, GA may avoid the problem of local optimal. However, GA technique is not developed for a stable environment, and it cannot address the CF problem in a changing product-mix environment.

An ANN is a mathematical model of biologically motivated computation. It is designed to exploit the massively parallel local processing and distributed representation capability. ANN is a highly parallel computation system, loosely modeled after the human brain. It is especially powerful for identifying patterns, trends, and internal relationships [41]. As a result, ANN methods have been applied to many manufacturing areas, including CF problem. Basically, ANN could further be classified into two types, unsupervised or supervised. To use supervised ANN, a training data set including a series of input/output pairs is required to train the network by adjusting the weights between the individual nodes, neurons. The network with the trained weights is then employed as the basis for classifying new inputs. The most popular technique in this category is the back propagation algorithm [42]. However, because the manufacturing environment is dynamic, it is difficult to know the patterns of existing parts and processes in advance. Therefore, the other type of ANN, unsupervised ANN, is more appropriate than the supervised ANN for the CF problems due to unsupervised ANN is able to self-organize the presented data to discover common properties without using any classified output data. Wong et al. concluded six main areas that ANN is applicable: accounting/auditing, finance, human resource, information systems, marketing/distribution, and production/operations. Among these various application areas, production/operation had the largest number of applications. Moreover, in production/operations, the most popular research areas were part family/machine cell formation, job shop scheduling, CMS design, and etc [43]. Basically, the CF problems can be classified into binary and comprehensive formation problems depending on whether or not the processing times and the machine capacities are considered. The binary formation problem arises if the part demands are unknown when the manufacturing system is being developed. If the part demand can be forecast accurately, both the processing times and machine capacities have to be included in the analysis. This gives rise to comprehensive formation problem [44]. Considering the large number of parts and machines involved in the industrial design problem, efficient solution methods are highly desirable. As a result, we can believe that ANN is a very suitable research method to solve CF problem for the following reasons [22]:

a) To employ multi-criteria objective functions;

b) Conveniently, and inter-changeably to utilize several non-linear evaluation measure;

c) Selectively including or excluding constraints on the number of part families/machine cells;

d) Simultaneously to form part families and machine cells without visual inspection of the output;

e) Quickly to execute and obtain good clusters;

f) The ability to solve large data sets.

III. Empirical Work

As discussed in Section 3, although for most CF techniques, the concept of machine-sharing, one of the most important aspects of RCMS is not allowed, these methods provide some basic ideas and information of developing RMCs. So in this research, we will use one of the most promising AI techniques, ANN, for solving RMC formation problem. The flow chart (as shown in Figure 4) of RMC formation procedure can be described as follows:

Step 1: The required data need to be provided such as the varieties of parts, their process plans and their batch sizes, and the due time of the order;

Step 2: Based on this information, part family should be grouped;

Step 3: The available machines with specific processing capacities need to be given such as which machines should be chosen to serve the orders;--

Step 4: After the machines required to fulfill the orders have been identified by previous step, a candidate RMCs' organization should be worked out by using ANN approach;

Step 5: Once the machines and parts have been grouped, the remaining problem is group scheduling which is how to sequence part families and schedule operations of the parts within each part family so that some planning goals can be achieved. ANN method will be used as well for solving group scheduling problem;

Step 6: Evaluation and selection of the cells to be implemented;

Step 7: Determination of the final intra-cell layout and the shop layout.

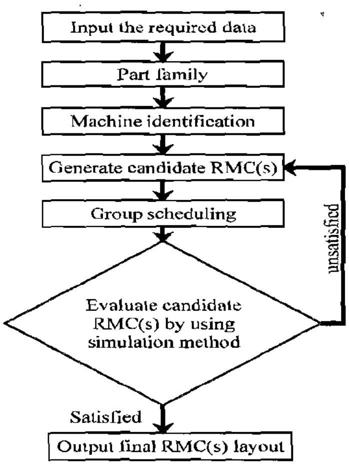

Fig. 4. Flow chart of RMC formation procedure.

To evaluate the performance of ANN approach in this research, some test problems appeared in the literature were listed in Table II. An in-depth discussion will be given after the comparison has been done.

TABLE II
CELL FORMATION TEST PROBLEMS

Test Problems	Size	References
1	15 x 10	*Balasubramanian & Panneerselvam* [45]
2	5 x 7	*Waghodekar & Sahu* [46]
3	5 x 7	*King & Nakornchai* [47]
4	20 x 35	*Boe & Cheng* [48]
5	20 x 35	*Carrie* [49]
6	8 x 20	*Chandrasekharan & Rajagopalan* [50]
7	16 x 30	*Boctor* [51]
8	24 x 40	*Chandrasekharan & Rajagopalan* [50]
9	30 x 41	*Kumar & Vannelli* [52]
10	7 x 12	*Kusiak* [31]
11	16 x 43	*King & Nakornchai* [47]
12	16 x 43	*Brubidge* [53]
13	14 x 24	*King* [54]
14	12 x 10	*McAuley* [14]

IV. CONCLUSIONS

The following conclusions can be obtained from this research work:

a) A pure cellular arrangement is not practical in typical industrial environments. The idea of RCMS is proposed. In a dynamic changing product mix environment, ability to adapt to changes to improve production efficiency is desirable;

b) The RCMS design problem is conveniently decomposed in a sequence of sub-problems, i.e. part family/machine cell formation and evaluation, RMC layout, and shop layout;

c) These sub-problems may be solved more than once to arrive at a good solution;

d) Practice issues, such as similarities in setups and changes in production mix, should be considered, if the final solution is to have practical significance;

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