

Design of Cellular Manufacturing Systems for Dynamic and Uncertain Production Requirements with Presence of Routing Flexibility

Anan Mungwattana

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John P. Shewchuk, Chairperson
Michael P. Deisenroth
Jesus M. de la Garza
Kimberly P. Ellis
Robert H. Sturges, Jr.

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Blacksburg, Virginia

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(ABSTRACT)

Shorter product life-cycles, unpredictable demand, and customized products have forced manufacturing firms to operate more efficiently and effectively in order to adapt to changing requirements. Traditional manufacturing systems, such as job shops and flow lines, cannot handle such environments. Cellular manufacturing, which incorporates the flexibility of job shops and the high production rate of flow lines, has been seen as a promising alternative for such cases. Although cellular manufacturing provides great benefits, the design of cellular manufacturing systems is complex for real-life problems. Existing design methods employ simplifying assumptions which often deteriorate the validity of the models used for obtaining solutions. Two simplifying assumptions used in existing design methods are as follows. First, product mix and demand do not change over the planning horizon. Second, each operation can be performed by only one machine type, i.e., routing flexibility of parts is not considered. This research aimed to develop a model and a solution approach for designing cellular manufacturing systems that addresses these shortcomings by assuming dynamic and stochastic production requirements and employing routing flexibility. A mathematical model and an optimal solution procedure were developed for the design of cellular manufacturing under dynamic and stochastic production environment employing routing flexibility. Optimization techniques for solving such problems usually require a substantial amount of time and memory space, therefore, a simulated annealing based heuristic was developed to obtain good solutions within reasonable amounts of time. The heuristic was evaluated in two ways. First, different cellular manufacturing design problems were generated and solved using the heuristic. Then, solutions obtained from the heuristic were compared with lower bounds of solutions obtained from the optimal solution procedure. The lower bounds were used instead of optimal solutions because of the computational time required to obtain optimal solutions. The results show that the heuristic performs well under various circumstances, but routing flexibility has a major impact on the performance of the heuristic. The heuristic appears to perform well regardless of problem size. Second, known solutions of two CM design problems from literature were used to compare with those from the heuristic. The heuristic slightly outperforms one design approach, but substantially outperforms the other design approach.

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Chapter 1

Introduction

1.1 Cellular Manufacturing

Manufacturing industries are under intense pressure from the increasingly-competitive global marketplace. Shorter product life-cycles, time-to-market, and diverse customer needs have challenged manufacturers to improve the efficiency and productivity of their production activities. Manufacturing systems must be able to output products with low production costs and high quality as quickly as possible in order to deliver the products to customers on time. In addition, the systems should be able to adjust or respond quickly to changes in product design and product demand without major investment. Traditional manufacturing systems, such as job shops and flow lines, are not capable of satisfying such requirements.

Job shops are the most common manufacturing system in the United States [13]. In general, job shops are designed to achieve maximum flexibility such that a wide variety of products with small lot sizes can be manufactured. Products manufactured in job shops usually require different operations and have different operation sequences. Operating time for each operation could vary significantly. Products are released to the shops in batches (jobs). The requirements of the job shop — a variety of products and small lot sizes — dictate what types of machines are needed and how they are grouped and arranged. General-purpose machines are utilized in job shops because they are capable of performing many different types of operations. Machines are functionally grouped according to the general type of manufacturing process: lathes in one department, drill presses in another, and so forth. Figure 1.1 illustrates a job shop. A job shop layout can also be called a functional layout.

In job shops, jobs spend 95% of their time in nonproductive activity; much of the time is spent waiting in queue and the remaining 5% is split between lot setup and processing [4]. When the processing of a part in the job shop has been completed, it usually must be moved a relatively large distance to reach the next stage. It may have to travel the entire facility to complete all of the required processes, as shown in Figure 1.1. Therefore, to make

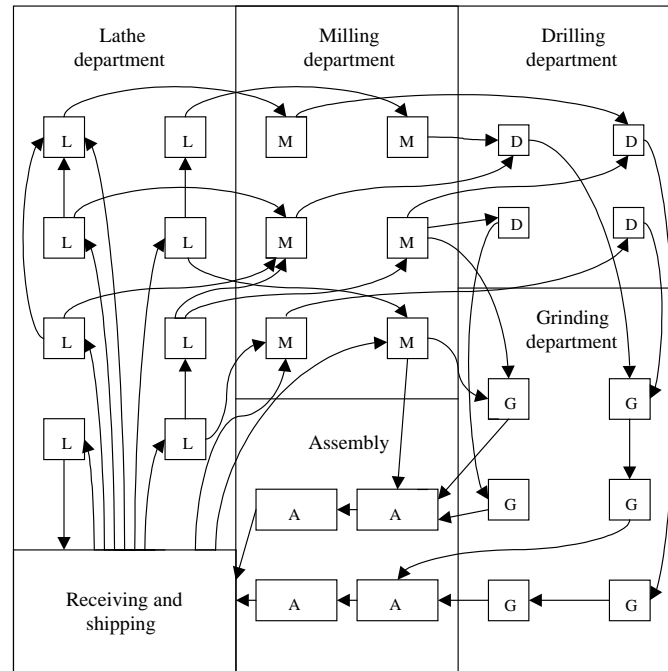


Figure 1.1: Job Shop Manufacturing (Black [13])

processing more economical, parts are moved in batches. Each part in a batch must wait for the remaining parts in its batch to complete processing before it is moved to the next stage. This leads to longer production times, high levels of in-process inventory, high production costs and low production rates.

In contrast to job shops, flow lines are designed to manufacture high volumes of products with high production rates and low costs. A flow line is organized according to the sequence of operations required for a product. Specialized machines, dedicated to the manufacture of the product, are utilized to achieve high production rates. These machines are usually expensive; to justify the investment cost of such machines, a large volume of the product must be produced. A major limitation of flow lines is the lack of flexibility to produce products for which they are not designed. This is because specialized machines are setup to perform limited operations and are not allowed to be reconfigured. Figure 1.2 shows an example of a flow line.

As indicated above, job shops and flow lines cannot meet today's production requirements where manufacturing systems are often required to be reconfigured to respond to changes in product design and demand. As a result, cellular manufacturing (CM), an application of group technology (GT), has emerged as a promising alternative manufacturing system. Within the manufacturing context, GT is defined as a manufacturing philosophy identifying similar parts and grouping them together into families to take advantage of their similarities

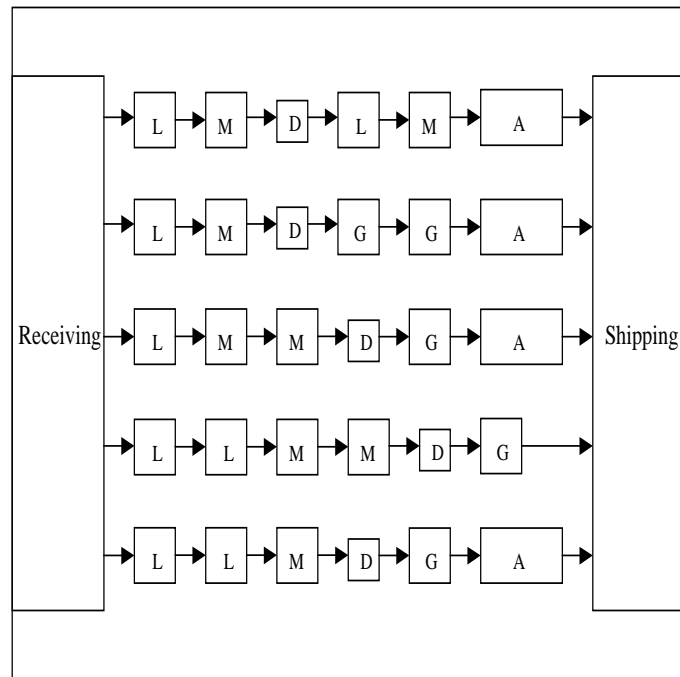


Figure 1.2: Flow Line Manufacturing

in design and manufacturing [76]. CM involves the formation of part families based upon their similar processing requirements and the grouping of machines into manufacturing cells to produce the formed part families. A part family is a collection of parts which are similar either because of geometric shape and size or similar processing steps required in their manufacture [33]. A manufacturing cell consists of several functionally dissimilar machines which are placed in close proximity to one another and dedicated to the manufacture of a part family.

The tenet of CM is to break up a complex manufacturing facility into several groups of machines (cells), each being dedicated to the processing of a part family. Therefore, each part type is ideally produced in a single cell. Thus, material flow is simplified and the scheduling task is made much easier. As reported in the survey by Wemmerlov and Johnson [97], production planning and control procedures have been simplified with the use of CM. The job shop in Figure 1.1 is converted into a cellular manufacturing system (CMS) as shown in Figure 1.3. Obvious benefits gained from the conversion of the shop are less travel distance for parts, less space required, and fewer machines needed. Since similar part types are grouped, this could lead to a reduction in setup time and allow a quicker response to changing conditions. On the other hand, in the job shop, each part type may have to travel through the entire shop; hence scheduling and materials control are difficult. In addition, job priorities are complex to set and hence large inventories are needed so as to ensure that ample work is available.

1.2 Benefits of Cellular Manufacturing

The advantages derived from cellular manufacturing in comparison with traditional manufacturing systems in terms of system performance have been discussed in [4], [15], [23], [27], [39], [40], [41], [51], [82], [96] and [97]. These benefits have been established through simulation studies, analytical studies, surveys, and actual implementations. They can be summarized as follows:

1. **Setup time is reduced** [4], [89]. A manufacturing cell is designed to handle parts having similar shapes and relatively similar sizes. For this reason, many of the parts can employ the same or similar holding devices (fixtures). Generic fixtures for the part family can be developed so that time required for changing fixtures and tools is decreased.
2. **Lot sizes are reduced** [82]. Once setup times are greatly reduced in CM, small lots are possible and economical. Small lots also smooth production flow.
3. **Work-in-process (WIP) and finished goods inventories are reduced** [32], [78]. With smaller lot sizes and reduced setup times, the amount of WIP can be reduced. Askin and Standridge [4] showed that the WIP can be reduced by 50% when the setup time is cut in half. In addition to reduced setup times and WIP inventory, finished goods inventory is reduced. Instead of make-to-stock systems with parts either being run at long, fixed intervals or random intervals, the parts can be produced either just-in-time (JIT) in small lots or at fixed, short intervals.
4. **Material handling costs and time are reduced** [17]. In CM, each part is processed completely within a single cell (where possible). Thus, part travel time and distance between cells is minimal.
5. **A reduction in flow time is obtained** [78]. Reduced material handling time and reduced setup time greatly reduce flow time.
6. **Tool requirements are reduced** [32]. Parts produced in a cell are of similar shape, size, and composition. Thus, they often have similar tooling requirements.
7. **A reduction in space required** [82]. Reductions in WIP, finished goods inventories, and lot sizes lead to less space required.
8. **Throughput times are reduced** [82]. In a job shop, parts are transferred between machines in batches. However, in CM each part is transferred immediately to the next machine after it has been processed. Thus, the waiting time is reduced substantially.
9. **Product quality is improved**. Since parts travel from one station to another as single units, they are completely processed in a small area. The feedback is immediate and the process can be stopped when things go wrong.

10. **Better overall control of operations.** In a job shop, parts may have to travel through the entire shop. Scheduling and material control are complicated. In CM, the manufacturing facility is broken down into manufacturing cells and each part travels with a single cell, resulting in easier scheduling and control.

The benefits gained from implementing CM also have been reported. Collet and Spicer [23], in a case analysis of a small manufacturing company, found that cellular manufacturing systems resulted in a number of performance improvements when compared to job shops. Reductions in operating time and less work space, due to less work in process, were achieved by CM. Setup cost was also reduced.

In another case study at PMI Food Equipment Group, Howard and Newman [39] reported the results of moving from a job shop to a CMS. Some of the benefits included doubling of capacity for part families due to cell configuration, \$25,000 in labor saving from setup reductions, over \$2 million decline in finished goods inventory, improved customer service, and an improvement in quality of employee work life.

Levasseur *et al.* [51] studied a case implementation of the CMS in Steward, Inc. The results were overwhelmingly in favor of the CMS. Every criteria in the case analysis showed dramatic improvement. These criteria included WIP, lead time, late orders, scrap, labor cost and manufacturing space. Table 1.1 summarizes the benefits gained from implementing CM.

Table 1.1: Benefits of CM after the First Two Months of Operation in [51]

Criteria	Job Shop	CMS	Resulting Improvement
Work in process	\$590,000	\$116,336	\$473,664 (80%)
Finished goods	\$880,000	\$353,167	\$526,833 (60%)
Refractory supplies	\$8,333/month	0	\$8,333 (100%)
Lead time	14 days	2 days	12 days (86%)
Late orders	100	4	96%
Scraps	22%	14%	8%
Direct labor	198	145	53 employees (27%)
Mfg. Space (sq. ft.)	45,000	20,000	25,000 sq. ft. (56%)

Hyer [40] collected data on 20 U.S. firms. A detailed questionnaire was employed to gather information on the costs and benefits of CM. A large majority of the respondents reported that the actual benefits from implementing CM met or exceeded their expectations. Specific savings generally occurred in reductions of lead times, throughput times, queuing times, setup times, work in process, labor costs, material handling costs, and in easier process plan preparation.

Wemmerlov and Hyer [96] reported the cost savings obtained by utilizing CM from a survey study of 32 U.S. firms. These 32 firms produced a wide variety of product lines such as

machinery and machine tools, agricultural and construction equipment, hospital and medical equipment, defense products, piece parts and components, and engines. Table 1.2 shows the reported benefits from CM.

Wemmerlov and Johnson [97] conducted another similar survey in implementation experiences and performance improvements of CM at 46 user plants. In the survey, products manufactured in these 46 plants are electrical/electronic products and components, fluid handling and flow control devices, machinery and machine tools, heating and cooling products and components, tools, engines, and bearings. Note that the surveyed firms in this publication are not the same firms in the previous survey by Wemmerlov and Hyer [96]. Table 1.3 displays the reported performance improvements.

CM is considered as a prerequisite for just-in-time (JIT) manufacturing [82]. JIT requires manufacturing systems to have little or zero setup time, small lot sizes, and low inventory. Obviously, CM is well-suited for such requirements. Black [13] also emphasized that forming manufacturing cells is the first critical step to achieve JIT manufacturing.

1.3 Design of Cellular Manufacturing Systems

As described above, the benefits resulting from CM can be substantial. Getting CM in place, however, is not a simple task. Design of cellular manufacturing systems (CMSs) is a complex, multi-criteria and multi-step process. Ballakur [7] showed that this problem, even under fairly restrictive conditions, is *NP*-complete. The design of CMSs has been called cell formation (CF), part family/machine cell (PF/MC) formation, and manufacturing cell design. Given a set of part types, processing requirements, part type demand and available resources (machines, equipment, etc.), the design of CMSs consists of the following three key steps:

1. Part families are formed according to their processing requirements.
2. Machines are grouped into manufacturing cells.
3. Part families are assigned to cells.

Note that these three steps are not necessarily performed in the above order, or even sequentially. Part families and manufacturing cells can be formed simultaneously, along with the assignment of part families to the cells. After the design steps have been completed, a manufacturing cell configuration (or cell configuration, for short) is obtained. It is referred to as a cellular manufacturing system (CMS) which consists of a set of manufacturing cells; each cell is constituted of a group of machines and is dedicated to produce a part family. The layout or arrangement of machines in each cell belongs to the layout design problem, and is not considered in this research.

Table 1.2: Reported Benefits from Cellular Manufacturing in [96]

Types of Benefit	Number of Responses	Average % Improvement	Minimum % Improvement	Maximum % Improvement
1. Reduction in throughput time	25	45.6	5.0	90.0
2. Reduction in WIP inventory	23	41.4	8.0	90.0
3. Reduction in material handling	26	39.3	10.0	83.0
4. Improvement of operator job satisfaction	16	34.4	15.0	50.0
5. Reduction in number of fixtures for cell parts	9	33.1	10.0	85.0
6. Reduction in setup time	23	32.0	2.0	95.0
7. Reduction in space needed	9	31.0	1.0	85.0
8. Improvement of part quality	26	29.6	5.0	90.0
9. Reduction in finished good inventory	14	29.2	10.0	75.0
10. Reduction in labor cost	15	26.2	5.0	75.0
12. Increase in utilization of equipment in the cells	6	23.3	10.0	40.0
9. Reduction in pieces of equipment required to manufacture cell parts	10	19.5	1.0	50.0

Table 1.3: Reported Performance Improvements in [97]

Performance Measure	Number of Responses	Average % Improvement	Minimum % Improvement	Maximum % Improvement
1. Reduction of move distance/time	37	61.3	15.0	99.0
2. Reduction in throughput time	40	61.2	12.5	99.5
3. Reduction of response time to orders	37	50.1	0.0	93.2
4. Reduction in WIP inventory	40	48.2	10.0	99.7
5. Reduction in setup times	33	44.2	0.0	96.6
6. Reduction in finished goods inventory	38	39.3	0.0	100.0
7. Improvement in part/product quality	39	28.4	0.0	62.5
8. Reduction in unit costs	38	16.0	0.0	60.0

Ballllkur and Steudel [8] suggested three solution strategies based on the procedure used to form part families and manufacturing cells. They can be used as a framework to classify existing CM design methods. The three solution strategies are as follows:

1. Part families are formed first, and then machines are grouped into cells according to the part families. This is called the *part family grouping solution strategy*.
2. Manufacturing cells are created first based on similarity in part routings, then the parts are allocated to the cells. This is referred to as the *machine grouping solution strategy*.
3. Part families and manufacturing cells are formed simultaneously. This is the *simultaneous machine-part grouping solution strategy*.

In the design of CMSs, design objective(s) must be specified. Minimizing intercell moves, distances, costs, and the number of exceptional parts (parts that need more than one cell for processing) are common design objectives. An exceptional part can be also called an exceptional element or a bottleneck part. A small example is given next in order to introduce some of the terminology to be used in this dissertation.

An example from [48] of five part types and four machine types are used in order to form cells. A machine-part matrix is one way to represent the processing requirements of part

types on machine types as shown in Table 1.4. A 1 entry on row i and column j indicates that part type j has one or more operations on machine type i . For instance, part type 1 has operations on machine types 1 and 3. Manufacturing cells are formed with the objective of minimizing intercell moves.

Two cells (clusters) are formed as shown in Table 1.5. Cell 1 consists of machine type 2 and 4, and produces part type 5 and 2. Cell 2 consists of machine type 1 and 3, and produces part type 3, 1 and 4. Part type 3 needs to be processed on machine type 1 and 3 in cell 2, however, it also needs to be processed on machine type 2 which is assigned in cell 1. Therefore an intercell move is required: the symbol “*” represents an intercell move of part type 3. Part type 3 is an exceptional part, so these two cells (clusters) are called partially separable.

Table 1.4: Machine-Part Matrix

Machine Type	Part Type				
	1	2	3	4	5
1	1		1	1	
2		1	1		1
3	1		1		
4		1			1

Table 1.5: Cell Formation

Machine Type	Part Type				
	5	2	3	1	4
2	1	1	*		
4	1	1			
1			1	1	1
3			1	1	0

Analogous to an exceptional part, a bottleneck machine is one that processes parts belonging to more than one cell. Two possible approaches to eliminate exceptional parts are by considering alternative process plans for parts or additional machines [49] (detailed discussion in Section 1.3.1). In Table 1.5, 0 represents a void in cell 2. A void indicates that a machine assigned to a cell is not required for the processing of a particular part in the cell. In this example, machine type 3 is not necessary for part type 4. The presence of voids leads to inefficient large cells, which in turn could lead to additional intracell material handling costs and complex control requirements.

In addition to intercell material handling cost, other costs, such as machine cost, operating cost, etc., should be considered in the objective function in order to obtain more valid solutions. The design objective could be the minimization of the total of the sum of intercell material handling cost, equipment cost, operating cost and intercell material handling cost. Typical costs used in the design objective are as follows:

1. Equipment cost.
2. Intercell material handling cost.
3. Inventory cost.
4. Machine relocation cost.

5. Operating cost.
6. Setup cost.

Costs in the design objectives may be conflicting, hence tradeoffs may need to be made during the design process. For instance, we can always create cells without intercell material handling cost simply by adding machines as required. This will reduce the intercell material handling costs, but equipment costs will increase. On the other hand, we can reduce the number of machines required by allowing parts to move between cells.

In addition to the design objectives, a number of strategic issues such as machine flexibility, cell layout, machine types, etc., need to be considered as a part of the CM design problem. Further, any cell configuration should satisfy operational goals (constraints) such as desired machine utilization, production volume, number of manufacturing cells, cell sizes, etc. The followings are typical design constraints in the design of CMSs.

1. **Machine capacity.** It is obvious that, in the design of CMSs, one of the basic requirements is that there should be adequate capacity to process all the parts.
2. **Cell size.** The size of a cell, as measured by the number of machines in the cell, needs to be controlled for several reasons. First, available space might impose limits on the number of machines in a cell. If a cell is run by operators, the size of the cell should not be so large that it hinders visible control of the cell. Ranges of cell sizes can be specified instead of a single value of cell size. This would allow more flexibility in the design process.
3. **Number of cells.** In practice, the number of cells would be set by organizational parameters such as the size of worker teams, span of supervisory authority, and group dynamics [6]. Given a range of cell sizes, the number of cells are determined and the resultant solutions can be compared. Detailed discussion on the complexity of considering different numbers of cells is presented in Section 3.1.1.
4. **Utilization levels.** Two levels of machine utilization are normally used. Maximum utilization is specified to ensure that machines are not overloaded. Minimum utilization for a new machine ensures that it is economically justifiable to include the new machine in a cell.

In the last three decades, over 200 research papers and practical reports have been published in the field of CM, seeking effective methods for designing CMSs. Reviews of existing CM literature can be found in [2], [32], [42], [44], [46], [60], [76] and [81]. According to those reviews, the existing CM design methods in the CMSs can be classified into the following categories: part coding analysis, cluster techniques, similarity coefficient, graph partitioning, mathematical programming, heuristic search, and AI-based approaches.

1. Part coding analysis (PCA) uses a coding system to assign numerical weights to part characteristic and identifies part families using some classification scheme. PCA-based systems are traditionally design-oriented or shape-based, therefore, they are ideal for component variety reduction. Some PCA-based systems, for example Opitz [61], incorporate production-based codes as supplemental codes, which can be used for production planning.
2. Array-based clustering is the most commonly used clustering technique. In array based clustering, the processing requirements of parts on machines can be represented by an incidence matrix, referred to as the machine-part matrix. The machine-part matrix has zero and one entries (a_{ij}). A 1 entry in row i and column j ($a_{ij} = 1$) of the matrix indicates that part j has one or more operations on machine i , whereas a 0 entry indicates that it does not. These techniques try to allocate machines to groups and parts to families by appropriately rearranging the order of rows and columns to find a block diagonal form of the $a_{ij} = 1$ entries in the machine-part matrix. Examples of array based algorithms can be found in [16], [45] and [46].
3. The similarity coefficient approach requires identification of measures of similarity between machines, tools and design features. These similarity measures are used to form part families and machine groups based on methods such as single linkage cluster analysis [53], average linkage method [75], etc.
4. Graph partitioning approaches treat the machines and/or parts as nodes and the processing of parts as arcs connecting these nodes [3], [65]. These models aim at obtaining disconnected subgraphs from a machine-machine or machine-part graph to identify manufacturing cells and allocate parts to cells.
5. Mathematical programming approaches are widely employed in the design of CMSs, since they are capable of incorporating certain design requirements in the design procedure. They can be further classified into four categories based upon the type of formation: linear programming (LP) [14], linear and quadratic integer programming (LQP) [91] and [98], dynamic programming (DP) [88], and goal programming (GP) [79].
6. Heuristic search approaches, such as simulated annealing [91], genetic algorithms [98] and tabu search [91], have been introduced in designing CMSs as alternatives to mathematical programming approaches when computational time is prohibitive and/or linear objectives cannot be formulated.
7. AI-based approaches, such as expert systems [9], [22] and neural networks [82], have been employed for designing CMSs because of their attractiveness in terms of computational time and ability to capture and employ design knowledge. Both heuristic search and AI-based approaches are relatively new in this area.

Each design approach considers different numbers of design objectives and constraints, to different extents, depending upon the scope and interest of each design approach. For instance, clustering analysis approaches consider only one objective, the minimization of intercell moves. In the design process of clustering techniques, only part operations and the machines for processing those operations are considered. Other product data (such as operational sequences and processing times) and production requirements (such as production rate) are not incorporated into the design process. Thus, solutions obtained may be valid in limited situations. However, they are simple to implement and solutions can be obtained in reasonable amounts of time.

Each design approach has its advantages and limitations. Some are simple to implement and to obtain solutions. Some capture the design problem more accurately by considering a number of objectives and constraints, but could require a substantial amount of time to obtain solutions. Among the available design approaches, mathematical programming can capture the reality of the design problem better than others, since product data and production requirements can be incorporated. Product data includes processing times and costs, operational sequences, etc. Production requirements include product mix and demand in each period, available resources, machine cost, material handling cost, etc.

A major drawback of mathematical programming approaches is computational time required for large problems. Obtaining optimal solutions from mathematical programming approaches can be infeasible due to the combinatorial complexity of the CM design problem [76], [82]. Thus, heuristic approaches have been used as alternatives to obtain reasonably good solutions within acceptable amount of times.

Heuristics can be classified into two categories. The first category is the problem-specific heuristic. This type of heuristic only works for one problem; it cannot be used to solve a different one. For instance, a specific heuristic developed to solve a traveling salesman problem is unlikely to be applied to solve the general assignment problem. The second category is the metaheuristics which are more general and can be used for different types of problems. Such heuristics include genetic algorithms, simulated annealing, tabu search, etc. With some adjustment, they can be used for a wide range of problems. Examples of such heuristics for designing CMSs are in [14], [18], [34], [43], [52], [91], and [94].

1.3.1 Drawbacks in Current CM Design Methods

In this section, two major drawbacks in current CM design methods are discussed. First is the lack of consideration of dynamic and uncertain production requirements. Second is the lack of accounting for the presence of routing flexibility in cellular systems, which often exists due to the availability of multi-function machines. The availability of routing flexibility presents alternative process plans to the system.

Static, Known Product Mix and Demand

Most of the current CM design methods have been developed for a single-period planning horizon (static); they assume that problem data (e.g., product mix and demand) is constant for the entire planning horizon. Product mix refers to a set of part types to be produced, and product demand is the quantity of each part type to be produced. With shorter product life-cycles and time-to-market, it is likely that product mix and demand may change frequently [11], [19], [80]. Wemmerlov and Hyer [96] reported in their survey that the demand for finished products whose parts were manufactured in cells was not highly predictable. Therefore, a planning horizon can be divided into smaller periods where each period has different product mix and demand requirements. In such cases, we are faced with **dynamic production requirements** or a **dynamic environment**. Note that in a dynamic environment, product mix and/or demand in each period is different but is deterministic (i.e., known in advance).

In addition to dynamic production requirements, the product mix and/or demand in each period can be stochastic (uncertain), especially in future periods, due to customized products, shorter product life-cycles and unpredictable demand [11], [93]. We refer to uncertainty of product mix and demand as **stochastic production requirements** or as a **stochastic environment**. In other words, stochastic pertains to not knowing exactly what changes in product mix and/or demand occur each period. The dynamic and stochastic nature of production requirements are independent.

In employing a single-period planning horizon with known demand, current CM design methods assume a static, deterministic environment. This approach, however, could decrease the validity of any CM solutions so obtained. With frequent changes in the product mix and/or demand, manufacturing cells must be modified from time to time. The optimal cell configuration generated from earlier data may not be valid after such changes occur in the system. Intercell material handling costs could increase after such changes. In order to successfully utilize CM in such environments, the original system must evolve over time to match the changing conditions. This evolution results from reformulation of part families, manufacturing cells and reconfiguration of the cellular manufacturing system as required. Reconfiguration consists of swapping existing machines between cells, adding new machines to cells, removing existing machines from cells, and/or replacing existing machines in cells [80].

Unfortunately, few works in the design of CMSs have addressed dynamic and stochastic production requirements. However, they have gained interest from researchers in recent years [19], [36], [74], [85] and [92]. Certain CM design strategies have been suggested to deal with dynamic production requirements. A *robust design strategy* is to design a cellular manufacturing system that is good for the entire planning horizon even though it may not be optimal in any period. An *adaptable design strategy* is to design a CM that responds to changing product mix and/or demand in future periods by rearranging the current manufacturing system. By rearranging the system, it is hoped that the reduction in material handling costs

will offset the rearrangement costs.

One of the efforts partially addressing the problem of dynamic and stochastic production requirements is called “agile manufacturing.” Agility is defined as the ability to thrive in an environment of continuous and unpredictable change [58]. Agile manufacturing refers to manufacturing utilizing resources and people which can be changed, or reconfigured, quickly and easily to cope with variability and uncertainty [80]. The concept of agile manufacturing is motivated by the unpredictability in demand and how it can be handled. Several papers have been published in the area of agile manufacturing, however, most of the research is in the area of information integration to support agile manufacturing [10], [30], [31], [35], [56], [84] and [86]. A few efforts have addressed the actual reconfiguration of machines, equipment and facilities to respond to the changing demand [28], [64], [68], [69], [80] and [90].

System-Independent Reconfiguration

When a manufacturing cell configuration needs to be reconfigured from period to period during the planning horizon, it is necessary to consider the current manufacturing cell configuration. Thus, benefits will be gained from such consideration. (See Section 3.2.1 for detailed discussion.) Most of CM design methods do not consider the current manufacturing configuration in their design procedures. If the current system is considered during the design process, we refer to it as “system-dependent reconfiguration.” Otherwise, we will refer to it as “system-independent reconfiguration.”

Lack of Routing Flexibility

Several CM design methods have assumed that each operation of a part type can be processed only on a specific machine type [3], [8], [16], [46], [53]. This may no longer be true when machines capable of multiple processes (and hence operations) are employed. The use of such machines may result in alternate machine routings for each operation. That is, each part type operation can be processed on multiple machine types with different costs and times. When a part type can be processed by alternate routings through a manufacturing system, it is referred to as “routing flexibility” [77]. Routing flexibility is a function of machine flexibility and operation flexibility. Machine flexibility refers to the various types of operations that a machine can perform without requiring a prohibitive effort in switching from one operation to another [77]. Operation flexibility of a part is its ability to be produced in different ways [77].

Routing flexibility of a part type implies that the part type has alternative process plans. It is important to recognize that in an actual manufacturing environment, each part type will have more than one process plan if one or more operations can be processed on alternative machines [52]. According to Rajamani *et al.* [66], assigning a machine to an operation does not in advance does not necessary provide an optimal route, thereby increasing capital cost

and decreasing utilization (which are the major disadvantages of cellular manufacturing). The consideration of alternative process plans may improve the groupability of a machine-part matrix. The following example is modified from [1] to demonstrate the improvement of groupability through alternative process plans. The partition in Table 1.6 (Matrix a_2) is an example of an imperfect diagonalization. When an additional process plan for part 5 exists as shown in Table 1.7 (matrix b_1), where the first operation of part type 5 can be done on machine type 1 as well, the improved partition is obtained in Table 1.7 (matrix b_2). The number of exceptional parts has been reduced from 3 to 2. Alternatively, improvement can be gained through adding an additional machine of type 2. Table 1.8 shows such improvement.

Table 1.6: An Imperfect Decomposition of a Machine-Part Matrix

Matrix a_1							Matrix a_2							
Part Type	Machine Type						Part Type	Machine Type						
	1	2	3	4	5	6		1	3	5	2	4	6	
1	1	1	1		1		1	1	1	1	*			
2			1		1	1	4	1	1	1				
3			1		1	1	5		1	1	*			
4	1			1			2	*			1	1	1	
5			1	1		1	3				1	1	1	
6			1		1	1	6				1	1	1	

Table 1.7: Improvement in Decomposition from Alternate Process Plan

Matrix b_1							Matrix b_2							
Part Type	Machine Type						Part Type	Machine Type						
	1	2	3	4	5	6		1	3	5	2	4	6	
1	1	1	1		1		1	1	1	1	*			
2			1		1	1	4	1	1	1				
3			1		1	1	5 (2)	1	1	1				
4	1			1			2	*			1	1	1	
5 (1)			1	1		1	3				1	1	1	
5 (2)	1			1		1	6				1	1	1	
6			1		1	1								

As shown above, considering routing flexibility of parts during the design process can improve groupability in the cellular design as well as increase the utilization of machines. Alternate routings are usually not considered by many CM design methods. In this research, we focus on the design perspective where routing flexibility will be taken into account in the design procedure. However, during the operation stage, it is possible that we may not be able to process part types according to the plan obtained during the design stage due to machine

Table 1.8: Improvement in Decomposition from an Additional Copy of Machine 2

Part Type	Machine Type							
	1	3	5	2	2	4	6	
1	1	1	1	1				
4	1	1	1					
5			1	1	1			
2				*		1	1	1
3						1	1	1
6						1	1	1

breakdowns, and unexpected changes in product mix and/or demand. With the presence of routing flexibility, it is possible to reroute part types such that they still can be processed in the CM system without having to reconfigure the system. However, the performance of the system may not be as great as planned in the design stage. In this research, we do not deal with operational issues.

Summarizing the above we see that, despite the growing importance of CMSs, available methods for designing CMSs do not consider in an integrated manner several important factors. These factors are the dynamic and stochastic nature of production requirements, and the availability of routing flexibility. By considering these factors, CM design solutions can be improved. A mathematic model will be developed to capture those requirements. Given the combinatorial complexity of the mathematical model, a heuristic will be needed in order to obtain solutions. In this research, simulated annealing is employed as a part of a solution approach to obtain solutions. A detailed discussion of simulated annealing is presented in Section 2.5

1.4 Problem Statement

Although the benefits of CM are substantial, a large number of design methods for CMSs proposed over years still have major shortcomings. The motivation of this research is to develop a design method that can accurately and realistically capture two important characteristics of the CMS design problem which have not been well addressed:

1. The existence of dynamic and stochastic production requirements.
2. The existence of routing flexibility.

Research Question: How can we design and reconfigure cellular manufacturing systems in dynamic and stochastic production environments, exploiting the inherent routing flexibility often present in cellular manufacturing?

1.5 Research Objectives

A new design methodology that addresses the problems discussed in section 1.4 is needed. The objectives of this research can be summarized as follows:

1. Develop a design methodology for cellular manufacturing systems in dynamic and stochastic production environments which employs system-dependent reconfigurations and routing flexibility.
2. Justify the CM design methodology via an experimental design and a comparison with known solutions.

1.6 Research Approach

To achieve the development of the new CM design methodology, the research approach consists of the following steps:

1. Formulate a mathematical model for dynamic and deterministic production requirements.
2. Develop an optimal solution procedure for the model using an available software package.
3. Generate problem instances to be used for validating the developed model.
4. Solve the problem instances via the optimal procedure and analyze results.
5. Evaluate the potential benefits gained through the consideration of system-dependent reconfiguration and routing flexibility.
6. Incorporate uncertain production requirements into the developed model.
7. Develop and validate a heuristic approach for dynamic and uncertain production requirements due to the computational time required for large problems.
8. Evaluate: perform experimental design to compare performance of heuristic versus optimal and vs. other heuristics.
9. Draw conclusions and discuss the directions for future work.

1.7 Outline of Document

The remainder of this dissertation is organized as follows. Chapter 2 reviews the literature which helps in defining and solving the design of CMSs. Chapter 3 is divided into three sections. The first section involves the development of a mathematical model dynamic and deterministic CMS design. Potential benefits of the proposed CMS design approach in the first section are evaluated in the second section. Uncertainty in manufacturing is incorporated into the developed mathematical mode in the third section. The third section also presents a heuristic to solve large CM design problems under dynamic and uncertain production requirements. An evaluation methodology for the heuristic is presented in Chapter 4. The evaluation process is carried out in two ways. First, CM design problems are generated for a comparison purpose. Solutions obtained from the heuristic are compared with those obtained from the lower bound to observe the performance of the heuristic. CM design problems from publications with known solutions are used in the second part of the evaluation process. Chapter 5 presents and discusses the results from the evaluation. Finally, Chapter 6 presents the conclusions, contributions, and future research.

Chapter 2

Literature Review

The survey of literature can be loosely divided into areas that seem to have major impact in defining and solving the problem. These areas are:

1. Design of cellular manufacturing systems;
2. Layout design under dynamic and uncertain production requirements;
3. Routing flexibility;
4. Agile manufacturing and;
5. Simulated annealing.

2.1 Design of Cellular Manufacturing Systems

Shorter product life-cycles, higher product variety, unpredictable demand, and shorter delivery times have caused manufacturing systems to operate under dynamic and uncertain environments these days [11], [19]. Manufacturing systems must be able to adapt/respond to such changes and uncertainties quickly and with reasonable investment and operating costs. Several efforts in different research areas such as dynamic plant layouts [57], [70]; flexible plant layouts [11], [100]; dynamic cellular manufacturing [19], [98]; and agile manufacturing [58], have been proposed to deal with these dynamic and/or stochastic production requirements.

Before reviewing CM literature, terminologies used to classify the production requirements are introduced. They are **static** versus **dynamic production requirements** and **deterministic** versus **stochastic production requirements**. Static production requirements implies a single period when designing a CMS. That is, product mix and demand for the

entire planning period are constant. However, product mix and demand in such cases can be deterministic or stochastic. For static and deterministic production requirements, there is only one possible set of product mix and demand which are known. In contrast, static and stochastic production requirements have a set of possible product mixes and demands to occur; each has its probability of occurrence. Therefore, designing a CMS for such requirements needs to consider all possible product mixes and demands.

Dynamic production requirements imply multiple periods when designing a CMS. In this case, the entire planning horizon is divided into multiple periods according to the differences in product mix and/or demand in each period. In each period, production requirements can be deterministic or stochastic. If they are deterministic, product mix and demand in each period are known. If they are stochastic, the possible product mixes and demands in each period are known with certain probabilities. In this section, we review the literature on static and stochastic, dynamic and deterministic, and dynamic and stochastic production requirements. Note that we do not consider the static and deterministic case since it has already been researched extensively (current CM design methods assume that product mix and demand are static and deterministic). Literature in the design of CMSs is reviewed according to the above classifications which are as follows:

1. Design of CMSs for dynamic and deterministic production requirements;
2. Design of CMSs for static and stochastic production requirements; and,
3. Design of CMSs for dynamic and stochastic production requirements.

2.1.1 Dynamic and Deterministic Production Requirements

Chen [19] developed a mathematical programming model for system reconfiguration in a dynamic cellular manufacturing environment. A mixed integer programming model is developed to minimize intercell material and machine costs as well as reconfiguration cost in a dynamic cellular manufacturing environment with anticipated changes of demand or production process for multiple time periods. The reconfiguration cost occurs when at the end of period t , additional machines need to be installed or existing machines need to be removed for period $t + 1$. Solving the above model is *NP*-complete, therefore, it is decomposed into simpler cell formation subproblems by removing the system reconfiguration cost from the objective function and the corresponding coupling constraints from the model. Thus, the decomposed subproblems correspond to different time periods t . Since the decomposed subproblems are formulated as binary-integer programming problems, they can be solved optimally using commercial optimization software packages. A heuristic method can be used instead to obtain solutions for large problems.

Once the best cell configuration for each time period is obtained, dynamic programming is then employed to find a solution of the original problem. Assume that all these subproblems

have feasible solutions and let $n^*(t)$ be the best cell configuration corresponding to time period t . Note that $n^*(t)$ for different t are not necessarily the same since demand may change with t . Let $S[f(t), n^*(t)]$ be the intercell material handling cost and machine cost found in the solution of period t . It is feasible to meet demand of time period t using the best cell configuration of a different time period t' , then a corresponding cost value $S[f(t), n^*(t')]$, $t' \neq t$, can be calculated. In this case, it is possible that the overall cost value without changing the system is lower than the cost incurred in a changed system. For instance, $S[f(1), n^*(1)]$ and $S[f(2), n^*(2)]$ are the minimum intercell material handling and machine costs at time $t = 1$ and $t = 2$, respectively. If both of the combinations $[f(2), n^*(1)]$ and $[f(1), n^*(2)]$ are feasible, then there is a choice among $S[f(1), n^*(1)] + S[f(2), n^*(1)]$, $S[f(1), n^*(1)] + Q(1, 2) + S[f(2), n^*(2)]$ and $S[f(1), n^*(2)] + S[f(2), n^*(2)]$ for the first two time periods, where $Q(1, 2)$ is the cost to change cell configuration from $n^*(1)$ and $n^*(2)$. Dynamic programming is used to make the best decision from a number of combinations for the entire time horizon.

Song and Hitomi [85] developed a methodology to design flexible manufacturing cells. The method integrates production planning and cellular layout via a long-run planning horizon. The integrated planning model is formulated as a mixed-integer problem which contains two types of integer programming problems: determining the production quantity for each product and the timing of adjusting the cellular layout in a finite planning horizon period with dynamic demand. The objective of the model is to minimize the sum of inventory-holding cost, group-setup cost, material handling cost, and layout-adjusting cost. The Benders decomposition method is employed to solve the problem. Demands fluctuate from period to period and the fluctuation of demand is absorbed by adjusting both layout configuration and inventory level. The demand for each part family in each period is known and constant. The decisions in this problem are different from the typical design of CMSs.

Wicks [98] proposed a multi-period formation of the part family and machine cell (PF/MC) formation problem. The dynamic nature of production environment is addressed by considering a multi-period forecast of the product mix and resource availability during the formation of part families and machine cells. The design objectives are the minimization of intercell material handling cost, the minimization of investment in additional machines, and the minimization of the cost of system reconfiguration over the planning horizon. A mixed-integer formulation of the multi-period PF/MC formation problem is first developed. It serves as a blueprint for the development of a genetic algorithm to solve the problem. The multi-period PF/MC formation procedure belongs to machine-grouping solution strategy where machine cells are formed first, followed by the assignment of parts to the machine cells. The assignment of machines to cells over the planning horizon is made via a genetic algorithm. A heuristic for assigning parts to cells is also embedded in the algorithm.

2.1.2 Static and Stochastic Production Requirements

Seifoddini [74] presented a probabilistic machine cell formation model to deal with the uncertainty of the product mix for a single period. He suggested that the best way to handle the uncertainty in the product mix is to predict it and to incorporate it into the design process. The design objective is to minimize the expected intercell material handling costs of the system. Given a set of possible product mixes and their probabilities of occurrence, the algorithm seeks to create part families and manufacturing cells. Three major steps are used in the cell formation process.¹

1. The data on the product mixes (machining requirements) are organized into machine-part matrices and the probabilities of occurrence for these machine-part matrices are determined.
2. For each machine-part matrix, one manufacturing cell configuration is designed. This is done by employing the similarity coefficient method (SCM) by Seifoddini and Wolfe [75] for cell formation. The sum of intercell material handling costs is used as a criteria for selecting the best machine cell configuration. The intercell material handling cost for a cell configuration for a specific product mix is determined as follows:

$$IMC = \sum_{i=1}^M \sum_{i=2}^M \sum_{k=1}^{N_{ij}} P_{kij} n_{kij} c_{ij} \quad i \neq j \quad (2.1)$$

where,

IMC	=	intercell material handling cost
M	=	number of manufacturing cells
N_{ij}	=	number of part types moved between cell i and j
P_{kij}	=	number of part type k moved between cell i and j
n_{kij}	=	number of times part type k moved between cell i and j
c_{ij}	=	unit transportation cost between cell i and j

3. For each manufacturing cell configuration, the intercell material handling costs under different product mixes are calculated and used to determine the expected intercell material handling cost. The expected intercell material handling cost for a cell configuration is calculated as follows:

$$EIMC_n = \sum_{j=1}^L IMC_{nj} P_j \quad (2.2)$$

where,

¹Notation and expressions shown are taken exactly from Seifoddini [74]. Note, however, that 2.1 is incorrect and should read $IMC = \sum_{i=1}^M \sum_{j=1}^M \sum_{k=1}^K P_{kij} n_{kij} c_{ij} \quad i \neq j$, where K is the total number of part types.

$EIMC_n$	=	expected intercell material handling cost for cell configuration n
L	=	number of product mixes
IMC_{nj}	=	intercell material handling cost for cell configuration n under product mix j
P_j	=	probability of having product mix j

4. The expected intercell material handling costs of all cell configurations are compared, and the cell configuration with the lowest expected cost is chosen.

2.1.3 Dynamic and Stochastic Production Requirements

Harhalakis *et al.* [36] presented an approach to obtain robust CM designs with satisfactory performance over a certain range of demand variation. They focused on product demand changes over a system design horizon which is broken down into elementary time periods. The objective is to obtain a cellular design with the minimum expected intercell material handling cost over the entire design horizon. A two-stage design approach is used. The first stage is to determine a production volume for each product. The second stage is to obtain a cell formation using a heuristic method. The first stage begins with mapping the forecast of product demand to a set of feasible production volumes, given resource capacity constraints. If sufficient capacity exists to produce all products at their demand level, product demand gives feasible production volumes. Otherwise, the projected demands are used in a linear program that finds a set of feasible production volumes such that profit is maximized. Given several product mixes, a procedure for calculating the joint probabilities for every feasible production mix is presented. The joint probabilities are used to evaluate the mean production volume for each product.

The heuristic method by Harhalakis *et al.* [37] is used to obtain a near-optimal cell formation in the second stage. This paper assumes that the product mix for each period is the same; no new products are introduced nor old products discontinued. Product demand in each period is assumed to be normally distributed, where the mean and standard deviation are time-invariant. Additional machines are not considered.

It is interesting to note that no research in the design of CMSs for dynamic and stochastic production requirements where product mix changes from period to period appears to have been conducted. However, such requirements often exist in real-world manufacturing.

2.1.4 Conclusions on Design of CMSs

A number of publications related to the design of CMSs have been published over the last twenty-five years. However, few publications have addressed dynamic and/or stochastic production requirements. Only Chen and Wicks addressed the multi-period planning horizon with the introduction of new products and the discontinuation of old products. Both

considered the rearrangement of machines in different fashions. Thus, manufacturing configurations (from both methods) could be different from period to period depending upon the production requirements. The work by Song and Hitomi has different decisions to be made over the planning horizon which may not be relevant for the design of CMSs, however, the consideration of multi-period may be applicable.

Likewise, stochastic production requirements have received little attention. Only Seifodini incorporates stochastic production requirements in his CM design method for a single planning period. Interestingly, only research by Harhalakis *et al.* considers a multi-period planning with the demand subject to change, however, it assumes that product mix is stable over the planning horizon.

2.2 Layout Design

The layout design problem can be loosely classified into two categories: static layout design and dynamic layout design. The static layout design problem assumes that flow data (from-to matrix) is constant over the planning period while the flow data in the dynamic layout design problem is not. In the static layout design problem, the goal is to minimize the total material handling costs associated with assigning different facilities (e.g., departments, machines) to various locations [54]. Many layout design algorithms have been proposed for the static layout problem, however, they might not be applicable for dynamic and stochastic production requirements. Recently, researchers have developed layout algorithms to deal with such requirements. Note that our research is not concerned with layout (move cost between cells is assumed to be constant). Methods used to model and solve dynamic and stochastic production requirements and reconfiguration methods for layout design, however, may still be relevant. Review in this section is organized in similar manner to Section 2.1:

1. Layout design for dynamic and deterministic production requirements.
2. Layout design for static and stochastic production requirements.
3. Layout design for dynamic and stochastic production requirements.

2.2.1 Deterministic and Dynamic Production Requirements

Rosenblatt [70] discussed the general dynamic layout problem. He developed a dynamic programming approach to solve the multi-period layout selection problem. In each period, a number of potential static layout alternatives need to be generated. The objective is to select the sequence of layouts which minimizes the overall sum of the material flow costs and relayout costs. If all possible static layout alternatives are considered at each period, the optimal sequence can be obtained. This approach, however, can be computationally

prohibitive. Therefore, a heuristic is advocated to generate a set of static layout alternatives in each period. The quality of the overall solution depends strongly upon the number of static layout alternatives generated in each period. He assumed that flow data in each period is given and constant over the planning period. In addition, departments are assumed to be equal in size.

2.2.2 Static and Stochastic Production Requirements

Benjaafar and Sheikhzadeh [11] addressed the problem of designing flexible plant layouts for manufacturing facilities when product demands are subject to variability. Their definition of a flexible layout is a layout that maintains low material handling costs despite fluctuations in the product demand levels. Three key features in their design procedure are explicitly accounting for the stochastic nature of product demands, allowing for multiple separate departments of the same type to exist in the same facility, and letting material flows between pairs of individual departments be determined simultaneously with department locations. Their procedure for designing a flexible layout can be summarized as follow:

1. Possible demand scenarios are determined according to product distributions, product process routings, and product unit transfer loads.
2. Probability of occurrence of each demand scenario is obtained from individual product demand distributions.
3. For each demand scenario, the corresponding optimal layout is generated.
4. Once all the layouts have been generated, each layout is evaluated over the entire set of possible demand scenarios and the most flexible layout is selected.

This is a robust design strategy. It considers only a single period of planning where product demands are subject to variability.

Rosenblatt and Lee [72] proposed a robust approach to deal with the single period plant layout under stochastic demand. The objective is to minimize total material handling costs. All departmental sizes are assumed to be equal. They define the robustness of a layout as the number of times that the total material handling cost lies within a prespecified percentage of the optimal solution. The uncertainty regarding the demand for each item is presented by a three-point estimate, high (H), most likely (M), and low (L) as shown in Table 2.1. Each point has the same probability of occurrence.

If the number of products is n , 3^n scenarios are possible. For instance, when n is 2, all possible scenarios are HH, HM, HL, MH, MM, ML, LH, LM, and LL. HH means that the demands for item 1 and 2 are 100 and 200, respectively. For m departments, the total number of possible layouts is $m!$. With $m!$ layouts and 3^n scenarios, $m! * 3^n$ costs for

Table 2.1: A Use of the Three-Point Estimate

Product	Production Process	Demand		
		H	M	L
1	A-B-C-D	100	60	20
2	A-C-B-D	200	140	60

different layouts and scenarios must be evaluated. Given all possible scenarios, a layout cost matrix for different scenarios and layouts can be generated as shown in Table 2.2. c_{1HH} is the cost of layout 1 under HH scenario. Using the above robustness criteria, the most robust layout is selected. In their publication, a small example with three products, a three-point estimate and four departments is used. The total of 324 ($4! * 3^3$) costs for different layouts and scenarios are evaluated. The computation grows exponentially as the number of departments and products increase.

Table 2.2: Layout Cost Matrix for Different Scenarios and Layouts

Layout	Scenario								
	HH	HM	HL	MH	MM	ML	LH	LM	LL
1	c_{1HH}	c_{1HM}	.				.	c_{1ML}	c_{1LL}
2	c_{2HH}	c_{2HM}	.				.	c_{2ML}	c_{2LL}
.	.								.
.	.								.
$m!$	$c_{m!HH}$	$c_{m!HM}$.				.	$c_{m!ML}$	$c_{m!LL}$

Rosenblatt and Kropp [71] presented an optimal solution procedure for the single-period plant layout problem. This study is different from that of Rosenblatt and Lee [72] because it assumes that some prior knowledge about the different levels of the product mix and demand, and their associated probabilities of occurrence, is known. They assume that a finite number of possible scenarios, s , can occur with a probability of occurrence, p_s . Each scenario has its unique from-to flow matrix, F_s . The objective is to minimize the expected material handling cost which can be done using the following procedure:

1. Find the weighted-average flow matrix, \bar{F} , where:

$$\bar{F} = \sum_{s=1}^s p_s F_s. \quad (2.3)$$

2. Find the best layout for the flow matrix, \bar{F} .

The solutions from this procedure depend heavily upon the probability assigned to each scenario. It also requires less computation than the robustness approach.

2.2.3 Dynamic and Stochastic Production Requirements

Montreuil and Laforge [57] introduced a dynamic layout design model which explicitly takes into consideration the probabilistic nature of the future requirements. Some observations in their publication are worth considering.

1. When applying layout dynamics concepts, the input to a layout design study is no longer based upon a simple steady-state requirement set. Instead, the designer seeks to take advantage of advanced knowledge about the future behavior of requirement sets, yet recognizing their inherent uncertainties.
2. Given the actual state of the system, it is rarely possible to specify with certainty what are going to be the space and interaction requirements over the year to come.
3. When the cost of relayout is known to be negligible, specific treatment of dynamic layout is not necessary. The layout for the imminent future may be designed considering only the expected requirements for this imminent future. At the other extreme, when the relayout costs are prohibitive, they impose that the same layout be used for the entire life cycle. In such cases, explicit treatment of dynamic layout is again not necessary.

They addressed the stochastic multi-period plant layout design. Uncertainty about the evolution of dynamic future requirements is dealt explicitly by building a scenario tree of probable time-phased futures as shown in Figure 2.1. They assumed that products to be made in each period are known and remain the same for the entire planning horizon. No new products are introduced and no old products are discontinued. However, demand for each product can be increased or decreased according to specification of the various futures in the scenario tree. Each future period also has a weight associated with it. Figure 2.2 is an example of scenario tree of probable futures. Period 1, which is coded $(0, 0, 0)$, leads to two alternative futures 2A and 2B. Future 2A is optimistic, stating demand increases for part families A, B and C. Its code is $(25, 5, 10)$ for 25%, 5% and 10% demand increases, respectively, for part families A, B and C.

The above information and requirements are used to develop a mathematical model. The objective function is to minimize the material handling cost and interfuture relayout cost. The output includes a series of proposed time-phased layouts. The model is linear, therefore, it can be efficiently solved using standard linear programming software packages.

Palekar *et al.* [62] classified the plant layout problem into two categories: static plant layout problem (SPLP) and dynamic plant layout problem (DPLP). DPLP is further divided into

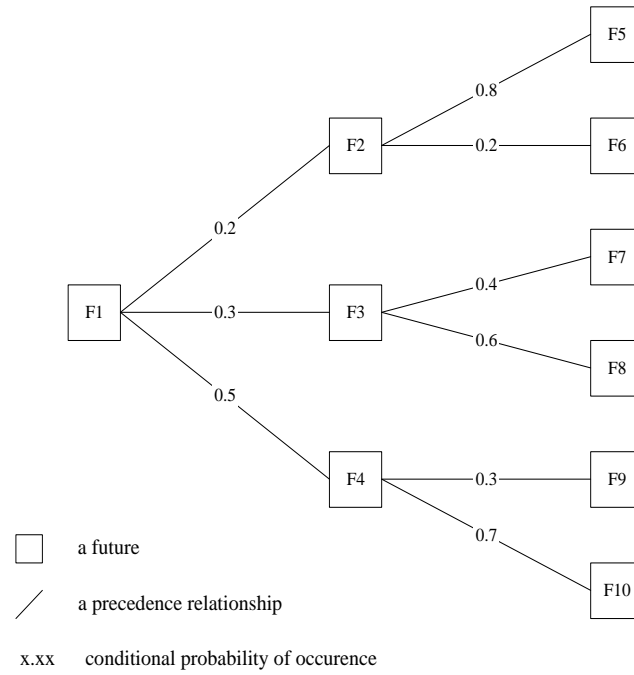


Figure 2.1: A Typical Scenario Tree of Probable Futures in [57]

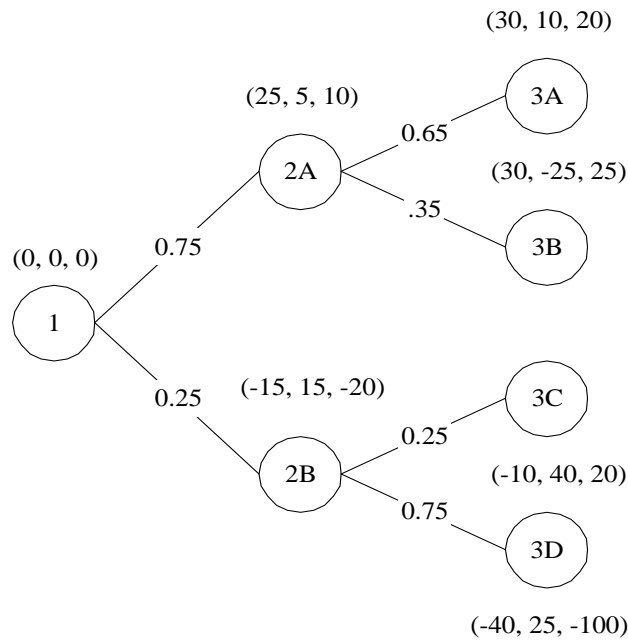


Figure 2.2: Scenario Tree

two classes of problem — deterministic or stochastic — based upon the degree of uncertainty with which the input information is known. A major assumption in the publication is that the probability of occurrence of material flow in a period is most likely to be conditioned on the situation in prior periods. Using the above assumption, a mathematical model is developed to determine a set of layouts, one for each period, with the objective of minimizing the expected material handling and relocation costs. The developed SPLP is a quadratic integer program. Dynamic programming can be used to solve the problem to obtain optimal solutions. However, it can be computationally expensive for large problems. Due to the computation required, an approximation algorithm for SDLP is developed. The approximation algorithm considers only C best layouts in each period instead of all layouts. Branch and bound can be used to obtain the C best layouts. Then, dynamic programming is used to obtain solutions.

Yang and Peters [100] developed a design method for flexible machine layout problem (FMLP) for dynamic and uncertain production environments. The FMLP is a multiple-period design problem with uncertainties in product demand in each period. They suggested that layouts can respond to demand changes in two ways: through robustness to changes in production requirements and through adaptability of the layout to these new requirements. A robust layout is one that is good for a wide variety of demand scenarios even though it may be not optimal under any specific demand scenarios. For a specific planning horizon, a robust layout design procedure attempts to minimize the total expected material handling costs over this horizon. An adaptable (dynamic) layout is one that is able to be rearranged to respond to changing production requirements in order to decrease the material handling costs. The rearrangement costs will hopefully be offset by the reduction of material handling costs.

The design procedure generates a flexible layout for a set of unequal size machines over a planning horizon by optimizing the tradeoffs between increased material handling costs and machine rearrangement costs as the production requirements change over time. It may choose robust layouts, adaptable layouts, or a combination of the two. The basic approach is to determine a robust machine layout over a planning time window. A planning time window is a set of consecutive time periods where a layout rearrangement occurs only at the beginning of the first time period. The number and length of the planning time windows are determined based on the tradeoffs between material handling costs and machine relayout costs. Thus, the strategy is to modify the layout at the beginning of each time window, but not to change the layout within these time windows. Hence, a pure robust strategy will have a one time window equal to the entire planning horizon, whereas a pure adaptable strategy will have as many windows as periods in the planning horizon. In their publication, the strategy is to choose the quantity of time windows that minimize the total cost and includes robust and adaptable strategies.

A mathematical model is developed as an integer programming formulation with the objective of minimizing the material handling cost and machine rearrangement cost. The problem formulation is computationally prohibitive for a realistic size problem. Therefore, they used

the concept of the combined adjacency graph/integer problem formulation for a machine layout design problem from Peters and Yang [63] to solve the robust machine layout design subproblems.

2.2.4 Conclusions on Layout Design

Layout design for dynamic and stochastic production requirements has gained more attention than the design of CMSs for such conditions. Several techniques such as dynamic programming, robustness, and markov chains have been used to deal with such requirements. Some techniques from the layout design problem could be applicable to handle dynamic and stochastic production requirements in designing CMSs.

2.3 Routing Flexibility in Design of Cellular Manufacturing Systems

In this section, routing flexibility in cellular manufacturing is reviewed. As previously mentioned, routing flexibility of a manufacturing system is defined as the ability to produce a part by alternate routes through the system [77]. In our context, routing flexibility of a part implies that the part has alternative process plans. Most of the research in CM design to date assumes that parts are processed on specific machine types and the assignment of operations to machines is determined *a priori* [6]. The following literature review focuses on those works which consider alternative process plans or routing flexibility in their CM design methods.

Adil *et al.* [1] considered alternate routings (e.g., alternative process plans of a part and additional machines) in the cell formation process in order to improve the groupability of the machine-part matrix. They developed a non-linear integer programming model and an efficient solution procedure to partition a machine-part matrix addressing the following issues:

1. Simultaneous grouping of parts and machines;
2. Consideration of alternate process plans;
3. Consideration of additional machines as available; and,
4. Minimization of a weighted sum of the voids and the exceptional parts.

They considered cell formation as reorganization of an existing shop into a GT shop. The ability to purchase new machines is not considered, nor is the ability to change product

design. Tradeoffs between cell size (number of parts and machines) and number of exceptional parts (intercell moves) need to be considered. Large cells make production planning, scheduling and control difficult. On the other hand, decomposing into smaller cells may lead to more exceptional parts, therefore, more coordinating efforts may be required. The above non-linear integer programming model is then transferred into a linear integer programming model and solved optimally using HYPERLINDO on PC 486/33Hz for small instances. For large problems, simulated annealing is used to obtain solutions in reasonable amounts of time. The over all approach is to select a process plan for each part as well as simultaneously grouping parts and machines.

Askin *et al.* [6] developed a CM design method that considers routing flexibility and volume flexibility during the design process. Their definition of routing flexibility is the ability of the cell system to process parts completely in multiple cells, whereas volume flexibility is the ability of the cell system to deal with volume changes in the current part mix. They assumed that an operation can be processed on more than one machine type. The cell formation method consists of four phases. Phase I identifies the most economical set of machine types to process the required operations of the entire part set, based upon machine costs, capabilities, and capacities. Phase II assigns individual part-operations to individual machines with the objective of providing an assignment that will lead to minimum material handling cost in the final system design. After the first two phases, the decision on part-machine assignments has been accomplished. Next, Phase III forms candidate cells. After cells have been formed, Phase IV evaluates and improves the cell configuration as follows. First, the routing flexibility of each part is calculated by counting the number cells that can process each part completely. The routing flexibility of the cellular system is then calculated by adding the routing flexibility of each part together. An approach is suggested to improve the routing flexibility of the system by reassigning parts, individual machines and/or part-operations in that order.

A general procedure to improve the routing flexibility is as follows. Each part is considered for reassignment to another cell that contains all the necessary equipment to process the part provided that machine capacity is available in that cell. After performing this for every part, machine reassignment is considered if it will result in an increase in the number of cells which can process one or more part types. The reassignment of part-operations is performed for those part types that cannot be completely processed in one cell. The objective of the reassignment is to check whether it is possible to identify another cell to completely process each part. The volume flexibility of the cellular system is computed as the maximum percentage increase in volume for all parts that can be handled without changing the system configuration. The improvement in volume flexibility is done by identifying the bottleneck machine in the system, and then rerouting some load from this machine to another machine in the same cell that can perform the same operation. If this is not possible, the workload is rerouted to a machine of the same type in another cell.

With alternative process plans, an operation on a part can be performed on alternative machines. Logendran *et al.* [52] suggested that cell formation should be divided into two

phases. The first phase is to determine the number of machines of each type and a unique process plan for each part type. In the second phase, the assignment of part types and machine types to cells is determined. In their paper, they only investigated the first phase comprehensively. After it is completed, the second phase can be dealt with by using one of the known cell formation algorithms ([8], [59]). In the first phase, three decisions to be made are the number of machines of each type, a process plan for each part type, and a machine type to perform each operation of a process plan. They assumed that a part can have more than one process plan and each operation can be performed by more than one machine. A mathematical model is developed with the objective of minimizing the total annual cost evaluated as the sum of the amortized cost of machines and the operating cost of producing all parts. They assumed that demand is deterministic and stable over the planning horizon. They showed that this model is *NP*-hard. Two heuristic algorithms, based upon a concept of tabu search, are developed to solve the problem.

Nagi *et al.* [59] addressed the problem of manufacturing cell formation, given multiple routings and multiple functionally-similar workcenters. They assumed that an operation of a part can be performed on more than one machine. A routing for each part is selected during the design process, not in advance. The objective is to minimize the intercell traffic while the part demand and machine capacity constraints are satisfied. The problem can be formulated as a two-stage problem which addresses routing selection and cell formation. An algorithm is proposed to solve the above two problems iteratively until convergence is accomplished. The routing selection problem can be formulated and solved as a linear programming problem, while the cell formation is solved by the algorithm presented in by Harhalakis *et al.* [37].

Sankaran and Kasilingam [73] developed a 0-1 integer programming formulation to select part routings and to form cells based upon the total cost of processing costs and annualized machine operating costs. The formulation is modified to form cells in order to maximize the routing flexibility of the system. The optimal solution to the second formulation would yield the cell configuration and the maximum number of alternate feasible routing for the production of all parts. The authors suggested that a decision maker needs to compare the incremental cost of the increased flexibility arising from the second formulation against the cost of the first formulation. Then, one has to decide whether the increased flexibility is worth the incremental cost. They assumed that an operation of a part can be performed on more than one machine.

Sofianopoulou [83] proposed a comprehensive model for the design of medium-sized cellular manufacturing systems with duplicate machines and/or alternative process plans for some or all of the parts produced. He assumed that an operation of a part can be performed on more than one machine. The objective is to assign machines and parts to cells as well as to determine part routings (process plans for parts) in order to minimize intercell traffic. First, a mathematical model for allocating machines to cells as well as selecting the most advantage process plan to each part is developed. Given a machine-to-cell assignment, a mathematical model to assign parts to cells and to form part families is developed. His CM design method is classified to the machine grouping solution strategy. A heuristic algorithm

based on simulated annealing is employed to solve the above model.

2.3.1 Conclusions on Routing Flexibility

The literature reviewed in this section has considered the availability of alternative process plans or alternative part routings. They take advantage of such availability so that groupability of the systems is improved as well as the machine utilization. Works by Askin *et al.* [6], Nagi *et al.* [59], Sankaran and Kasilingam [73], and Sofianopoulou [83] have the same concept that an operation of a part can be processed on more than one machine. Work by Adil *et al.* [1] assume that a part can have more than one process plan and each process plan can have a different number of operations. Work by Logendran *et al.* [52] is the most complex among the above works since they assume that a part can have more than one process plan and each operation can be performed on more than one machine. In this research, we assume that an operation can be performed on more than machine which is similar to most research conducted in this area.

2.4 Agile Manufacturing

Agile manufacturing was first introduced in 1991 by Nagel and Dove [58]. Since then, several efforts have been made to achieve agile manufacturing. The majority of the literature on agile manufacturing to date is presented from a business perspective and focuses on organizational, informational, management and workforce issues. Few have recognized the need for agility in manufacturing facilities, which could be in the form of reconfigurable machines, equipment and facilities.

Garcia *et al.* [28] presented Agile Manufacturing Prototyping System (AMPS) at Sandia National Laboratories. A primary design goal for the AMPS was ease of reconfiguration. The AMPS is used as a national testbed. AMPS consists of modular assembly process modules or workcells centered on robotic arms, with two conveyors in front of the cells for work-in-process pallets, and in the back for parts pallets. The robotic workcells were designed such that they are easy to be reconfigured when a new assembly task needed to be automated. The entire structure of the AMPS was designed in an integrated manner such that it could be moved as a single unit. And it has already been successfully demonstrated. Each workcell is controlled by its own local computer or process module controller. The workcells can be programmed to operate autonomously, or they can be controlled or coordinated via ethernet by a supervisory computer.

Hollis and Quaid [38] proposed an Agile Assembly Architecture (AAA) to support the creation of minifactories built from small modular robotic components. It is used for automated assembly of precision high-value products such as magnetic storage devices, palmtop and wearable computers, and other high-density equipment. The goal is to substantially reduce

design and development times and product changeover time. The AAA can be described using the following scenario. First a manufacturing engineer designs an assembly system (minifactory) for a product through the internet that allows the designer to access the vendors of various robotic modules to make up the assembly system. During the creation of the minifactory design, the manufacturing engineer is free to select and simulate a wide variety of configurations using modules from many different sources to obtain the final design (virtual minifactory). The modules are then ordered and shipped to the manufacturing site. After the modules arrive, the minifactory is rapidly setup manually by snapping together modules and hooking them up to four bus services (power, air, vacuum, network). Next the minifactory is programmed by graphically connecting outputs to inputs and specifying actions to be performed. Once the minifactory is programmed, execution takes place in an event-driven, asynchronous manner, without supervisory control at any level. At any later time, the minifactory can be reconfigured to respond to changing market requirements. Modules can be added or removed, and new minifactory models can be automatically regenerated. At any time, modules no longer needed can be returned to the vendors for use by other manufacturers.

Quinn *et al.* [64] introduced design-for-agile-manufacturing workcells which intended for light mechanical assembly of products made from similar components (i.e., parts families). Their definition of agile manufacturing is the ability to accomplish rapid changeover from the assembly of one product to the assembly of a different product. With the use of robots, flexible part feeders, modular grippers, and modular assembly hardware, they could make rapid hardware changeovers possible. Workcell software provides the flexibility of the agile manufacturing. Rapid software changeover is accomplished by the use of a real-time, object-oriented software environment utilizing graphical simulation for off-line software development.

The above efforts have been at the machine or equipment level, which would allow the machines to perform several operations by changing their components with little effort. This could be seen as a foundation of agile manufacturing. However, at the cell or shop levels, in term of relocation machines, little attention has been paid.

Shewchuk [80] proposed a framework for modeling and design for agile discrete-part manufacturing facilities. The purpose of the framework is to provide a foundation for developing techniques for analyzing and designing agile manufacturing facilities. The framework contains four items: design variables, reconfiguration variables, reconfiguration activities, and reconfiguration effort functions and parameters. The framework can be used to identify and define different agility types and develop suitable measures. He used an example to show how to model agile cellular manufacturing systems with the use of the framework and how agility can be measured and interpreted.

The proposed framework by Shewchuk can be applied to the CM design process when relocations of machines are considered. Reconfiguration (relocation) activities consist of swapping existing machines between cells, adding new machines to cells, removing existing machines

from cells, and/or replacing existing machines in cells. Effort (cost) functions associated with the activities must be specified and they will be used during the CM design process. With the reconfiguration cost functions, we can use them to compare with other costs such as intercell material handling cost and machine investment cost in order to obtain the best CM design possible.

Most works in this section are not directly relevant to our work, except that of Shewchuk [80] where the effort of reconfiguration of the system will be taken into account.

2.5 Simulated Annealing

Heuristic algorithms are often used as alternatives to optimization techniques in the design of CMSs due to the following reasons. First, most mathematical models are computationally intractable for realistically-sized problems. Second, objective functions of some mathematical models cannot be formulated as linear problems, therefore, solving such problems can be extremely difficult. Heuristic methods such as genetic algorithms, simulated annealing, and tabu search methods can overcome the above shortcomings of optimization techniques. They provide reasonably good solutions within acceptable amounts of time. A major concern about using heuristics, however, is that they do not guarantee optimality.

Three major heuristic search methods, genetic algorithms, simulated annealing and tabu search, have been investigated extensively and simulated annealing is chosen to be used as a heuristic for solving large CM design problems in our research. Simulated annealing is a randomized search method that has been used to solve computationally complex optimization problems. The use of simulated annealing as a technique for discrete optimization dates back to the early 1980s [47]. It was originally developed as a simulation model for a physical annealing process and hence it is referred to as simulated annealing [55]. Essentially, this method differs from local search methods since it allows the acceptance of an inferior solution in the general neighborhood of a current solution with some positive probability.

In simulated annealing, a problem starts at an initial solution, and a series of moves (changes in the values of decision variables) are made according to a user-defined annealing schedule. It terminates when either the optimal solution is attained or the problem becomes frozen at a local optimum which cannot improve. To avoid freezing at a local optimum, the algorithm moves slowly (with respect to the objective value) through the solution space. This controlled improvement of the objective value is accomplished by accepting non-improving moves with a certain probability which decreases as the algorithm progresses. Simulated annealing algorithms for the design of CMSs in literature may be slightly different depending upon the objective functions and the parameter values such as initial solutions and terminating conditions. The algorithm of simulated annealing is stated as follows:

```

Select an initial solution,  $s_0$ ;
Select an initial temperature,  $t_0$ ;
Select a cooling schedule,  $\alpha$ ;
Repeat
  Repeat
    Randomly select  $s \in N(s_0)$ ;
     $\delta = f(s) - f(s_0)$ ;
    if  $\delta < 0$ 
      then  $s_0 = s$ 
    else
      generate random  $x$  uniformly in the range  $(0, 1)$ ;
      if  $x < \exp(-\delta/t)$  then  $s_0 = s$ ;
  Until  $iterationCount = nrep$ 
  Set  $t = \alpha(t)$ ;
Until stopping condition = true.
 $s_0$  is the approximation to the optimal solution.

```

Simulated annealing is used in this research for the improvement phase of the design of CMSs. (See Section 3.3.2.) The algorithm given above is very general. In general, to implement the simulated annealing based approach to CM design problems, the following issues need to be addressed.

1. In this research, a solution, s , represents a cell configuration.
2. An initial solution, s_0 , is a starting solution (point) that will be used in the search process. In this research, an initial solution is obtained using an algorithm presented in Section 3.3.2.
3. An initial temperature, t_0 , and a cooling schedule, α are used to control a series of moves in the search process. In general, the initial temperature should be high enough to allow all candidate solutions to be accepted. Cooling schedule, α , is the rate at which the temperature is reduced. The most widely used cooling schedule is a geometric reduction function $\alpha(t) = at$, where $a < 1$ [26]. Relatively high values of a perform best and most reported successes in the literature use values between 0.8 and 0.99 [26].
4. Number of iterations at a temperature level, $nrep$, may vary from temperature to temperature. It is important to spend a long time at lower temperatures to ensure that a local optimum has been fully explored. Thus, it can be beneficial to increase the value of $nrep$ either geometrically (by multiplying a factor greater than one), or arithmetically, (by adding a constant factor) at each new temperature.
5. Neighbouring solutions, $N(s_0)$, are a set of feasible solutions which can be generated from the current solution.

6. Cost of a solution, $f(s)$, is the cost of having a particular cell configuration
7. The final temperature, t_f is used as a stopping criteria. Simulated annealing terminates when the final temperature is below 0.005.

A detailed discussion of implementing simulated annealing is described in Section 3.3.2.

2.5.1 Simulated Annealing in Design of CMSs

Boctor [14] formulated a zero-one linear formulation for the cell formation problem. Given a set of machines, a set of part types, and a machine-part incidence matrix, the goal is to assign parts and machines to no more than N cells, where each cell does not possess more than m machines, so as to minimize the interaction between cells. Simulated annealing is used to solve the machine-part cell formation problem. He used the 16-machine, 43-part example introduced by Burbidge to demonstrate the efficiency of the SA. The comparison shows that the SA is able to find the optimal solution for 58 (64.4%) of the 90 solved problems. The percentage of the optimal solution can be increased by using different parameters.

Chen *et al.* [18] developed a simulated annealing-based heuristic applied to cell formation problems. It is designed to minimize the number of intercell moves for large size problems. They claimed that the major benefits obtained from their heuristic are the flexibility in the maximum number of machines allowed in a cell and the ability to solve large size problems. The simulated annealing-based heuristic was tested with eight CM design problems from the literature. The numerical results show that the solutions from the SA are as good as or better than those from the existing CM design methods.

Sofianopoulou [83] used simulated annealing for solving manufacturing design with alternative process plans and/or replicate machines. A mathematical model is developed with the objective of producing the minimum intercell moves and determining part routes that minimize the minimum intercell moves. A two-dimensional version of simulated annealing is employed. neighbouring solutions are generated by choosing not only a machine to cell allocation, but also a particular process plan from all possible processing alternatives for each part.

Vakharia and Chang [91] developed two heuristic methods for generating solutions to the cell formation problem. These methods are based on two combinatorial search methods, simulated annealing and tabu search. A mathematical model is developed with the objective of minimizing the total cost of the machines required, as well as the intercell material handling cost. At the same time, acceptable levels of machine utilization need to be maintained and maximum cell size needs to be specified. A simulated annealing algorithm is then developed to solve the above mathematical model. Ten data sets (8 randomly generated data sets, 1 published data set and 1 industrial data set) were used to evaluate the algorithm. Numerical results indicate that the simulated annealing algorithm provides close to optimal or optimal

solutions for the tested problems. The difference of the results between best solutions and those from the algorithm ranges from 2.98% to 11.53%.

Venugopal and Narendran [95] developed simulated annealing to solve the machine grouping which is an important aspect of cellular manufacturing systems. They compared their results from the simulated annealing with the K -mean algorithm. It yielded a better results. They recommended this method for large problems.

2.5.2 Conclusions on Simulated Annealing

The primary reason that simulated annealing has been used for the design of CMSs is that it obtains solutions within a reasonable amount of time. In contrast, getting global optimal solutions is sometimes prohibitive in terms of time and memory required. According to the literature, the quality of solutions obtained is also promising. Among three heuristic search methods investigated, simulated annealing is the simplest to implement, but still provides good solutions. A comparison between tabu search and simulated annealing for designing of CMSs was conducted by Vakharia and Chang [91]. According to their results, simulated annealing provides better results than tabu search. This leads us to employ simulated annealing as a part of solution approach for the design of CMSs.

Chapter 3

Approach

This chapter is divided in three sections. Section 3.1 develops a mathematical model and solution procedure for dynamic and deterministic production requirements. System-dependent reconfiguration is used in the development of the model. The model also considers routing flexibility of part types provided by the flexible machines. It is assumed that a machine is capable of performing more than one operation type. Solution procedure is presented in the subsequent section. Section 3.2 illustrates the potential benefits gained through the use of system-dependent reconfiguration and routing flexibility. These correspond to Steps 1-4 of Section 1.6(Research Approach). The problem complexity is also discussed in this section. Uncertainty in production requirements, incorporated into the developed mathematical model, is presented in Section 3.3. This corresponds to Step 6. A proposed heuristic is developed in Section 3.3.2 which corresponds to Step 7 of Section 1.6.

3.1 Dynamic, Deterministic CMS design

This section covers the developed mathematical model for dynamic, deterministic production requirements with presence of routing flexibility. System-dependent reconfiguration is employed in the model. An optimal solution procedure is developed to obtain design solutions from the model. An example of a design problem is given in order to illustrate the use of the model. Potential benefits of system-dependent reconfiguration and routing flexibility are shown as well.

3.1.1 Mathematical Model

A mathematical model is developed in this section. This corresponds to Step 1 of the research approach. The model addresses the dynamic and deterministic production requirements and

routing flexibility. This model is developed under the following assumptions.

Assumptions

1. The operating times for all part type operations on different machine types are known.
2. The product mix and demand for each part type in each period are known.
3. The capabilities and capacity of each machine type are known and constant over time.
4. Amortized cost per period to procure one machine of each type is known.
5. Operating cost of each machine type per hour is known.
6. Parts are moved between cells in batches. The intercell material handling cost per batch between cells is known and is constant (independent of quantity of cells).
7. The number of cells to be used must be specified in advance, and remains constant over time. See Section 3.1.1 for a further elaboration.
8. Bounds on quantity of machines in each cell need to be specified in advance, and remains constant over time. Section 1.3 provides further details concerning cell size.
9. Machine relocation from one cell to another is performed between periods and requires zero time.
10. The machine relocation cost of each machine type is known and is independent of where machines are actually being relocated.
11. Each machine type can perform one or more operations. Likewise, each operation can be done on one or more machine types with different times.
12. Intercell material handling cost is constant for all moves regardless of distances.
13. No inventories are considered.
14. Setup times are not considered.
15. Backorders are not allowed. All demand must be satisfied the period it occurs.
16. No queueing in production.
17. Machine breakdowns are not considered.
18. Processing capabilities are 100% reliable (i.e., no rework/scrap).
19. Batch size is constant for all products and all periods.

20. Machines are available at the start of the period (zero installation time).
21. Finally, note that the time value of money is not considered in the above problem formulation due to the following reasons:
 - (a) The length of a planning horizon is relatively short. It could be between one to two years at most. Thus, the time value of money is insignificant.
 - (b) Existing CM design methods addressing dynamic production requirements do not consider this aspect. Such works include Chen [19], Harhalakis *et al.* [36], Song and Hitomi [85], and Wicks [98].
 - (c) Research in layout design is not concerned with the time value of money when dynamic production requirements are considered. Such research includes Montreuil and Laforge [57], Palekar *et al.* [62], Rosenblatt [70], and Yang and Peters [100].

Design Objectives

As described in Section 1.3, multiple costs should be considered in the design objective in an integrated manner. All costs involved in the design of CMSs should be incorporated, however, it is not possible to explicitly consider all costs in the model due to the complexity and computational time required. In this research, costs are limited to those which are also related to the research objectives set in Section 1.5, addressing dynamic and stochastic production environments and the use of routing flexibility. The objective is to minimize the sum of the following costs in an integrated manner since they could be contradicting in nature.

1. **Machine cost:** The amortized cost per period to procure machines. The amortized cost per period of each machine type is calculated based on the machine life, not horizon. This cost depends upon the number of machines of each type used in the CMS for a specific period.
2. **Operating cost:** The cost of operating machines for producing parts. This cost depends on the cost of operating each machine type per hour and the number of hours required for each machine type.
3. **Intercell material handling cost:** The cost of transferring parts between cells when the parts can not be produced completely in a single cell. The intercell material handling cost is incurred when batches of parts have to be transferred between cells. This occurs when parts need to be processed in multiple cells, because all the machine types required to process the parts are either not available in the cell to which the parts are allocated or because the cell does not have sufficient capacity. Intercell moves decrease the efficiency in the cellular manufacturing system by increasing material handling requirements and flow time, and complicating production control.

4. **Machine relocation cost:** The cost of relocating machines from one cell to another between periods. In dynamic and stochastic production environments, the best cellular manufacturing design for one period may not be an efficient design for subsequent periods. By rearranging the manufacturing cells, the CMS can continue operating efficiently as the product mix and demand change. However, there are some drawbacks with the rearrangement of manufacturing cells. Moving machines from cell to cell requires effort and could lead to the disruption of production.

These four costs are interrelated and could be conflicting. For example, the intercell material handling cost should be considered with the machine investment cost since both objectives are conflicting. The intercell material handling cost can be minimized by duplicating the machines, and the machine investment cost can be minimized at the expense of increased intercell material handling cost. Similar arguments can be used for the combination of other costs as well. Therefore, the decisions associated with these costs need to be made simultaneously in an integrated manner.

The proposed CM design method employs system-dependent reconfigurations. Changes in demands and/or product mix may require the CM to be reconfigured. That is, the new design could depend heavily upon the current cell configuration.

Design Decisions

The following decisions must be made during the design process:

1. The assignment of operations of each part type to machine types in each period.
2. The assignment of machine types to cells in each period.
3. The number of each machine type in each cell in each period.
4. The relocation of machines when the product mix and/or the demand changes between periods.

System and Input Parameters

The input parameter values must be supplied for each period in the planning horizon.

1. **Product mix:** A set of part types to be produced in the CMS in each period. The product mix varies from period to period as new parts are introduced and old parts are discontinued. The product mix in each period is known with certainty (this assumption will be relaxed later).

2. **Product demand:** The quantity of each part type in the product mix to be produced in each period. The product demand of each part type is expected to vary across the planning horizon. It is also known with certainty (this assumption will be relaxed later).
3. **Operation sequence:** An ordered list of operations that the part type must be performed.
4. **Operating time:** Time required by a machine to perform an operation on a part type.
5. **Machine type capability:** The ability of a machine type to perform operations.
6. **Machine type capacity:** The amount of the time a machine of each type is available for production in each period.
7. **Available machines:** The available machines are the set of machines that will be used to form manufacturing cells. The number of machines available must be specified at the beginning of each period.

The following system cost parameters are used to establish the CMS design with respect to the objective of minimizing the total cost: machine cost, operating cost, intercell material handling cost, and machine relocation cost. They are defined in Section 3.1.1.

Constraints

The following constraints must be imposed in the model.

1. There must be sufficient machine capacity to produce the specified product mix, at the specified demand level, in each period.
2. Cell size must be specified. Upper and lower bounds can be used instead of a specific number.
3. The number of cells in the system must be specified. This information could be specified by management or by system designers.

Notation

Indices

- c = index for manufacturing cells ($c = 1, \dots, C$)
- m = index for machine types ($m = 1, \dots, M$)
- p = index for part types ($p = 1, \dots, P$)
- h = index for time periods ($h = 1, \dots, H$)
- j = index for operations required by part p ($j = 1, \dots, O_p$)

Input Parameters

- t_{jpm} = time required to perform operation j of part type p on machine type m
 D_{ph} = demand for product p in period h
 B = batch size
 α_m = amortized cost of machine of type m
 β_m = Operating cost per hour of machine type m
 γ = intercell material handling cost per batch
 δ_m = relocation cost of machine type m
 T_m = capacity of each machine of type m (hours)
 L_B = lower bound cell size
 U_B = upper bound cell size
 a_{jpm} = 1, if operation j of part type p can be done on machine type m
 0, otherwise

Decision Variables

- N_{mch} = number of machines of type m used in cell c during period h
 K_{mch}^+ = number of machines of type m added in cell c during period h
 K_{mch}^- = number of machines of type m removed from cell c during period h
 x_{jpmch} = 1, if operation j of part type p is done on machine type m
 in cell c in period h ; 0, otherwise

Mathematical Formulation

The mathematical formulation for the design of CMSs is developed such that part families and machine cells are simultaneously formed. The simultaneous machine-part grouping strategy generally yields better results than those of sequential strategies (part-grouping and then machine-grouping or reversal process), since all the decisions are made at the same time. However, it could be more complicated to model and would result in a large mathematical model which requires a substantial amount of time to solve. Using the above notation, the objective function and constraints are now written in an equation form. The mathematical formulation for the design of CMSs is presented next.

$$\begin{aligned} \text{Min: } & \sum_{h=1}^H \sum_{c=1}^C \sum_{m=1}^M N_{mch} \alpha_m + \sum_{h=1}^H \sum_{c=1}^C \sum_{m=1}^M \sum_{p=1}^P \sum_{j=1}^{O_{p-1}} D_{ph} t_{jpm} x_{jpmch} \beta_m + \\ & \sum_{h=1}^H \sum_{p=1}^P \left[\frac{D_{ph}}{B} \right] \left(\sum_{c=1}^C \sum_{m=1}^M \sum_{j=1}^{O_{p-1}} \gamma |x_{j+1,pmch} - x_{jpmch}| \right) + \sum_{h=1}^H \sum_{c=1}^C \sum_{m=1}^M \delta_m (K_{mch}^+ + K_{mch}^-) \end{aligned} \quad (3.1)$$

$$\text{Subject to: } \quad \sum_{c=1}^C \sum_{m=1}^M a_{jpm} x_{jpmch} = 1; \quad \forall j, \quad \forall p \quad \text{and} \quad \forall h \quad (3.2)$$

$$\sum_{p=1}^P \sum_{j=1}^{O_p} D_{ph} t_{jpm} x_{jpmch} \leq T_m N_{mch}; \quad \forall m, \quad \forall c \quad \text{and} \quad \forall h \quad (3.3)$$

$$\sum_{m=1}^M N_{mch} + \sum_{m=1}^M K_{mch}^- - \sum_{m=1}^M K_{mch}^- \geq L_B; \quad \forall c \quad \text{and} \quad \forall h \quad (3.4)$$

$$\sum_{m=1}^M N_{mch} + \sum_{m=1}^M K_{mch}^- - \sum_{m=1}^M K_{mch}^- \leq U_B; \quad \forall c \quad \text{and} \quad \forall h \quad (3.5)$$

$$N_{mc,h-1} + K_{mch}^+ - K_{mch}^- = N_{mch}; \quad \forall m, \quad \forall c \quad \text{and} \quad \forall h \quad (3.6)$$

$$\begin{array}{ccc} & x_{jpmch} & \text{binary} \\ N_{mch} & K_{mch}^+ & K_{mch}^- \\ & & \text{integer} \end{array}$$

The objective function (3.1) is a nonlinear integer equation. It minimizes the total sum of the machine investment cost, the operating cost, the intercell material handling cost, and the machine relocation cost over the planning horizon. The first term represents the cost of all machines required in all the CMS. The machine investment cost is obtained by summing the product of the number of machines of each type and their respective costs. The second term is the cost of operating machines. It is the sum of the products of the number of hours of each machine type and their respective costs. The third is the intercell material handling cost. Total intercell material handling cost is obtained by summing the products of the number of intercell transfers for each part type and the cost of transferring a batch of each part type. The last term is the machine relocation cost. It is the sum of the products of the number of machines relocated and their respective costs.

Constraint set 3.2 ensure that each part operation is assigned to one machine and one cell. Constraint set 3.3 ensures that machine capacities are not exceeded and can satisfy the demand. Constraint sets 3.4 and 3.5 specify the lower and upper bounds of cells. Constraint set 3.6 ensure that the number of machines in the current period is equal to the number of machines in the previous, plus the number of machines being moved in and minus the

number of machines being moved out. In other words, they ensure conservation of machines over the horizon.

The above mathematical model incorporates a pre-determined number of cells, C . However, the number of cells is usually not known in advance. Venugopal and Narendran [95] show that the number of ways in which m machines may be assigned to exact k cells is given by the Stirling number of the second kind

$$S^{(k)} = \frac{\sum_{j=1}^k (-1)^{k-j} \binom{k}{j} j^m}{k!}. \quad (3.7)$$

For example, there are only 34,105 distinct partitions of 10 machines into 4 cells, but this number increases to 11,259,666,000 approximately, if 19 machines are to be partitioned into 4 cells, which is a combinatorial explosion. However, if k is not pre-specified, with m machines, the total possible number of cells ranges from 1 (every machine is assigned to the same cell) to m (each cell has only 1 machine). The total number of ways in which machine-cell assignment may be made explodes to

$$\sum_{k=1}^m S^{(k)} = \sum_{k=1}^m \left[\frac{\sum_{j=1}^k (-1)^{k-j} \binom{k}{j} j^m}{k!} \right]. \quad (3.8)$$

It has been shown that this class of problem is *NP*-complete [29]. Thus, in the problem formulation, the number of cells needs to be pre-specified in order to maintain tractability. This decision is generally based on several factors such as total number of machines to be assigned into a cells, physical constraints on the shop floor, and labor relation issues [34]. Wemmerlov and Hyer [96] in a survey of 32 US manufacturing firms reported that the average of the manned cells was 6.2 machines. The second largest size of a cell was 15 machines (the largest is 40 machines). The smallest typical cell size for a manned cell was 2 machines.

3.1.2 Optimal Solution Procedure

Equation 3.1 is a nonlinear integer equation because of the absolute terms. To transform it into a linear mathematical model, non-negative variables (yp_{jpmch} and ym_{jpmch}) are introduced, and allowing reformulation into a linear integer equation as follows. Rewrite equation 3.1 as:

$$\begin{aligned} \text{Min: } & \sum_{h=1}^H \sum_{c=1}^C \sum_{m=1}^M N_{mch} \alpha_m + \sum_{h=1}^H \sum_{c=1}^C \sum_{m=1}^M \sum_{p=1}^P \sum_{j=1}^{O_{p-1}} D_{ph} t_{jpm} x_{jpmch} \beta_m + \\ & \sum_{h=1}^H \sum_{p=1}^P \left[\frac{D_{ph}}{B} \right] \left(\sum_{c=1}^C \sum_{m=1}^M \sum_{j=1}^{O_{p-1}} \gamma (yp_{jpmch} + ym_{jpmch}) \right) + \sum_{h=1}^H \sum_{c=1}^C \sum_{m=1}^M \delta_m (K_{mch}^+ + K_{mch}^-) \end{aligned} \quad (3.9)$$

Introduce a new set of constraints:

$$x_{j+1,pmch} - x_{jpmch} = yp_{jpmch} - ym_{jpmch}, \quad \forall j, \quad \forall p \quad \forall c \quad \text{and} \quad \forall h \quad (3.10)$$

Since the objective function has been converted to a linear integer equation (3.9), it can be solved optimally via optimal software packages. The above model is solved using simultaneous machine-part grouping solution strategy. CPLEX [24] is selected to solve the problem. However, the problem formulation contains binary variables as well as integer variables which could require substantial computational time. For a CM design problem, the number of constraints and number of variables of a problem include:

- Number of variables
 1. Integer variables: $2MCH + ((C - 1)MC + 2MC)(H - 1)$
 2. Binary variables: $(P\bar{J}\bar{R} + 2P(\bar{J} - 1)\bar{R})CH$
- Number of constraints: $(P\bar{J} + P(\bar{J} - 1)\bar{R}) + MC + 2C)H + 2MC(H - 1)$

For a small problem with 15 part types, 10 machine types, 3 cells, 2 periods and 2-3 operation/part type. The total number of variables and constraints are 886 and 372, respectively.

3.1.3 Example

The following hypothetical example is employed to illustrate the developed model and optimal solution procedure. The data in the example is randomly generated based upon published data in the CM design literature. A two-period planning horizon is assumed. There are ten different machine types available in the system. Eleven part types will be produced in two periods: five in the first and six in the second. The following assumptions are used to generate data for this example and to simplify the design example:

1. Each part type requires 2-4 operations. The machining requirements of part types are shown in Table 3.1. Each operation can be performed on at most two machine types. For instance, the first operation of part type 1 can be processed on either machine type 1 or 5 with different processing times and hence costs (shown in Table 3.1). The second operation, however, can be done on machine type 8 only.
2. Machine types for each operation are randomly generated.
3. Processing time for each operation was generated using a continuous uniform distribution with parameters (0.5 min., 1.5 min.) as shown in Table 3.1
4. Operating costs of machine types were generated using a normal distribution with parameters (\$50, \$20) as displayed in Table 3.3.

5. Part demands are assumed to be a discrete uniform distribution of (800 units, 1100 units). Demands for both periods are shown in Table 3.2.
6. Parts are transferred between cells in batches. A batch size for all part types is 50 units. The intercell transfer cost per batch is \$20.
7. Machine costs and capacities as well as machine relocation costs are shown in Table 3.3. Machine costs are assumed to be between \$1,200 and \$1,800. Machine cost of type 8 is approximately about half of other machine costs because it can perform only one operation. Machine relocation costs are assumed to be about half of machine costs. Machine capacities are arbitrarily set to 7,000 hours available per period for all machines.
8. Three manufacturing cells are assumed.
9. Each cell must contain at least two machines and at most ten machines, and produce at least one part type.

Numerical Results for Example

Numerical results from the proposed mathematical model and optimal solution procedure are shown in Table 3.4. Table 3.5 and Table 3.6 illustrate the cell configurations for both periods. The configurations can be summarized as follows. In the first period, five part types, 2, 3, 5, 7, and 8, are produced. A total of ten machines are needed in this period. Two units of machine type 4 and 3, and one unit of machine type 1, 2, 6, 7, 8 and 10 are required. Cell 1 consists of one machine each of types 1, 3, 4, 6, and 10, and part types 3 and 5 are produced in this cell. Cell 2 consists of one machine each of types 2, 3 and 7 and produces part types 2 and 7. Cell 3 contains one machine each of types 4 and 8, and produces only part type 8. The total cost in period 1 includes:

1. The machine cost of \$14,940 for ten machines.
2. The operating cost of \$5,992.92.
3. The intercell material handling cost of \$1,600 for transferring batches of part type 2 from cell 1 to cell 3 (\$800) and cell 3 to cell 2 (\$800).
4. No machine relocation cost.

In the second period, six part types, 1, 4, 5, 9, 10, and 11, are produced. A total of 11 machines are required. An additional unit of machine types 5, 6 and 9 are added into cell 2. The unit of machine type 10 in cell 1 is moved to cell 3. In summary, two units of machine types 3, 4, and 6, and one machine of each type 1, 2, 6, 9, and 10 are required. Note that the

Table 3.1: Machine Types, Processing Times, and Operation Costs for Part Type Operations

Part Type p	Data Type	Operation, j							
		1		2		3		4	
		1	2	1	2	1	2	1	2
1	M/C, m Time, t_{jpm}	M1 0.25	M5 0.78	M8 0.98					
2	M/C Time	M10 0.47		M5 0.7	M8 0.65	M2 1		M7 0.92	
3	M/C Time	M10 0.33		M4 0.75		M1 0.5			
4	M/C Time	M9 0.32		M2 0.17	M4 0.82	M10 0.47			
5	M/C Time	M3 0.13		M2 1	M4 0.55	M1 0.5		M6 0.93	
6	M/C Time	M2 0.35	M4 0.53	M10 0.73					
7	M/C Time	M3 1.05		M3 0.62					
8	M/C Time	M5 0.35	M8 0.2	M4 0.63					
9	M/C Time	M1 0.2	M5 0.47	M2 0.65	M4 0.35	M2 1.08		M3 0.15	
10	M/C Time	M1 0.18	M5 0.47	M5 0.4	M8 0.9	M6 0.83			
11	M/C Time	M9 0.2		M8 0.47		M2 0.62			

unit of machine type 7 in cell 2 is no longer required for manufacturing purpose; however, the machine remains in cell 2. The total cost in period 2 includes:

1. The machine investment cost of \$4,050; \$1,700 for a unit of machine type 8 and \$1,500 for a unit of machine type 9. Both machines are added to cell 2.
2. The operating cost of \$7,423.00.
3. The intercell material handling cost of \$2,440.
4. The machine relocation cost of \$700. The single machine of type 3 in cell 1 is moved at the end of period 1 to cell 3 for the start of period 2.

Table 3.2: Part Demand

Period	Demand for Part Type p in Period h , D_{ph} , $p =$										
	1	2	3	4	5	6	7	8	9	10	11
1	0	990	980	0	860	0	990	880	0	0	0
2	1,030	0	0	1,000	980	0	0	0	870	990	1,100

Table 3.3: Resource Data

Machine type	Machine cost (\$), α_m	Relocation cost (\$), δ_m	Capacity (min.), T_m	Operating Cost, β_m
1	1,640	700	7,000	24
2	1,800	600	7,000	74
3	1,600	600	7,000	36
4	1,300	800	7,000	40
5	1,750	750	7,000	47
6	800	350	7,000	40
7	1,700	680	7,000	28
8	1,700	700	7,000	42
9	1,500	640	7,000	27
10	1,500	700	7,000	49

Numbers in the parenthesis are the number of machines required for each type. *'s represent intercell moves. For example, in period 1, part type 2 is primarily produced in cell 2, but intercell moves occur when batches of this part type are moved from cell 1 (machine 10) to cell 3 (machine 8) and then to cell 2 (machine 2 and 7). A part type belongs to a certain cell when at least half of its operations are processed in that cell.

Table 3.4: Cellular Design Costs

Cost	Period 1	Period 2
Operating	5,995.92	7,423.00
Equipment	14,940.00	4,050.00
Intercell Move	1,600.00	2,440.00
Relocation	0	700.00
Total	19,980.60	12,065.80

Table 3.5: Design Solution for Period 1

Cell	M/C Type (N_{mch})	Part type				
		3	5	2	7	8
1	1 (1)	1	1			
	3 (1)		1			
	4 (1)	1	1			
	6 (1)		1			
	10(1)	1		*		
2	2 (1)			1		
	3 (1)				1	
	7 (1)			1		
3	4 (1)					1
	8 (1)			*		1

Table 3.6: Design Solution for Period 2

Cell	M/C Type (N_{mch})	Part type					
		5	9	1	10	4	11
1	1 (1)	1	1				
	3 (1)	1					
	4 (1)	1	1				
	6 (1)	1					
2	2 (1)		*				*
	3 (1)		*				
	5 (1)			1	1		
	6 (1)				1		*
3	7 (1)						
	4 (1)					1	
	8 (1)			*			1
	9 (1)					1	1
	10 (1)					1	

3.2 Evaluation of Potential Benefits of Proposed CMS Design Approach

Two major differences between this research and others are the consideration of dynamic and stochastic production environments (employing system-dependent reconfigurations) and of routing flexibility. Experiments are conducted in the next two sections in order to demonstrate the potential benefits of system-dependent reconfigurations and routing flexibility using the mathematical model and optimal solution procedures of the previous section. First, the improvement through the consideration of system-dependent reconfiguration is investigated in Section 3.2.1. Section 3.2.2 presents the benefits of routing flexibility.

3.2.1 Potential Benefits of Incorporating System-Dependent Reconfiguration

In this section, the potential benefits of considering system-dependent reconfigurations are demonstrated through four numerical examples. Note that routing flexibility (i.e., alternate machines for one or more operations) is not considered so that the effect of routing flexibility does not come into play. Table 3.7 shows the design parameters for the problem instances. Product data, production requirements, and machine costs and capacities for the first three problems are randomly generated as shown in Appendix A.1. Problem number 1 consists of 15 part types and 12 machine types. In the first period, 7 part types are randomly chosen from those 15 part types and 9 part types are randomly selected in the second period. For the details of which part types are selected in each period, see Table A.1. Problem numbers 2 and 3 have different processing and other requirements from problem number 1 and each other (see Tables A.3 - A.6). Problem number 4 is taken from Wicks [98] (see Tables 4.17 - 4.19).

Table 3.7: Design Parameters for Problem Instances

Problem No.	Total Diff. Part Types	No. of Parts		No. of Mc. Types	No. of Cells	Data Tables
		Period 1	Period 2			
1	15	7	9	12	3	A.1 and A.2
2	15	9	10	12	3	A.3 and A.4
3	15	7	10	12	3	A.5 and A.6
4	21	16	21	11	3	4.17, 4.18 and 4.19

Table 3.8 shows the comparison between system-independent reconfiguration and system-dependent reconfiguration. System-independent reconfiguration is obtained without considering the current CM configuration as shown in Table 3.10. In other words, two single-period problems are solved independently and the total equipment cost is that incurred for all equip-

ment in period 1 and any additional equipment needed in period 2. That is, relocation costs of machines are not taken into account but are totalled in to find total cost afterwards when designing the CMS in period 2. However, to arrange manufacturing cells as obtained for period 2, relocation costs need to be considered. As a result, the cost for system-independent reconfiguration is higher as show in Table 3.8. Table 3.11 shows the cell configuration of period 2 for the system-dependent reconfiguration.

Table 3.8: Potential Benefits from System-Dependent Reconfiguration

Problem Data	System-Independent	System-Dependent	Improvement	
1	\$52,980	\$51,474	\$1,506	(2.84%)
2	\$55,434	\$49,969	\$5,465	(9.86%)
3	\$46,073	\$42,113	\$3,960	(8.60%)
4	\$50,000	\$38,000	\$12,000	(24.00%)

Solution Example

Problem number 3 is employed to illustrate how the system-independent and system-dependent reconfiguration costs are obtained. The CMS configuration in period 1 is shown in Table 3.9. The system-independent reconfiguration result is shown in Table 3.10. To obtain the configuration in Table 3.10 from Table 3.9, a total cost of \$17,368 is needed which can be broken down as follows: additional machine cost \$9,068 (for a unit of machine type 1, 6, 8, and 10), intercell cost \$2,200, and relocation cost \$6,100. On the other hand, system-dependent reconfiguration is generated based upon the configuration of CM in period 1 (Table 3.9). The cost of the new design includes an additional machine cost of \$9,068 (for a unit of machine type 1, 6, 8, and 10), and intercell cost of \$4,340.

Analysis and Comments

As discussed above, system-dependent reconfiguration always provides better solutions than those of system-independent reconfiguration due to the current cell configuration. Also, system-dependent reconfiguration is more practical in actual manufacturing systems. In addition, the above experiments have supported the potential improvement as previously discussed. From the experiments, the following can be concluded.

1. Improvement ranges from 3% to 24% for the four problems.
2. Savings are gained when additional periods are considered.
3. Solutions from the system-dependent reconfiguration are better or at least as good as those from the system-independent reconfiguration.

Table 3.9: Design Solution for Period 1

Cell	M/C Type	Part type						
		7	12	4	9	15	2	13
1	2 (1)	1						
	7 (1)		1	*				
	9 (1)	1	1					
2	1 (1)	*		1		1		
	3 (1)				1	1		
	4 (1)		*			1		
	6 (1)		*	1	1			
3	5 (1)			*				1
	8 (1)						1	1
	11 (1)				*		1	1
	12 (1)							1

4. If demands in future periods are known with certainty, we should take advantage of the knowledge about the future requirements. However, the above experiment did not take advantage of such knowledge. This issue needs further investigation.
5. As point out by Montreuil and Laforge [57], it is rarely possible to specify with certainty what the future requirements are going to be. Therefore, uncertainty of future requirements must be employed in the design procedure.

Table 3.10: Design Solution for Period 2, System-Independent Reconfiguration

Cell	M/C Type	Part type									
		3	6	5	10	11	12	1	2	7	8
1	3 (1)	1	1								
	6 (1)		1								
	7 (1)	1				*					
	8 (1)	1	1								
2	1 (1)		*		1		1				
	4 (1)			1		1					
	5 (1)		*		1		1				
	10 (1)			1							*
	12 (1)				1	1	1				*
3	1 (1)									1	1
	2 (1)								1	1	
	6 (1)							1			1
	8 (1)			*			*		1		1
	9 (1)			*				1		1	
	11 (1)	*						1	1		

Table 3.11: Design Solution for Period 2, System-Dependent Reconfiguration

Cell	M/C Type	Part type									
		1	3	7	5	6	11	2	8	11	14
1	2 (1)			1				*			
	7 (1)		1				*				
	8 (1)		1		*						
	9 (1)	1		1	*						
2	1 (1)			*	1						
	3 (1)		*		1						
	4 (1)				1		1				
	6 (1)	*			1		1				
	10 (1)				1				*		
3	1 (1)							1	1	1	
	5 (1)					*			1	1	
	6 (1)							1			
	8 (1)					*		1	1		1
	11 (1)	*	*					1			
	12 (1)						*	1	1	1	

3.2.2 Potential Benefits of Routing Flexibility

This section demonstrates the potential benefits that could be obtained from considering routing flexibility during the design process through five numerical examples. Note that only a single-period planning horizon is considered so that effects of system-dependent and system-independent reconfigurations do not come into play. When routing flexibility (RF) is considered during the design process, part types have alternate routings, increasing the number of ways cells can be formed. Four randomly-generated data sets and one problem from the literature are used for this purpose. Problem number 5 is taken from Wicks [98]. Design parameters are shown in Table 3.12. The details of product and production requirements are presented in Appendix A.2. Note that Problem numbers 1 and 2 have the same product and production requirements, but are different in the number of cells required in the design solutions.

Table 3.12: Parameters for Problem Instances for Routing Flexibility

Problem No.	No. of Part Types	No. of Machine Type	No. of Cells	No. of Periods	Data Tables
1	6	9	3	1	A.7 and A.8
2	6	9	2	1	A.7 and A.8
3	12	10	3	1	A.9 and A.10
4	12	10	3	1	A.11 and A.12
5	24	19	3	1	4.14, 4.15 and 4.16

When routing flexibility is not considered, it is assumed that each operation can be done on one machine type. For instance in Table A.9, operation 1 of part type 1 can be done on machine type 3 only. However, when routing flexibility is considered, the operation can be done on either machine type 3 or 2 with the same processing time and cost. Operating times and costs are kept constant so that any benefit obtained can be directly attributed to differences in routing flexibility. Table 3.13 is the summary of how the potential benefits are gained through the routing flexibility (RF). The solutions in Table 3.13 were obtained by solving the mathematical model in Section 3.1.1 using CPLEX.

Table 3.13: Potential Benefits from Routing Flexibility

Problem Data	Without RF	With RF	Improvement (\$)
1	19,748.73	17,169.73	2,579 (13.06%)
2	19,408.73	16,498.73	2,910 (14.99%)
3	34,966.00	33,618.00	1,348 (3.86%)
4	35,868.00	33,999.00	1,869 (5.21%)
5	1,700.00	1,300.00	400 (23.53%)

Solution Example

Problem number 1 is used to demonstrate how CM configuration costs are obtained with and without flexibility as shown in Table 3.15. Table 3.15 shows the CM configuration without considering routing flexibility and Table 3.15 shows the CM configuration with routing flexibility. Routing flexibility provides a lower cost because of higher machine utilization which in turn means that fewer machines are required and equipment cost are reduced. When machines can perform more than one operation, more operations can be assigned to the machines resulting in higher utilization. As discussed in Section 1.3.1, routing flexibility increases groupability of machines into cells. However, in this example, groupability does not come into play because the intercell material handling cost for RF is higher.

Table 3.14: Costs Comparison between without RF and wit RF

Cost	Without RF	With RF
Machine	11,369.00	8,750.00
Processing	8,039.73	8,039.73
Intercell	340.00	380.00
Total	19,748.73	17,169.73

Table 3.15: Design Solution without RF

Cell	M/C Type	Part type					
		3	1	2	5	4	6
1	2 (1)	1					
	7 (1)	1				*	
2	1 (1)				1		
	3 (2)		1	1			
	4 (1)		1		1		
	5 (1)		1				
	6 (1)					1	
	8 (1)						1
3	9 (1)		1	1			
	1 (1)					1	
	2 (1)						1
	4 (1)					1	1
	8 (1)						1

Table 3.16: Design Solution with RF

Cell	M/C Type	Part type						
		4	5	2	3	6	1	
1	1 (1)		1					
	5 (1)		1					
	6 (1)		1					
	9 (1)		1	1				
2	2 (1)				1	1		
	4 (1)				1		1	
	7 (1)				1	1		
	8 (1)						1	
3	4 (1)		*				1	
	5 (1)						1	
	7 (1)						1	

Analysis and Comments

From the above experiment, the following conclusions are made.

1. Improvement ranges from 3% to 23% for the tested problems.
2. Higher utilization of machines leads to fewer machines. Thus, machine costs are reduced.
3. Routing flexibility could increase groupability, resulting in better cell configurations.

3.3 Dynamic, Stochastic CMS design

In Section 3.1.1, the mathematical model is developed for the multi-period design of CMSs with known production requirements. However, in real-world manufacturing, production requirements may not be known exactly at the time of designing CMSs. It is likely that a set of possible production requirements (scenarios) with certain probabilities may be given at the design time. This circumstance corresponds to the situation where a company has submitted proposals for production of a fixed number of customers [71]. Therefore, uncertainty in production requirements needs to be incorporated into the CM design method.

3.3.1 Mathematical Model

Dealing with uncertain production requirements in the design of CMSs has not been extensively investigated. Only the work by Seifoddini [74] considered the uncertainty when designing CMSs. As discussed in Section 2.1.2, the algorithm proposed by Seifoddini chooses a cell configuration from a set of cell configurations generated from different product mixes. The chosen configuration is the one that has the lowest expected intercell material handling cost. The primary drawback in his algorithm is that only the optimal designs of each product mix are considered. It is possible that a system design exists with a lower expected intercell material handling cost over all product mixes, although, it is not optimal with respect to any individual product mix. In this section, a procedure to obtain CM design solutions for a single-period planning considering uncertainty is presented. Such a procedure can be extended for multi-period planning which will be discussed later. The following assumptions are made for this model:

1. There exists a finite number of possible product mixes (scenarios) which can occur.
2. Each product mix is represented by a unique set of part types and their associated demands.
3. Each product mix has a known probability of occurrence.

Additional notation is added as follows:

- s = index for possible product mixes ($s = 1, \dots, S$)
 Γ_s = product mix s
 π_s = associated probability of occurrence of product mix s
 x_{jpmc}^s = the assignment of part type operation j to machine type m in cell c for product mix s
 N_{mc}^s = number of machine of type m used in cell c for product mix s
 Z_{sw} = solution cost of using configuration s (designed for product mix s) for product mix w

The decision variables for the model are x_{jpmc}^s and N_{mc}^s . For a single-period planning, a mathematical model for a particular product mix can be rewritten as follows:

$$\text{Min: } \sum_{c=1}^C \sum_{m=1}^M N_{mc}^s \alpha_m + \sum_{c=1}^C \sum_{m=1}^M \sum_{p=1}^P \sum_{j=1}^{O_{p-1}} D_p t_{jpm} x_{jpmc}^s \beta_m + \sum_{p=1}^P \left\lceil \frac{D_p}{B} \right\rceil \left(\sum_{c=1}^C \sum_{m=1}^M \sum_{j=1}^{O_{p-1}} \gamma |x_{j+1,pmc}^s - x_{jpmc}^s| \right) \quad (3.11)$$

$$\text{Subject to: } \sum_{c=1}^C x_{jpmc}^s = 1; \quad \forall j_p, \quad \text{and} \quad \forall p \quad (3.12)$$

$$\sum_{i=1}^P \sum_{j=1}^{O_p} D_p^s t_{jpmc} x_{jpmc}^s \leq T_m N_{mc}^s; \quad \forall m, \quad \text{and} \quad \forall c \quad (3.13)$$

$$\sum_{m=1}^M N_{mc}^s \geq L_B; \quad \forall c \quad (3.14)$$

$$\sum_{m=1}^M N_{mc}^s \leq U_B; \quad \forall c \quad (3.15)$$

$$\begin{array}{ll} x_{jpmc}^s & \text{binary} \\ N_{mc}^s & \text{integer} \end{array}$$

This model does not include the consideration of relocation cost because it is for a single-period planning. It can be solved optimally using the technique presented in Section 3.1.2.

The following example is employed to illustrate a solution procedure to obtain a solution when uncertainty in production requirements is involved in the CM design process by [74]. Two possible product mixes are likely to be produced with equal probabilities in a single period planning. The first possible product mix consists of part types 1, 2, 3, 5, 7, 9 and 10. The second product mix consists of part types 2, 3, 4, 5, 6, 7 and 8. Eleven machine types are required to produce these part types. Operation sequences and processing times

are shown in Table 3.17. Table 3.18 shows the possible product mixes to be produced. Table 3.19 shows the machine and operating costs. The optimal solutions for each product mix are obtained by using CPLEX and are shown in Table 3.20.

Table 3.17: Part Type Attributes

Part Type Number, p	Number of Operations, O_p	Machine Type Routes	Processing Time, t_{jpm}	Number of Alt. Routes
1	6	3-11-9-8-5-2	0.83-0.77-0.48-0.42-0.78-0.23	1
2	4	1-9-7/8-4	0.13-0.40-0.78/0.45-0.87	2
3	4	3-11-9-7	0.22-0.86-0.75-0.22	1
4	3	5-2-1	0.76-0.26-0.14	1
5	3	9-8-5	0.72-0.88-0.88	1
6	3	2-11-8	0.30-0.72-0.16	1
7	3	7-4-2	0.41-0.63-0.60	1
8	2	10-9/5	0.95-0.43/0.66	2
9	2	6/2-4	0.70/0.54-0.48	2
10	2	3-11	0.52-0.95	1

Table 3.18: Part Type Demand

Part Type Number, p	Demand, D_p	
	Scenario 1, Γ_1	Scenario 2, Γ_2
1	800	0
2	800	700
3	800	600
4	0	800
5	1,000	900
6	0	1,000
7	500	1,000
8	0	500
9	600	0
10	700	0

If cell configuration 1 is used for product mix 2, the solution cost will be higher than \$30,953. Similarly, if cell configuration 2 is used for product mix, the solution cost will be higher than \$34,041. Table 3.21 shows the solution costs for using different cell configurations for different product mixes.

From the above example, Theorem 1 is presented.

Table 3.19: Machine Type Attributes

Machine Type Number, m	Machine Cost, α_m	Operating Cost, β_m
1	1,500	71
2	1,500	95
3	1,200	59
4	1,200	43
5	1,400	50
6	1,500	52
7	1,100	34
8	1,100	86
9	1,300	50
10	1,400	50
11	1,200	85

Table 3.20: Optimal Solution Costs

Product Mix, s	Optimal Solution Cost, Z_{ww}
1	\$34,041
2	\$30,953

Theorem 1 $Z_{sw} \geq Z_{ww}$, where $s \neq w$

Proof of Theorem 1 Z_{ww} is the optimal solution for product mix w , therefore, any other solution cannot be better than this solution. QED.

To determine the cell configuration to be used for a given set of possible product mixes, a performance measure needs to be established. Let Z_s^* be the solution cost when using configuration s . The expected cost of using configuration s given a set of possible product mixes, $E[Z_s^*]$, can be determined as follows:

$$E[Z_s^*] = \sum_{w=1}^S Z_{sw} \pi_w, \quad w = 1, \dots, S. \quad (3.16)$$

Given S product mixes and S solutions, the expected total cost under all possible product mixes for each solution should be calculated and used as a performance measure. The

Table 3.21: Product Mixes, Probabilities and Solution Costs

Product Mix, s	π_s	Z_{1w}	Z_{2w}
1	0.5	\$34,041	\$38,373
2	0.5	\$36,624	\$30,954

solution providing the lowest expected total cost is selected according to Seifoddini [74]:

$$\min E[Z_s^*] \quad (3.17)$$

From the above example, the expected total cost for each cell configuration is calculated as follows:

$$E[Z_1^*] = \$34,041 \cdot 0.5 + \$38,373 \cdot 0.5 = \$36,207.$$

$$E[Z_2^*] = \$36,624 \cdot 0.5 + \$30,954 \cdot 0.5 = \$33,789.$$

According to the calculation, the best cell configuration is 2 with respect to the expected total cost. However, it is possible that a solution exists with a lower expected intercell material handling cost over all product mixes, although, it is not optimal with respect to any individual product mix.

Weighted-Average Product Mix

Instead of selecting a solution from possible S solutions generated from S possible product mixes, the weighted-average product mix is used to obtain the solution which is described as follows:

1. Find the weighted-average product mix, $\bar{\Gamma}$, where:

$$\bar{\Gamma} = \sum_{s=1}^S \Gamma_s \pi_s \quad (3.18)$$

2. Obtain the solution using the weighted-average product mix, $\bar{\Gamma}$.

The idea is to compress the various product mixes into a single weighted-average product mix. This idea was originally proposed by Rosenblatt and Kropp [71] for solving the single period stochastic plant layout problem.

Theorem 2 The solution obtained using $\bar{\Gamma}$ is optimal with respect to the expected total cost. That is,

$$E[Z_{\bar{\Gamma}}] \leq E[Z_s^*] \quad (3.19)$$

It has an expected cost which is at least as low as the expected cost of any other solution. To prove this theorem, the following theorems are presented:

Jensen's Inequality Theorem Let g be a convex function on the interval (a, b) , and let X be a random variable such that $Pr\{X \in (a, b)\} = 1$ and the expectation $E(X)$ and $E[g(X)]$ exist. Then $E[g(X)] \geq g[E(X)]$. See the proof for this theorem in [25].

Convex Functions A function $f(x)$ is convex if

$$f(x^{(1)} + \lambda(x^{(2)} - x^{(1)})) \leq f(x^{(1)}) + \lambda(f(x^{(2)}) - f(x^{(1)})) \quad (3.20)$$

for every $x^{(1)}$ and $x^{(2)}$ in its domain and every step $\lambda \in [0, 1]$. In addition, a linear function is convex [67].

Proof of Theorem 2 Let $g(x)$ be the cost function as shown in Equation 3.11 which is converted into a linear function as follow:

$$g(x) = \sum_{c=1}^C \sum_{m=1}^M N_{mc}^s \alpha_m + \sum_{c=1}^C \sum_{m=1}^M V_{mc}^s \beta_m + \sum_{c=1}^C \sum_{p=1}^P \left\lceil \frac{D_p}{B} \right\rceil \left(\sum_{j=1}^{O_p-1} \gamma |y p_{j+1,pmc}^s - y m_{jpmc}^s| \right) \quad (3.21)$$

Equation 3.21 is a linear function, therefore, it is convex and $E[g(x)]$ exists. $E[g(x)]$ is calculated as follows:

$$E[g(x)] = \sum_{s=1}^S \pi_s g(x). \quad (3.22)$$

$g[E(x)]$ also exists when $\bar{\Gamma}$ is used in solving Equation 3.21. According to the Jensen's Theorem, $E[g(X)] \geq g[E(X)]$. QED.

To illustrate the use of weighted-average product mix, the previous example is employed. Table 3.22 shows the solution costs when the weighted-average product mix is used. It is obvious that the solution cost obtained from using the weighted-average product mix is the lowest among the three.

Table 3.22: Costs Comparison

Solution, Z_s^*	Expected Solution Cost, $E[Z_s^*]$
Z_1^*	\$36,207
Z_2^*	\$33,789
$Z_{\bar{r}}$	\$33,479

3.3.2 Heuristic Solution Approach

As described in Section 3.1.1, the design of CMSs is combinatorially complex. Only small problems can be solved optimally using the solution procedure shown in Section 3.1.2. It is impossible to solve large problems with such methodology due to the resources (i.e., time, computer memory, etc) required. Therefore, a heuristic for designing CMSs is developed. It consists of six phases.

The heuristic will employ the weighted average production requirements method of Section 3.3.1 to handle the uncertainty in production requirements. A route for each part type is selected in the next step. The selected route will be used in forming part families and grouping machines. This is different from the optimal solution procedure where the optimal route for each part type is chosen when part types are formed and machines are grouped. With the route being selected in advance, only machine and operating costs are considered when the decisions are made, whereas the optimal routes are selected with all four costs being considered. Therefore, the selected route by the heuristic may not be optimal. Routes must be selected in advance, however, to maintain tractability in developing the heuristic.

A cell configuration is generated based upon the selected routes. The cell configuration is improved through simulated annealing in the next step. Tradeoffs between machine costs and intercell material handling costs are made in order to reduce the total cost. Finally, relocations of machines between periods are determined. The six phases of the heuristic are explained below.

For each period $h, h = 1, \dots, H$

1. Determine the weighted-average production requirements
2. Select a route (process plan) for each part
if ($h = 1$)
 - 3a. Generate an initial cell configuration,
 - else
 - 3b. Assign part types to the existing cell configuration
4. Improve the cell configuration
5. Eliminate excessive machines to reduce cost
6. Determine the machine relocations between h and $h + 1$

The first five phases are performed in each period; the last phase is done during the period. For a new cell configuration, the method in Phase 3a is used. For an existing cell configuration, the method in Phase 3b is used to assign part types to cells. Figure 3.1 shows the flow of the heuristic.

Phase 1: Determine Weighted-Average Product Mix As shown in Section 3.3, the total cost obtained from the expected production requirements is at least as low as the expected total cost of any other solution. To determine the expected production requirements, simply use the following equation:

$$\bar{\Gamma} = \sum_{s=1}^S \Gamma_s \pi_s \quad (3.23)$$

The weighted-average product mix, $\bar{\Gamma}$, will be used for generating a cell configuration in the later phases.

Phase 2: Select Routes for Part Types Certain operations of part types can be processed on different machine types. This allows part types to have multiple routes. A decision to be made is to select a route for a part type. Costs involved in the routing selection are machine and operating costs. The procedure for selecting routes for part types is as follows.

1. Calculate the number of machines and the number of hours required to process operations which can be performed by only one machine type. Use the results to compute the machine and operating costs according to each machine type.
2. For operations which can be processed on multiple machine types, arrange them in non-decreasing order according to their number of operations. If ties, arbitrarily arrange them.
3. To select a machine type for an operation that can be done on multiple machine types, evaluate each machine type by considering the increasing machine and operating costs. Choose the machine type which results in minimizing the cost.
4. Continue the procedure until all the operations have been chosen.

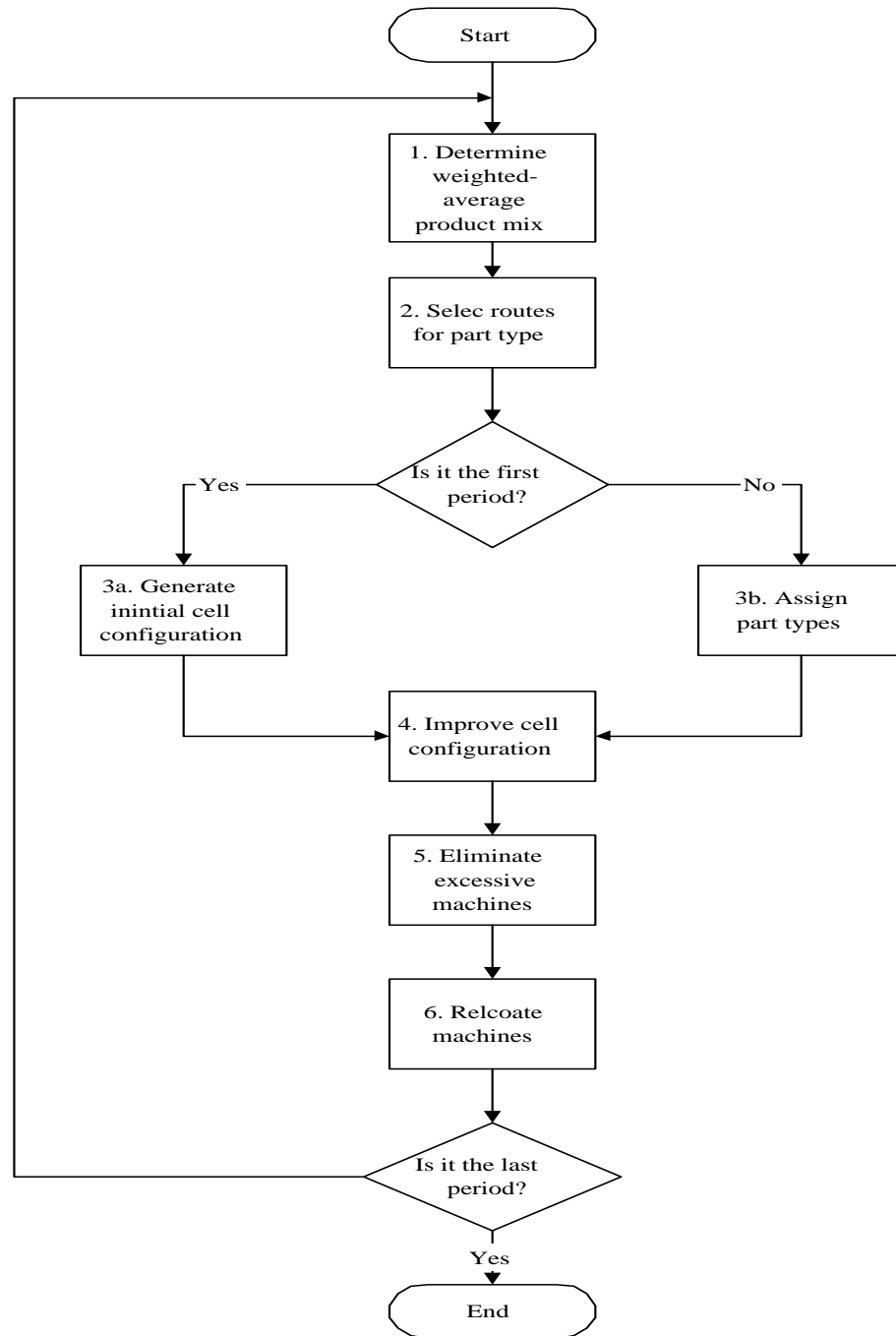


Figure 3.1: Heuristic Flow Chart

Phase 3a: Generate Initial Cell Configuration After a route of each part type has been selected, a cell configuration can be created. To generate a cell configuration, the number of cells must be pre-specified. In generating a cell configuration, the similarity between a cell and a part type, S_{pc} , is used and is defined as a similarity between operations of a cell and operations of a part type to be assigned in a cell. It is calculated as follows.

$$S_{pc} = \frac{NS_{pc}}{NO_{pc}}, \quad (3.24)$$

where S_{pc} is the similarity between part type p and cell c , NS_{pc} is the number of operations of part type p and c which require the same machine types, and NO_{pc} is the number of operations in cell c and in part type p minus S_{pc} . This measure is similar to Jaccard similarity coefficient [53] measuring similarity between two parts. A value of S_{pc} must be set and is used in assigning part types to cells when a cell is being created. The algorithm for generating an initial cell configuration is described below:

1. Specify the value of S_{pc} .
2. Arrange part types in non-increasing fashion with respect to their number of operations. If ties, arbitrarily arrange them.
3. Assign the first part type on the arranged list to the first cell. Note that machines are assigned to cells according to the part type assigned.
4. If the number of cells generated is not equal to the number of pre-specified cells, go to Step 5. Otherwise, go to Step 6.
5. Calculate the S_{pc} for the part type being assigned with the cells that have been generated. If the highest calculated value of S_{pc} is more than the specified S_{pc} , assign the part type to the cell which provides the highest S_{pc} . Otherwise, a new cell is created. The number of cells created is incremented by one.
6. Calculate the S_{pc} for the part type being assigned with all cells. Assign the part type to the cell which yields the maximum S_{pc} .
7. If any part types remain unassigned to a cell, go to Step 4. Otherwise, terminate.

Note that the above algorithm generates cell configurations without allowing intercell moves.

Phase 3b: Assign Part Types This phase is similar to Phase 3a. Step 2, 6 and 7 in Phase 3a are used in assigning part types to cells. This method will not produce intercell moves.

1. Arrange part types in non-increasing fashion with respect to their number of operations. If ties, arbitrarily arrange them.

2. Calculate the S_{pc} for the part type being assigned with each cell separately. Assign the part type to the cell which yields the maximum S_{pc} . Machine types are assigned according to the part type assigned.
3. If all part types have been assigned to cells, terminate. Otherwise, go to 2.

Phase 4: Improve Cell Configuration Simulated annealing is employed in this phase to improve the initial cell configuration generated in the previous phase. Improvement is carried out by exchanging part types between cells. In other words, neighborhood solutions are generated via the exchange of part types between cells. Values of parameters used in the simulated annealing must be specified first. The initial temperature is set between the maximum difference in cost between neighborhood solutions and the minimum difference in cost between neighborhood solutions. The neighborhood solutions are obtained from the initial cell configuration. The cooling rate is set to be 0.9. The number of iterations ($nrep$) at each temperature vary from temperature. The value of $nrep$ increases arithmetically at each new temperature. The initial value of $nrep$ is 5 and increases by 5 at each new temperature. The simulated annealing stops when the temperature is lower than 0.005. The following lists the SA steps:

1. An initial cell configuration, s_0 is generated using the procedure in Phase 3.
2. Calculate the total cost for the cell configuration, $f(s_0)$.
3. Initialize the parameters, t_0, t_f, α and $nrep$.
4. Set $t = t_0$
5. Randomly select a part type from a cell and select another part type from another cell. Exchange the part types to obtain a new configuration, s .
6. Calculate the total cost of the new configuration, $f(s)$.
7. Calculate the change in cost, $\delta = f(s) - f(s_0)$. If $\delta < 0$, s is accepted and set $s_0 = s$. If $\delta > 0$, a random variable $x \sim U(0, 1)$ is generated and is compared with the probability $P_{acc} = \exp(-\delta/t)$. If $x < P_{acc}$, the cell configuration, s , is abandoned and go to Step 5. Otherwise, s is accepted and set $s_0 = s$.
8. If the number of iterations at the current temperature has not been reached, go to Step 5. Otherwise, the temperature is decreased.
9. If the temperature is lower than the final temperature, t_f , terminate the algorithm. Otherwise, go to Step 5.

Phase 5: Eliminate Excessive Machines A cell configuration obtained through the first four steps is based upon the perception that no intercell moves are allowed. In other words, independent cells are created. However, under certain circumstances, it is more economical to have intercell moves instead of having extra machines. In this phase, a tradeoff of having extra machines versus having intercell moves is considered. If eliminating extra machines results in reducing the total cost, the extra machines will be eliminated. The following algorithm is used for deciding to eliminate extra machines.

1. Select a machine type to be considered. Calculate the number of machines required in order to meet the weighted-average production requirements.
2. If the number of machines obtained from the previous phases are more than the number of machines calculated in Step 1, go to Step 3. Otherwise, go to Step 4.
3. To eliminate extra machines of the machine type selected, calculate the work load which the machine type performs in each cell. The work load is defined as the amount of the part type to be produced. If the cost of saving in eliminating a unit of the machine type is greater than the increasing intercell material cost, eliminate the unit of machine in the cell which has the minimum work load.
4. Add a unit of the machine type needed in the cell which has the highest work load.
5. If all machine types have been considered, terminate. Otherwise, go to 1.

Phase 6: Relocate Machines In this phase, relocation of machines between periods is determined. The relocation cost and intercell material cost are employed in order to whether or not relocate machines. A machine is relocated when the relocation cost of the machine is lower than the intercell material handling cost incurred due to not having the machine in the right place. The notation below is used in the following algorithm.

$$\begin{aligned}
 \Omega(t) &= \text{cell configuration obtained in period } t \\
 \Omega(t') &= \text{cell configuration obtained in period } t' \\
 Q(m, t, t') &= \text{cost of relocating machine } m \text{ between period } t \text{ and } t' \\
 \Delta(m, c, c') &= \text{saving in intercell material handling cost when machine } m \\
 &\quad \text{is moved from cell } c \text{ to } c' \text{ between period } t \text{ and } t'
 \end{aligned}$$

1. A cell configuration in each period is created using the first five phases of the heuristic.
2. Between two periods, $\Omega(t)$ and $\Omega(t')$, consider a machine type, m , whose location in period t is different from its location in period t' .
3. Compare the relocation cost of a unit of the machine type and saving in intercell cost for having machine m in the proper location, $Q(m, t, t') - \Delta(m, c, c')$. If $Q(m, t, t') - \Delta(m, c, c') > 0$, relocate the machine. Otherwise, keep machine at the same location.
4. If all machine types have been considered, terminate. Otherwise, go to Step 2.

Chapter 4

Evaluation Methodology

In the previous chapter, a heuristic for designing CMSs under dynamic and uncertain production requirements was developed. The next step of the research approach is to evaluate the performance of the developed heuristic which corresponds to Step 8 of Research Approach. The evaluation process is carried out in two ways. First, an experimental study is conducted in order to investigate the performance of the heuristic. Randomly generated data for CM design problems will be employed. Solutions of CM design problems obtained from the heuristic are compared with those obtained from the optimal solution procedure presented in Section 3.1.2. Obtaining the optimal solution of a CMS design problem requires a substantial amount of time due to the complexity of the problem, therefore, the lower bound is used instead of the optimal solution. The lower bound is calculated by solving each period of the design problem independently and summing them up. Relocation costs are disregarded in obtaining the lower bound. Obviously, the lower bound is always lower or equal to the optimal solution.

Second, known solutions of CM design problems from literature are used to compare with those from the proposed solution technique. Some of these problems are larger, hence the comparison of the heuristic solutions to published results instead of optimal. Others are still small, but a comparison with published results still deems valuable. Design problems in Chen [19] and Wick [98] are employed for this purpose. This chapter describes the evaluation methodology in detail. Results are presented and discussed in Chapter 5.

4.1 Experimental Study

In the first part of the evaluation process, an experimental design is employed. It is specified in terms of:

1. The experimental design - type of design, design factors, number of replicates;

2. The set of values for each design factor; and
3. The set of values for parameters. (Parameters are variables that are not chosen to be design factors.)

4.1.1 Experimental Design

The purpose of this experimental design is to determine how the proposed heuristic performs under different circumstances. A partial 2^k factorial design is utilized in this experiment in order to maintain a reasonable number of experiments. The set of variables from which the design factors are to be selected are those affecting the cell configuration. They are summarized as follows:

1. **Part types:** The number of part types to be produced in the entire planning horizon. Each part type consists of a different operation sequence. A part type can have more than one route (routing flexibility).
2. **Machine types:** The number of machine types needed for manufacturing the given part types. A machine type can perform more than one operation.
3. **Operation sequence of a part type:** The order of machine types which the part type visits. This implies the number of operations of the part type.
4. **Alternate routes of a part type:** The number of routes the part type can be processed on.
5. **Production volume of a part type:** The units of the part type to be produced in each period.
6. **Processing time:** Time to perform a part type operation on a specific machine type (min).
7. **Machine capacity:** Available time on a machine type to process parts in a period (hr).
8. **Number of periods:** A number of intervals in a planning horizon.
9. **Number of cells:** The number of groups of machines which needs to be pre-specified.
10. **Lower/upper bounds:** The minimum/maximum number of machines in each cell.
11. **Batch size:** The quantity of part types to be transferred. It is constant for every part type.
12. **Scenarios per period:** A set of possible product mixes in the period.

13. **Associated scenario's probability:** The probability of occurrence of the product mix.
14. **Machine cost:** Cost of utilizing a unit of a machine type in any period.
15. **Intercell cost:** Cost of transferring a batch between cells in any period.
16. **Relocation cost:** Cost of moving a machine in and out of a cell.
17. **Operating cost:** Cost of a unit of a machine type to process parts per hour.

Although, a 2^k factorial design is desirable, it is unlikely that all variables can be considered in the experiment. This is due to the fact that designing a CMS is very time-consuming. Therefore, to keep the experiment manageable, four most important variables are chosen to be the design factors. These are part type, machine type, alternate routes per part type (routing flexibility of a part type), and machine cost. Therefore, 2^4 factorial design is used in this experiment and the values of design factors are set to small (low) and large (high).

In general, it is unlikely to have a small number of part types with a large number of machine types. Likewise, the combination of a large number of part types with a small number of machine types is not likely to occur. Information gathered by Chen and Cheng [20] also supports the claim. Therefore, the combination of a small number of part types with a large number of machine types and a large number of part types with a small number of machine types are not considered in this experiment. Therefore, the 2^4 factorial design is reduced to a 2^4 partial factorial design. Table 4.1 summarizes the 2^4 partial factorial design. Three replicates are run on each experiment. That is, the total of 24 CM design problems will be solved.

Table 4.1: 2^4 Partial Factorial Design Experiment

Experiment	Part Type	Machine Type	Alternate Route	Machine Cost
1	-	-	-	-
2	-	-	-	+
3	-	-	+	-
4	-	-	+	+
5	+	+	-	-
6	+	+	-	+
7	+	+	+	-
8	+	+	+	+

4.1.2 Values for Design Factors

The next step is to determine the values of the design factors and parameters in the experiment. This is carried out by surveying publications in the area of the design of CMSs. Table 4.2 and 4.3 summarize the values of design factors and parameters used in the literature.

Table 4.2: Surveyed Publications (1)

Pub. No.	No. of Opt.	Product Type	Machine Type	No. of Cells	LB/UB	Demand	Machine Capacity	Remark
[5]	2-4	24	14	-	-	500-1500*	-	*per year
[6]	2-6	19	12	4	-	476-7,700*	-	*per year
[16]	2-4	10	15	-	-	-	-	
[19]	2-3	12	7	3	-	-	-	
[20]	2-4	15	15	-	-	-	-	
[34]	1-3	14	7	2/3	-	-	8 hr.	
[36]	1-3	20	17	-	-	80-175	11200	-
[50]	3-6	15	9	-	4/4	1-4*	8 hr/day	*daily
[59]	2-4	20	20	-	-	2*	-	*unit not specified
[73]	2-3	10	6	2	1/4	600-1,800	-	
[79]	2-4	12	6	-	-	20K-25K	6,000	lot size 40-50
[83]	2-6	20	12	-	1/5	-	-	-
[98] (1)	3-7	30	19	3	4/	100-1,000	10K-14K	2 periods
[98] (2)	2-3	25	11	3	3/	100-1,000	15K-19K	3 periods
[98] (3)	1-3	22	7	3	2/	208-1,040	8,320	5 periods
[99]	2-5	5-15	15-20	4-5	-	N(700, 20)	2,000*	hr/yr

Note that [98] has three different design problems which have different values of design factors and parameters.

Since 2^4 factorial design is employed, the values of the design parameters are set to high (large) and low (small). Based upon the values used in the surveyed publications, the values for design factors and parameters are summarized as follows:

1. Small part types are generated from a discrete uniform distribution [8, 15], whereas large part types are generated from a discrete uniform distribution [15, 19].
2. Small machine types are generated from a discrete uniform distribution [5, 12]. Large part types are generated from discrete uniform distribution [13, 20].
3. Low flexibility of a part type is generated from a discrete uniform distribution [1, 2]. High flexibility of a part type is generated from a discrete uniform distribution [3, 4].
4. Small machine costs are generated from a discrete uniform distribution [\$1,000, \$2,000] and large machine costs are generated from a discrete uniform distribution [\$8,000, \$10,000].

Table 4.3: Surveyed Publications (2)

Pub. No.	Processing Time	Alternate Routes	Acuis. Cost	Opt Cost	Inter. Cost	Relocat. Cost	Remark
[5]	-	-	-	-	-	-	
[6]	10-420*	1.95	1.20-1.90	1.20-1.90	-	-	*Minutes/batch
[16]	-	-	-	-	-	-	
[19]	-	-	5-9	-	2-12	1, 4, 5	unit not specified
[20]	-	-	-	-	-	-	
[34]	0.50-4.74*	-	-	-	-	-	* in hr.
[36]	10-65	-	-	-	-	-	same time and cap.
[50]	0.1-0.87	-	-	-	-	-	
[59]	0.05-0.20*	2.55	-	-	-	-	*unit not specified
[73]	-	2	7K-12K	6-30*	-	-	* per part
[79]	1-5	-	23K-57K	-	-	-	-
[83]	-	1.3	-	-	-	-	-
[98] (1)	1-8	-	3K-9K	-	\$1/unit	1.5K-4.5K	-
[98] (2)	1-6	-	3K-9K	-	\$1/unit	5K-4.5K	-
[98] (3)	0.5-4.7	-	0.8K-3K	-	\$1/unit	0.6K-1.5K	-
[99]	0.2-0.8	-	-	N(50, 20)	-	-	-

4.1.3 Values for Parameters

The values of parameters are specified. To reduce the difficulty of the design of experiment, some parameters values are fixed to appropriate numbers as described below. The values in the surveyed publications are used as a guideline for determining the parameter values.

1. The number of operations is generated from a special distribution with the value between 2 and 6. There is a 30% chance for 2 and 3 operations, 20% chance for 4 operations, and 10% chance for 5 and 6 operations.
2. The number of periods in a planning horizon is generated from a discrete uniform distribution [2, 4].
3. Demand of each part type is generated from a discrete uniform distribution [500, 1,000] units.
4. Processing time is generated from a uniform distribution [0.1 min., 1.0 min.].
5. Machine capacity is fixed to 1,000 hours. It is assumed that machines operate 8 hours/day, 5 days/week for 25 weeks (6 months).
6. Intercell cost is generated from a discrete uniform distribution [\$20, \$50].
7. Relocation cost is generated from a uniform distribution $[\frac{1}{5}, \frac{3}{5}]$ of the machine cost.
8. A number of cells is fixed between 3-4, based upon the number of part types.
9. Lower and upper bounds (LB/UB) are set to 3 and 10, respectively.

10. Batch size is fixed to 40 units regardless of part types.
11. Scenarios per period and their associated probabilities are generated from a discrete uniform distribution [2, 3]. Each scenario has the same probability of occurrence.
12. Operating cost per hour on each machine is generated from a normal distribution with mean \$50/hour, standard deviation \$20, and minimum \$10.

Table 4.4 and 4.5 summarize the values for the design factors and parameters.

Table 4.4: Design Factors Values

Factor	Small	Large	Probability Distribution
Part types	$U(8, 14)$	$U(15, 20)$	Discrete uniform distribution
Machine types	$U(5, 12)$	$U(13, 18)$	Discrete uniform distribution
Alternate routes	$U(1, 2)$	$U(2, 4)$	Discrete uniform distribution
Machine cost	$U(\$1K, \$2K)$	$U(\$8K, \$10K)$	Discrete uniform distribution

Table 4.5: Parameter Values

Factor	Value	Remark
No. of operations	$T(2 - 6)$ /part type	Special distribution
Demand/period	$U(500, 1,000)$	Discrete uniform distribution
Processing time	$U(0.1, 1.0)$ min.	Discrete uniform distribution
Machine capacity	1,000 hr/period	Fixed
Intercell cost	$U(\$20, \$50)$ /batch	Discrete uniform distribution
Relocation cost	$U(\frac{1}{5}, \frac{3}{5})$ of machine cost	Discrete uniform distribution
Number of periods	$U(2, 4)$	Discrete uniform distribution
Number of cells	3-4	
LB/UB	2/10	
Batch size	40 units	Fixed
Scenarios/period	$U(2, 3)$	Discrete uniform distribution
Scenario's prob.	Equal	Each scenario has the same prob.
Operating cost	$N(\$50, \$20)$ /hr	Normal distribution

4.1.4 Generation and Use of Lower Bound

Due to the complexity of CM design problems, it takes a substantial amount of time to obtain optimal solutions. Therefore, the lower bound is used for the comparison instead.

The lower bound is obtained by solving the design problem in each period independently and summing up the costs over all periods. It does not consider the relocation costs between periods because the cell configuration in each period is designed independently. Therefore, the lower bound is always less than or equal to the optimal solution. The heuristic always takes relocation costs between periods into account. In general, when solving a CMS design problem, we would like solutions from the heuristic to be as close to those of the lower bound as possible. When the solutions of the heuristic are equal to those of the lower bound, the optimal solutions are found.

The use of the lower bound instead of the optimal solution can be misleading. This can be explained using Figure 4.1. Design Problem A has a bigger difference between the lower bound and the heuristic solution than Design Problem B. If the lower bound is used for the comparison instead of the optimal solution, it can be concluded that the heuristic performs better for Design Problem B. However, according to the picture, the heuristic solution of Design Problem A is actually closer to the optimal solution than Design Problem B. Therefore, the heuristic performs better for Design Problem A. This cannot be found by comparing to the lower bound.

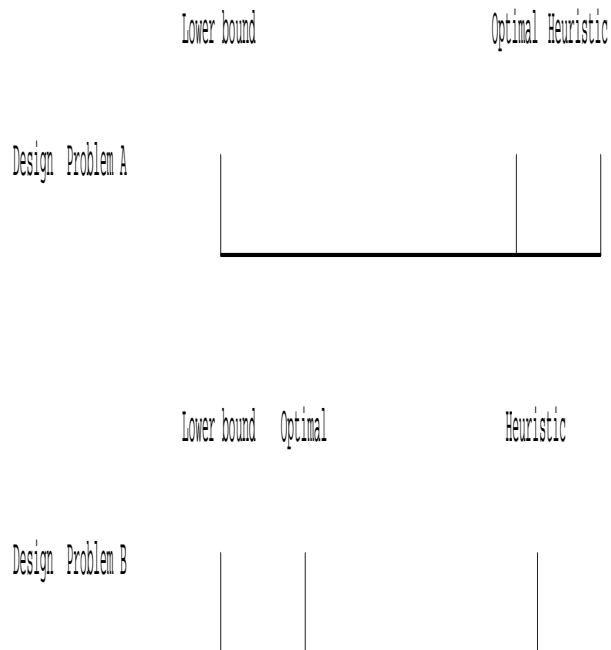


Figure 4.1: Lower Bound versus Optimal

4.1.5 Example Data

Since a large amount of data is involved in the experiment, only data for Replicate 1 of Experiment 1 is demonstrated below. The rest of the data is available in Appendix A.3. Design Problem 1 consists of 10 part types and 11 machine types. The number of cells to be used is three and the planning period is two. In each period, two possible product mixes are given with equal probabilities. Table 4.6 - Table 4.9 summarized the data sets for Replicate 1 of Experiment 1.

Table 4.6: Replicate 1 of Experiment 1

Variable	Value
Part types	10
Machine types	11
Number of period	2
Number of cells	3
Lower and Upper bounds	3/10
Scenario/period	2

Table 4.7: Part Type Attributes

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	6	3-11-9-8-5-2	0.83-0.77-0.48-0.42-0.78-0.23	1
2	4	1-9-7/8-4	0.13-0.40-0.78/0.45-0.87	2
3	4	3-11-9-7	0.22-0.86-0.75-0.22	1
4	3	5-2-1	0.76-0.26-0.14	1
5	3	9-8-5	0.72-0.88-0.88	1
6	3	2-11-8	0.30-0.72-0.16	1
7	3	7-4-2	0.41-0.63-0.60	1
8	2	10-9/5	0.95-0.43/0.66	2
9	2	6/2-4	0.70/0.54-0.48	2
10	2	3-11	0.52-0.95	1

Table 4.8: Part Type Demand

Part Type Number	Demand			
	Period 1		Period 2	
	Scenario 1	Scenario 2	Scenario 1	Scenario 2
1	800	0	0	700
2	800	700	0	600
3	800	600	1,000	0
4	0	800	500	0
5	1,000	900	500	700
6	0	1,000	500	800
7	500	1,000	800	900
8	0	500	0	800
9	600	0	900	800
10	700	0	1,000	0

Table 4.9: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	1,500	300	71
2	1,500	300	95
3	1,200	240	59
4	1,200	240	43
5	1,400	280	50
6	1,500	300	52
7	1,100	220	34
8	1,100	220	86
9	1,300	260	50
10	1,400	280	50
11	1,200	240	85

4.2 Comparative Study

Only a few publications have addressed the multi-period design of CMSs. Two publications on multi-period CM design problems by Chen [19] and Wick [98] are used in the second part of the evaluation process. Neither consider routing flexibility nor uncertainty in production requirements.

4.2.1 Chen's Heuristic/Design Problem

The CM design problem in [19] consists of 12 part types, 7 machines, 3 cells and 3 periods. He considered three values of relocation cost which are 1, 4 and 5. Table 4.10-Table 4.12 show the part operation requirement and machine cost from period 1 to period 3, respectively. Table 4.13 displays the material handling costs.

Table 4.10: Part Operation Requirement and Machine Cost in Period 1

Machine Number	Machine Cost	Part									
		1	2	3	4	5	6	7	8	9	10
1	6	2					2				3
2	9	1	1			2			2		
3	8		2	2		1			1		2
4	6			3	2			2		2	
5	5						1				
6	7			1							3
7	9				1			1		1	

Table 4.11: Part Operation Requirement and Machine Cost in Period 2

Machine Number	Machine Cost	Part										
		1	2	3	4	5	6	7	8	9	10	11
1	6	2					2				1	
2	9	1	1			2			2			1
3	8		2	2		1			1		2	
4	6			3	2			2		2		
5	5						1					2
6	7			1							3	
7	9				1			1		1		3

Table 4.12: Part Operation Requirement and Machine Cost in Period 3

Machine Number	Machine Cost	Part											
		1	2	3	4	5	6	7	8	9	10	11	12
1	6		1			1					1		1
2	9			2					2			1	
3	8	2					2		1		2		
4	6	1		3			1	2		2			
5	5			1								2	2
6	7		2		1						3		3
7	9				2	2		1		1		3	

Table 4.13: Material Handling Costs

Time Period	Part											
	1	2	3	4	5	6	7	8	9	10	11	12
1	3	5	4	7	2	9	3	5	6	2	-	-
2	3	5	4	7	2	9	3	5	6	2	12	-
3	6	9	4	7	3	5	8	2	6	2	10	12

4.2.2 Wick's Heuristic/Design Problem

Three multi-period CM design problems are considered in Wick [98]. The first design problem consists of 30 part types to be processed on a set of 19 machine types in two planning periods. Part types and machine types are grouped into three cells. Table 4.14 shows the processing time to perform operations of parts. Table 4.15 show the operations sequence of each part type and the demand for both periods. Table 4.16 shows the machine investment and relocation costs of each machine as well as the capacity of each machine.

Table 4.14: Part-Machine Incidence Matrix with Processing Times for Design Problem 1

Part Type	Machine																		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1																			
2		1						5				2					1		
3									8			5					6		
4								4	6			4			7				
5				5												7			
6	8	3	2		4										4		1	4	6
7					1			8				3							1
8							7			8	8		4	6			7	1	
9		5	4				4							8	3		8		
10		8			7					5									
11						3										6		4	
12						3			3	1					8				1
13			4					2		8					1				
14	5		5			2				6	2	6			4				
15		8			6	2		7						2		1		2	
16					1	6				1		4							
17				5		6			8								4		
18						4			8										
19				8			3		4		6	2		4	3				4
20		3						1				2							
21					7			7	7			7							
22				6	7		7	4	1			8							5
23	7		8			6								6					
24		5		4	2	6	8	8								8			
25						6							8	5				5	
26							2		8			2	6						
27		4		2										7					
28		1								2							5	2	
29	6						8								3				
30	2		7					7			6	2							

Table 4.15: Part Data for Design Problem 1

Part Type	M/H Cost per Unit	Operation Sequence	Demand	
			Period 1	Period 2
1	1	8-12-17	100	200
2	1	12-11-17-9	400	800
3	1	15-2-12	0	500
4	1	16-8-9	600	400
5	1	18-16-19-4	0	900
6	1	17-5-1-3-2	0	700
7	1	19-5-12-8	0	400
8	1	10-7-14-17-11-18-13	800	300
9	1	7-3-2-15-14-17	800	500
10	1	5-10-2	900	200
11	1	18-16-6	300	300
12	1	3-10-9-19-6-15	900	800
13	1	10-15-8-2	1000	200
14	1	10-3-15-12-6-11-1	0	700
15	1	5-8-16-14-18-2-6	600	400
16	1	6-12-10-5-3	500	300
17	1	4-9-6-17	400	800
18	1	6-9-15	0	200
19	1	19-4-9-7-14-11-12	400	800
20	1	2-12-8	800	300
21	1	9-12-4-5-8-3	400	700
22	1	9-7-4-8-5-12-19	1000	600
23	1	6-3-1-14	900	900
24	1	6-16-5-2-7-8-4	800	100
25	1	18-14-13-6	700	800
26	1	16-7-9-13-17-12	600	800
27	1	4-14-2	800	500
28	1	10-17-18-2	400	1000
29	1	7-1-15	200	500
30	1	8-12-11-1-3	100	100

Table 4.16: Resource Data for Design Problem 1

Machine Type	Investment Cost	Relocation Cost	Capacity
1	6,000	3,000	10,000
2	8,000	4,000	12,000
3	3,000	1,500	10,000
4	4,000	2,000	14,000
5	9,000	4,500	12,000
6	9,000	4,500	14,000
7	7,000	3,500	12,000
8	6,000	3,000	14,000
9	4,000	2,000	10,000
10	3,000	4,000	12,000
11	9,000	4,500	12,000
12	6,000	3,000	10,000
13	3,000	1,500	13,000
14	7,000	4,500	12,000
15	8,000	4,000	14,000
16	8,000	4,000	12,000
17	7,000	3,500	10,000
18	3,000	1,500	12,000
19	9,000	4,500	13,000

The second design problem consists of 11 machines types used to produce 25 parts in 3 cells. Three planning periods are used. Table 4.17 shows the processing times of part types on machine types. Table 4.18 displays the operations sequences of the part types and the demand of each part type in each period. Table 4.19 shows the machine investment and relocation costs of each machine as well as the capacity of each machine.

Table 4.17: Part-Machine Incidence Matrix with Processing Times for Design Problem 2

Part Type	Machine										
	1	2	3	4	5	6	7	8	9	10	11
1	5								2	1	
2					6			4			
3	1	3									4
4			1			6				1	
5		3			1				4		
6					4			6		5	
7					6	3				2	
8				4					6		1
9						2				6	3
10			2								4
11	3		6	4							
12							3		1		
13	4		6		2						
14							1	3		3	
15			3	1					2		
16				3						6	
17					3	6					
18	2					3				3	
19			4		3	1			4		
20				6							
21							2	1			5
22		3								5	2
23						6			1	3	
24		4					2				
25		5				2	6				

Table 4.18: Part Data for Design Problem 2

Part Type	M/H Cost per Unit	Operation Sequence	Demand		
			Period 1	Period 2	Period 3
1	5	10-1-9	300	200	500
2	5	5-8	700	600	500
3	5	1-2-11	0	600	400
4	5	3-10-6	0	700	800
5	5	2-5-9	800	600	1000
6	5	5-10-8	600	300	0
7	5	6-5-10	0	900	800
8	5	4-9-11	400	800	200
9	5	6-10-11	300	200	600
10	5	3-11	400	1000	500
11	5	3-1-4	0	0	200
12	5	7-9	700	700	1000
13	5	3-1-5	100	600	800
14	5	7-8-10	100	200	0
15	5	3-9-4	0	0	300
16	5	4-10	500	800	500
17	5	6-5	100	900	400
18	5	1-6-10	1000	1000	400
19	5	3-6-5	0	700	1000
20	5	11-9-4	800	300	500
21	5	8-7	500	400	1000
22	5	10-2-11	0	100	100
23	5	9-6-10	400	500	800
24	5	7-2	0	0	500
25	5	2-7-6	0	0	400

Table 4.19: Resource Data for Design Problem 2

Machine Type	Investment Cost	Relocation Cost	Capacity
1	4,000	2,000	15,000
2	7,000	3,500	18,000
3	5,000	2,500	18,000
4	9,000	4,500	19,000
5	5,000	2,500	15,000
6	3,000	1,500	17,000
7	9,000	4,500	17,000
8	7,000	3,500	19,000
9	5,000	2,500	18,000
10	8,000	4,000	15,000
11	3,000	1,500	19,000

The third design problem consists of 25 part types which are produced by 7 machine types in 3 cells. The planning period is three for the third problem. Table 4.20 shows the processing times of part types on machine types. Table 4.21 displays the operations sequences of the part types and the demand of each part type in each period. Table 4.22 shows the machine investment and relocation costs of each machine as well as the capacity of each machine.

Table 4.20: Part-Machine Incidence Matrix for Design Problem 3

Part Type	Machine						
	1	2	3	4	5	6	7
1		0.5				0.5	0.6
2	0.7				1.2		
3				3.1			
4		0.6					4.7
5	2.4	0.9					3.6
6		2.1				4.6	1.5
7		1.4		1.4			
8	2.4				4.4	2.3	
9	2.5			1.0			3.9
10			2.5				4.7
11			3.0	0.6			
12			0.7	1.0			
13			1.6				
14	2.7				3.8		
15	1.4		2.8	1.8			
16				1.6			
17		3.1			1.0	2.5	
18	2.5			3.6			
19	2.6		4.1	2.7			
20		2.5			2.6		
21			3.2				
22	1.9			0.6	1.8		

Table 4.21: Part Data for Design Problem 3

Part Type	M/H Cost per Unit	Operation Sequence	Demand				
			Period 1	Period 2	Period 3	Period 4	Period 5
1	1	2-6-7	1,040	347	0	0	0
2	1	1-5	1,040	1,388	1,388	833	278
3	1	4	1,040	1,040	624	208	0
4	1	2-7	1,040	1,388	1,388	833	278
5	1	1-2-7	1,040	1,010	624	208	0
6	1	2-6-7	1,040	347	0	0	0
7	1	2-4	1,040	1,560	2,080	2,080	1,248
8	1	1-5-6	1,040	347	0	0	0
9	1	1-4-7	1,040	1,388	1,388	833	278
10	1	3-7	1,040	1,388	1,388	833	278
11	1	3-4	1,040	1,560	2,080	2,080	1,248
12	1	3-4	1,040	347	0	0	0
13	1	3	1,040	624	208	0	0
14	1	1-5	1,040	347	0	0	0
15	1	3-1-4	0	0	879	1,319	1,759
16	1	4	0	0	983	1,475	1,966
17	1	2-6-5	0	0	1,023	1,535	2,046
18	1	1-4	0	0	913	1,370	1,826
19	1	3-1-4	0	0	963	1,446	1,926
20	1	2-5	0	0	0	958	1,437
21	1	3	0	0	0	0	1,035
22	1	4-5-1	0	0	0	0	873

Table 4.22: Resource Data for Design Problem 3

Machine Type	Investment Cost	Relocation Cost	Capacity
1	1,200	600	8,320
2	3,000	1,500	8,320
3	2,500	1,250	8,320
4	800	400	8,320
5	3,000	1,500	8,320
6	1,000	500	8,320
7	3,000	1,500	8,320

Chapter 5

Results and Discussion

Results from the experimental study and comparative study are shown in this chapter. Section 5.1 displays the results from the experimental study. The discussion of the experimental results is presented in Section 5.2. Section 5.3 illustrates the results of the comparative study. Finally, the discussion of the comparative study is presented in Section 5.4.

5.1 Results of Experimental Study

The purpose of the experimental study is to determine how the proposed heuristic performs under various circumstances. The focus of the experimental design is to investigate which combinations of factors give the best and worst performances so that they can be used for designing a CMS. The results for all replicates are summarized in Table 5.1. Solution costs obtained from the heuristic are compared with those obtained from the lower bound. The results show that the heuristic performed well for most of the various circumstances. The solution costs from the heuristic are close to those from the lower bound. The differences between solution costs of the lower bounds and the heuristic are within 18%, except one replicate (Replicate 1 of Experiment 7) which exceeds 20%. A further investigation shows that this design problem has high relocation costs. Thus, the percent difference is high. Note that the lower bound does not take relocation costs in account. Overall, the percent difference is approximately 9.33% with standard deviation of 5.18. Table 5.2 shows the average differences of solution costs and standard deviation of each experiment.

Table 5.1: Experimental Design Results

Exp. No.	Rep. No.	# of Part Type	# of MC Type	Alternate Routes	Machine Cost	Lower Bound	Heuristic	% Diff.
1	1	10	11	-	-	\$61,261	\$63,770	4.10%
	2	11	8	-	-	98,926	103,795	4.92%
	3	10	9	-	-	59,214	64,663	9.20%
2	1	13	10	-	+	262,289	277,539	5.81%
	2	13	12	-	+	333,870	342,037	2.45%
	3	10	8	-	+	335,422	345,124	2.89%
3	1	13	11	+	-	78,766	88,563	12.44%
	2	12	11	+	-	172,292	191,675	11.25%
	3	11	10	+	-	91,465	106,995	16.97%
4	1	9	8	+	+	354,730	390,188	10.00%
	2	8	9	+	+	380,543	431,653	13.43%
	3	10	11	+	+	338,418	396,102	17.04%
5	1	16	14	-	-	126,297	133,555	5.75%
	2	19	13	-	-	88,068	94,955	7.82%
	3	19	18	-	-	185,979	195,677	5.21%
6	1	17	18	-	+	306,716	370,584	2.73%
	2	20	18	-	+	664,610	693,253	4.31%
	3	19	17	-	+	394,007	420,206	6.65%
7	1	20	14	+	-	119,877	145,450	21.33%
	2	16	14	+	-	124,733	136,699	9.60%
	3	15	15	+	-	81,519	90,571	11.04%
8	1	18	16	+	+	379,822	419,641	10.50%
	2	17	18	+	+	369,719	430,249	16.37%
	3	18	18	+	+	405,481	441,456	8.87%

Table 5.2: Analysis of 2^4 Partial Factorial Design Experiment

Exp. No.	No. of Part Type	No of MC Type	Alternate Route	Machine Cost	Average % Diff.	Std.
1	-	-	-	-	6.07	2.74
2	-	-	-	+	3.72	1.83
3	-	-	+	-	13.55	3.02
4	-	-	+	+	13.43	3.50
5	+	+	-	-	6.26	1.38
6	+	+	-	+	4.56	1.97
7	+	+	+	-	14.00	6.40
8	+	+	+	+	11.91	3.90

Table 5.5: Solution of Period 1 from Proposed Heuristic

Cell, c	M/C Type (Quantity), N_{mch}	Part type									
		1	2	4	5	6	7	9	3	8	10
1	1 (1)		1	1							
	3 (1)	1						*		*	
	4 (1)		1								
	5 (1)	1		1	1						
	8 (1)	1	1		1						
	9 (1)	1	1		1						
2	2 (1)	*		*		1	1	1			
	4 (1)						1	1			
	7 (1)						1		*		
	8 (1)					1					
	11 (1)					1					
3	9 (1)								1	1	
	10 (1)									1	
	11 (1)	*							1	1	

Table 5.6: Lower Bound in Period 2

Cell, c	M/C Type (Quantity), N_{mch}	Part type									
		7	9	3	10	1	2	4	5	6	8
1	2 (1)	1	1								
	4 (1)	1	1								
	7 (1)	1		*							
2	3 (1)			1	1	*					
	9 (1)			1							
	11 (1)			1	1						
3	1 (1)						1	1			
	2 (1)					1		1		1	
	4 (1)						1				
	5 (1)					1		1	1		
	8 (1)					1	1		1	1	
	9 (1)					1	1		1	1	
	10 (1)									1	
11 (1)					1			1			

5.2 Discussion of Experimental Results

The results from the experimental design show that the proposed heuristic performs well under different circumstances for designing CMSs under dynamic and uncertain production requirements. Solutions obtained from the proposed heuristic are between 1.00% and 18% of the lower bounds. There is only one design problem which the solution from the heuristic is 21% higher than that of the lower bound. On average, the percent difference is 9.33% with standard deviation of 5.18. These numbers are likely to be smaller, when solutions obtained from heuristic can be compared with those from optimal solutions.

The focus of the experimental design is to investigate which combinations of factors give the best and worst performance so that they can be used as a guideline for designing a CMS. The direct study of the effects of the four design factors is not permitted because the 2_4 partial design is utilized. The following observations are made according to the experimental results shown in Table 5.1 and 5.2, and the computational experience.

1. According to Table 5.2, the heuristic performs best when the number of part types, the number of machine types and the routing flexibility are low, and the machine costs are high. This corresponds to Experiment 2. The average percent difference is 3.73% with standard deviation of 1.83. Experiments 1, 5 and 6 also perform relatively well with the average percent differences under 6.5%. It could be concluded that the heuristic performs well when the routing flexibility is low.
2. The worst performance of the heuristic is found at Experiment 7 where the number of part types, the number of machine types and the routing flexibility are high, and the machine costs are low. The average percent difference is 14% with standard deviation of 6.40. The heuristic also performs badly in Experiments 3, 4 and 8. It is likely that the heuristic does not perform well when the routing flexibility is high. A detailed discussion is presented next.
3. The average percent difference is high for Experiments 3, 4, 7, and 8. The common design factor in those experiments is alternate routes. The alternate routes per part seems to have a major effect on the performance of the heuristic. When the alternate routes per parts are low (1-2 alternate routes per part), the average percent difference is 5.4% with standard deviation of 2.3. When the alternate routes per part are high (3-4 alternate routes per part), the average percent difference is 13.23% with standard deviation of 3.85. A further investigation was made and discussed in Section 5.2.1. In addition, the computational time required increases exponentially as the alternate routes per part type increases. This is because the number of possible grouping machine types and assigning part types increase.
4. The average percent differences in Experiments 2, 4, 6 and 8 are slightly less than those in Experiments 1, 3, 5 and 7. The machine costs may have a little impact on the

performance of the heuristic. The average percent difference is 9.97% with standard deviation of 5.16, when the machine costs are low. When the machine costs are high, the average percent difference is 8.65% with standard deviation of 5.11. The reason might be because of the formula used to calculate the average percent difference which is $(\text{heuristic} - \text{lower bound}) / \text{lower bound}$. With the high machine cost, the denominators are high, thus giving lower percent differences.

5. In the experiments, the levels of the number of part types and the number of machine types are set to be the same, low and low, or high and high. When both are set to be low, the problem size is defined as small. When both are high, the problem size is defined as big. According to the experiment, the average percent difference of the first four experiments is 9.45% with the standard deviation of 5.08. The average percent difference of the last four experiments is 9.18% with standard deviation of 5.27. The effect of the problem size seems irrelevant to the performance of the heuristic. With large problem size, obtaining solutions with the optimal procedure requires a significant amount of time. The time required grows at the exponential rate with the size of the problem.
6. Although, the relocation cost was not chosen as a design factor, it substantially affects the difference between the lower bounds and the heuristic. Intuitively, the differences tend to get bigger as the relocation cost increases because the lower bound does not consider the relocation cost. Machines are unlikely to be relocated between periods when the relocation costs are high.
7. According to the computational experience with the experimental design, the computation time increases as the number of machines increases. The number of possible distinct partitions of machines into cells increases exponentially as the number of machines increase. This corresponds to the claim given by Venugopal and Narendran [95] in Section 3.1.1. Furthermore, the number of machines required in each CMS design problem depends upon the following parameters: machine capacities, production volume of part types, and processing times. When the machine capacities are high, the number of machines required decreases. As the production volumes of part types increase, the number of machines required increases. Likewise, when processing times are high, the number of machines required are also high.
8. Other variables which affect the computational time include the number of operations per part type, operation sequence of each part type, and number of cells. These parameters cause CMS design to be more complex, thus require substantial amount of time to solve CMS design problems. When the number of operations is large, say 5 or 6, it is more complicated to create independent cells because of the number of operations to be considered. This usually causes the material movements between cells to be high. If operation sequences of part types are similar, independent cells are likely to be created. However, if they are not, the material movements between cells will increase. When the number of cells increases, it is obvious that alternatives to assign

machine types and part types increase. Thus, it causes the CMS design to be more complex.

5.2.1 Impact of Routing Flexibility

In general, routing flexibility provides benefits in designing CMSs as shown in Section 3.2.2. According to the experiments, they showed that the heuristic does not take advantage of the routing flexibility. Therefore, the differences of solutions of the lower bound and those of the heuristic are substantial. The average difference is 13%. This can be explained as follows. A route of a part type is selected at the design time when a CM design problem is solved using the optimization technique in Section 3.1.2. The selected route for each part type is optimal since all four costs are considered when the decision is made. However, a route of the part type is selected in advance in the design process in Phase 2 of the heuristic approach. Only two costs, machine and operating costs, are used in the process, therefore, the optimal route for each part type is unlikely to be found.

A further investigation was made in order to analyze why the heuristic does not perform well when routing flexibility is high. This is done by removing the routing flexibility when comparing solutions from the heuristic and lower bound. That is, the same route will be used for each part type. The optimal route of each part type obtained from the lower bound is used in Phase 3 to Phase 6 of the heuristic. Four design problems were selected from the experimental design problems. Replicate 3 of Experiment 3, Replicate 3 of Experiment 4, Replicate 1 of Experiment 7 and Replicate 2 of Experiment 8 were chosen because they have the largest differences between the lower bound and heuristic of their experiments. Table 5.8 shows the results when the optimal routes were employed in the heuristic.

Table 5.8: Use of Optimal Routes

Experiment Number	Replicate Number	Previous % Diff.	New % Diff.	% Improvement
3	3	16.03%	7.70%	8.33%
4	3	17.04%	13.36%	3.68%
7	1	21.33%	18.59%	2.74%
8	2	16.37%	13.34%	3.03%

On average, 4% improvement is gained through the use of the optimal routes in the heuristic. Slight improvements were gained for most design problems, except Replicate 3 of Experiment 3. The heuristic still performs about the same as before for Experiments 4, 7, and 8, i.e. 10-20%. So, the reduced performance for Experiments 4, 7, and 8 is not due to the selection of routes (Phase 2 of the heuristic). The heuristic just does not appear to perform as well these particular factor combinations. Further work is needed to tackle this issue.

5.3 Results of Comparative Study

The results from the comparative study are shown in the following sections.

5.3.1 Chen's Heuristic/Design Problem

The CM design problem in [19] consists of 12 part types, 7 machines and 3 cells in 3 planning periods. He considered three values of relocation cost which are 1, 4 and 5. Table 5.9 summarizes the comparison between the approach in [19] and the proposed heuristic. The method proposed by Chen is not capable to consider production requirements such as production volume required, machine capability and routing flexibility.

Table 5.9: Comparison with Chen's Heuristic

Relocation Cost	Chen's Heuristic	Proposed Heuristic	Improvement
1	\$225	\$217	8 (3.6%)
4	248	238	10(4.0%)
5	252	245	7 (2.8%)

5.3.2 Wick's Heuristic/Design Problem

Three design problems from Wick were used for the comparative study. Table 5.10 summarizes the comparison of three design problems between Wick's heuristic and the proposed heuristic.

Table 5.10: Comparison of Design Problems with Wick's Heuristic

Design Problem	Wick's Heuristic	Proposed Heuristic	Improvement
1	\$49,470	\$28,300	\$21,170 (40.00%)
2	54,500	54,000	500 (1.00%)
3	18,906	12,600	6,305(33.35%)

The first design problem consists of 30 part types processed on a set of 19 machine types in two planning periods. The comparison of the results between the proposed heuristic and the procedure from [98] is shown in Table 5.11. The comparison shows that the proposed heuristic outperforms the design method in [98]. An improvement of \$21,170 (40%) is obtained.

Table 5.11: Comparison with Wick's Heuristic, Design Problem 1

Cost Types	Time Period	Wick's Heuristic	Proposed Heuristic
M/C Invest. Cost	Period 1	\$15,000	\$0
	Period 2	12,000	18,000
M/H Cost	Period 1	7,300	6,700
	Period 2	9,400	4,600
Relocation Cost	Period 1	0	0
	Period 2	6,000	0
Total Cost	Period 1	22,300	6,700
	Period 2	27,400	22,600
	All Periods	49,470	28,300

The second design problem consists of 11 machines types used to produce 25 parts. The planning horizon is three periods. The results from the proposed heuristic and from [98] are shown in Table 5.12. An improvement of \$500 (1.0%) is obtained from the proposed heuristic.

Table 5.12: Comparison with Wick's Heuristic, Design Problem 2

Cost Types	Time Period	Wick's Heuristic	Proposed Heuristic
Machine Investment Cost	Period 1	\$29,000	\$11,000
	Period 2	18,000	24,000
	Period 3	0	0
M/H Cost	Period 1	4,500	8,000
	Period 2	2,500	4,000
	Period 3	500	7,000
Machine Relocation Cost	Period 1	0	0
	Period 2	0	0
	Period 3	0	0
Total Cost	Period 1	33,500	19,000
	Period 2	20,500	28,000
	Period 3	500	7,000
	All Period	54,500	54,000

The third design problem consists of 25 part types which are produced by 7 machine types. The comparison of the results are shown in Table 5.13 and \$6,306 (33.35%) improvement can be obtained from the proposed heuristic.

Due to the limited availability of publications in this area, only a few design problems can be compared. However, the results show a significant improvement over the existing CM design method.

Table 5.13: Comparison with Wick's Heuristic Design Problem 3

Cost Types	Time Period	Wick's Heuristic	Proposed Heuristic
Machine Investment Cost (\$)	Period 1	\$2,200	\$1,800
	Period 2	5,000	2,500
	Period 3	4,600	4,200
	Period 4	800	800
	Period 5	800	3,300
M/H Cost (\$)	Period 1	0	0
	Period 2	0	0
	Period 3	0	0
	Period 4	0	0
	Period 5	556	0
Machine Relocation Cost (\$)	Period 1	0	0
	Period 2	0	0
	Period 3	1,100	0
	Period 4	600	0
	Period 5	3,250	0
Total Cost (\$)	Period 1	2,200	1800
	Period 2	5,000	2,500
	Period 3	5,700	4,200
	Period 4	1,400	800
	Period 5	4,606	3,300
	All Period	18,906	12,600

5.4 Discussion of Comparative Results

The results from the comparative study show that the heuristic outperforms existing multi-period CM design methods. In addition, none of the existing methods considers the uncertainty in the production requirements. A significant improvement is also found over the existing CM design method. An improvement of 2%-4% is found in Chen's design problems. Chen used dynamic programming in finding solutions, however, this technique may not be practical for larger problems due to the computational time required. A mixed improvement is found in Wick's design problems. An improvement of 1%-40% is achieved.

Chen's design problem consists of 12 part types, 7 machine types and 3 planning periods. The operation number of each part type is between 2 and 3, mostly 2. It also has a high similarity in part types. That is, part types need to be processed on similar machine types. Three part types require the same machine types and sequence. The other three part types also have the same machine types and sequence. Other factors such as machine capacity and processing times are not considered. Since the design problem is small, has high similarity between part

types, and does not take other production parameters into account, both heuristics perform well. Thus, solutions from both Chen's heuristic and the proposed heuristic are close.

The developed heuristic outperformed Wick's heuristic significantly in design problems 1 and 3. However, only a slight improvement was gained in design problem 2. This is due to the high material handling cost in design problem 2. The material handling cost in design problem 2 was set to \$5/unit, whereas it was only \$1/unit in design problems 1 and 3.

Chapter 6

Conclusions and Future Research

6.1 Conclusions

Research in design of cellular manufacturing systems has been conducted extensively, however, only a few publications have addressed dynamic and uncertain production requirements. Another aspect which is rarely addressed when designing cellular manufacturing is routing flexibility inherent in a system, even though it is available through the use of flexible machines.

The primary goal of this research was to develop a design methodology which addresses dynamic and uncertain production requirements with the presence of routing flexibility. In this research, a mathematical model was first developed. It considers dynamic, deterministic production requirements and routing flexibility. Potential benefits of the model through the use of system-dependent reconfiguration and routing flexibility were illustrated. Uncertainty later was incorporated into the model and an approach to handle the uncertainty was presented. However, the developed model is not suitable for realistic design problems due to the computational time required for large problems.

This led to the development of a heuristic which can handle large CM design problems in a reasonable amount of time. Simulated annealing was employed as a part of the heuristic to obtain design solutions. The heuristic consists of six phases as follows:

1. Determine the weighted-average production requirements.
2. Select a route for each part type.
3. Generate an initial cell configuration or assign part types to existing cell configurations.
4. Improve the cell configuration via simulated annealing.
5. Eliminate excessive machines to reduce the total cost.

6. Determine machine relocations between periods.

The heuristic was evaluated via an experimental study and comparative study with two existing heuristics. The experimental study was designed to investigate four design factors, namely, number of part types, number of machine types, alternate routes per part, and machine costs. Solutions from the heuristic were compared with those from the lower bound, not the optimal approach. This is because the computational times require to obtain optimal solutions are prohibitive. Overall, the heuristic performed well under different circumstances. The results from the experimental study can be summarized as follows.

1. The heuristic performs best when the number of part types, the number of machine types and routing flexibility are low, and machine costs are high.
2. The heuristic performs worst when the number of part types, the number of machine types and routing flexibility are high, and machine costs are low.
3. The average percent difference between the lower bound and the heuristic is approximately 9.33% with standard deviation of 5.18. This number would improve if the solutions from the heuristic were compared to those of the optimal procedure.
4. The percent differences of most design problems are under 18%, except for one design problem in which the percent difference is over 21%. However, this is because this design problem has high relocation costs, 0.6 of the machine costs. Note that the lower bound does not take the relocation costs into account.
5. Routing flexibility has a major impact on the performance of the heuristic. When the routing flexibility is high, the average percent difference is 13.23 with standard deviation of 3.85. In contrast, when the routing flexibility is low, the average percent difference is 5.40 with standard deviation of 2.30.
6. The heuristic does not appear to perform well in certain cases where routing flexibility is high. Further investigation showed that even when optimal routes were used, performance of the heuristic was reduced in some cases. Further work is needed to tackle this issue.
7. The problem size does not seem to affect the performance of the heuristic.
8. The computational time required depends upon the number of operations per part type, operation sequence of each part type, number of cells, and number of machines to be assigned to cells.

It must be stressed that the above conclusions from the experimental study are based on limited experimental work. Few replicates were employed for each design problem. Few

design problems are used. Therefore, more experimental work is needed in order to establish greater confidence, as will be described in Section 6.3.

Two existing heuristics by Chen and Wick were used for a comparison purpose with the proposed heuristic. The results show that the proposed heuristic outperforms both heuristics. The proposed heuristic slightly outperforms Chen's heuristic. This is because Chen's design problem is small, has high part similarity and does not consider many production parameters. This allows Chen's heuristic and the proposed heuristic to perform well. Therefore, the results from both heuristics are close. The heuristic performed well with Wick's Design problems 1 and 3. However, only a slight improvement was found in Design problem 2. This is because the material handling cost for Design problem 2 is higher than that of the other two design problems. If the material handling cost of Design problem 2 were set to be the same as Design problems 1 and 3, an improvement of 20% would be gained.

6.2 Contributions

The contributions of this research can be summarized as follows.

1. A mathematical model for dynamic and deterministic production requirements was developed.
2. A method for considering multiple production scenarios in an optimal manner was developed.
3. Quantitative evidence of the advantages of system-dependent reconfiguration and routing flexibility was shown.
4. A new methodology for tackling dynamic and uncertain production requirements in designing CMSs was developed.
5. A new heuristic for solving cellular manufacturing design problems in a reasonable amount of time was developed.
6. Experiments were conducted to analyze the performance of the heuristic. The heuristic performed well in all cases, and better in some cases than others. Based upon the experiments, a guideline for using the heuristic was given.

6.3 Future Research

From the experimental study, it shows that alternate routes per part has a major impact in the CM design process. Better solutions are more likely to be obtained, if a route of a

part type is selected at the design time, not in advance. Therefore, a new heuristic should be able to accommodate such a feature. For such requirement, a genetic algorithm may be a good tool for designing CM due to the problem structure and the GA's capabilities.

The experimental study employed to evaluate the performance of the heuristic was specified in terms of:

1. The experimental design - type of design, design factors, number of replicates,
2. The set of values of each design factor, and
3. The set of values for parameters.

Although several beneficial conclusions and observations were made according to the experimental study, the experiment study can be improved as follows:

1. A 3^k factorial design can be used instead of the 2^k factorial design. This allows designers to try different levels of design factors.
2. Different design factors can be investigated to observe their impact to the performance of the heuristic.
3. The number of replicates can be increased in order to gain better confidence. For instance, five replicates are utilized instead of three replicates.
4. Different sets of values for design factors and parameters can be tested.
5. Additional design parameters can added to the experimental study.

The above suggestions to improve the experiment, however, will require substantial efforts. Suggestions from industry experts could be valuable to aid how the experiment should be set up. For example, some insights may be gained such as what type of experiment should be used and what design factors and their levels should be. This research was developed based upon CM literature. However, industry data (cases) should be used investigate the performance of the heuristic. In addition, it could lead to modify the developed model to make the model more valid.

The heuristic does not consider all the requirements of the entire planning horizon simultaneously when designing a CMS. However, considering all the requirements at the same time requires a substantial amount of resources (e.g., time and memory). This could lead to a development of interaction solver between CPLEX and a heuristic algorithm. For instance, one can use the heuristic to find a good initial solution for CPLEX. This can reduce a substantial amount of time required to solve a CM design problem.

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Appendix A

Problem Data Sets

The followings are problem data sets used to assess the potential benefits of system-dependent reconfiguration and routing flexibility. Appendix A.1 consists of problem data sets for the evaluation of benefits obtained through the consideration of system-dependent reconfiguration in Section 3.2.1. Problem data sets for the evaluation of routing flexibility in Section 3.2.2 are in Appendix A.2.

A.1 Data for the Evaluation of the Potential Benefits of System-Dependent Reconfiguration

Table A.1: Machining Requirements and Processing Times of Parts for Problem 1

Part Type	Data Type	Operation					Demand	
		1	2	3	4	5	Period 1	period 2
1	M/C	M11	M9	M2	M8		943	932
	Time	1.78	5.98	5.33	1.55			
2	M/C	M10	M7	M9			0	0
	Time	2.90	3.67	5.54				
3	M/C	M12	M10	M8	M5		0	911
	Time	3.93	3.91	5.72	5.19			
4	M/C	M9	M11	M6	M7		0	916
	Time	3.12	5.80	3.88	4.39			
5	M/C	M3	M8	M2			0	967
	Time	5.27	1.76	3.50				
6	M/C	M5	M6	M8	M7	M4	914	0
	Time	2.40	5.26	4.60	5.21	1.58		
7	M/C	M2	M4	M6	M11		858	993
	Time	4.43	1.69	2.38	1.98			
8	M/C	M9	M1	M11			0	991
	Time	2.13	1.86	1.84				
9	M/C	M11	M9	M4	M7	M1	967	0
	Time	4.80	3.00	5.74	5.25	5.23		
10	M/C	M8	M4	M1	M10	M9	0	901
	Time	2.68	5.54	1.91	2.83	3.45		
11	M/C	M9	M7	M12			801	0
	Time	4.54	2.25	5.95				
12	M/C	M7	M3	M4	M10		0	0
	Time	1.68	5.39	2.23	2.10			
13	M/C	M10	M2	M12	M7	M3	0	878
	Time	5.95	3.12	2.90	4.35	2.03		
14	M/C	M2	M12	M8			981	0
	Time	2.30	3.02	2.43				
15	M/C	M11	M9	M3	M5	M12	819	889
	Time	3.29	2.05	1.84	2.89	2.97		

Table A.2: Resource Data for Problem Number 1

Machine Type	Machine Cost	Relocation Cost	Capacity
1	2,972	857	12,000
2	2,651	1,455	12,000
3	3,292	773	12,000
4	2,543	1,445	12,000
5	3,470	1,101	12,000
6	2,185	712	12,000
7	3,450	798	12,000
8	3,067	1,035	12,000
9	3,457	1,138	12,000
10	2,546	1,008	12,000
11	2,308	1,434	12,000
12	2,109	1,480	12,000

Table A.3: Machining Requirements and Processing Times of Parts for Problem 2

Part Type	Data Type	Operation					Demand	
		1	2	3	4	5	Period 1	period 2
1	M/C	M7	M4	M12	M2	M6	889	869
	Time	5.19	4.33	4.98	1.81	2.90		
2	M/C	M1	M5	M8	M9	M4	931	895
	Time	2.72	1.55	4.87	3.45	3.05		
3	M/C	M12	M11	M3	M4	M6	0	885
	Time	3.00	3.06	4.73	3.98	2.44		
4	M/C	M10	M12	M11	M2		0	996
	Time	2.89	2.99	4.62	2.89			
5	M/C	M9	M4	M1	M7		0	968
	Time	4.69	2.14	4.41	3.60			
6	M/C	M1	M10	M12	M9		835	0
	Time	5.84	2.16	4.08	5.78			
7	M/C	M6	M9	M10			0	897
	Time	4.42	2.16	5.66				
8	M/C	M12	M2	M1	M7		961	0
	Time	3.77	3.79	1.98	3.22			
9	M/C	M5	M4	M3	M11		825	926
	Time	2.88	3.09	1.84	1.61			
10	M/C	M11	M7	M12			880	986
	Time	5.94	5.63	5.47				
11	M/C	M5	M12	M4	M11		828	0
	Time	3.16	5.70	1.91	3.81			
12	M/C	M10	M11	M2			0	979
	Time	4.82	4.99	1.64				
13	M/C	M7	M4	M12	M11		981	0
	Time	5.21	2.45	3.67	3.09			
14	M/C	M2	M1	M7			0	888
	Time	2.03	2.89	4.81				
15	M/C	M5	M11	M8	M7		958	0
	Time	5.39	2.47	5.02	2.86	5.26		

Table A.4: Resource Data for Problem Number 2

Machine Type	Machine Cost	Relocation Cost	Capacity
1	2,106	928	14,000
2	2,912	1,266	14,000
3	2,965	950	14,000
4	2,243	1,045	14,000
5	2,916	972	14,000
6	2,328	1,359	14,000
7	3,298	759	14,000
8	2,657	860	14,000
9	3,422	939	14,000
10	3,491	1,177	14,000
11	2,787	932	14,000
12	2,658	1,440	14,000

Table A.5: Machining Requirements and Processing Times of Parts for Problem 3

Part Type	Data Type	Operation					Demand	
		1	2	3	4	5	Period 1	period 2
1	M/C	M6	M9	M11			0	941
	Time	5.29	3.21	2.93				
2	M/C	M11	M8	M2			911	873
	Time	4.59	2.06	4.15				
3	M/C	M3	M7	M8	M11		0	842
	Time	3.94	1.97	5.25	4.13			
4	M/C	M7	M6	M1	M5		985	0
	Time	5.71	4.23	2.94	2.21			
5	M/C	M9	M8	M10	M4		0	908
	Time	4.62	2.79	1.52	4.99			
6	M/C	M6	M3	M8	M5	M1	0	822
	Time	5.12	3.50	2.90	2.11	4.18		
7	M/C	M2	M9	M1			929	922
	Time	2.24	4.44	3.53				
8	M/C	M10	M12	M6	M1	M8	0	910
	Time	3.19	2.44	3.64	1.65	1.99		
9	M/C	M12	M5	M1			921	0
	Time	5.50	3.46	3.58				
10	M/C	M4	M12	M7			0	879
	Time	1.92	3.23	5.31				
11	M/C	M6	M4	M9	M7		0	851
	Time	3.61	1.58	1.70				
12	M/C	M8	M12	M5	M11		959	0
	Time	3.12	4.84	2.32	3.53			
13	M/C	M12	M5	M1	M8		826	0
	Time	2.86	2.73	5.36	1.75			
14	M/C	M12	M5	M1	M8		0	974
	Time	2.37	2.12	4.44	4.72			
15	M/C	M3	M1	M4			923	0
	Time	5.40	5.62	1.95				

Table A.6: Resource Data for Problem Number 3

Machine Type	Machine Cost	Relocation Cost	Capacity
1	2,972	857	14,000
2	2,651	1,455	14,000
3	3,292	773	14,000
4	2,543	1,445	14,000
5	3,470	1,101	14,000
6	2,185	712	14,000
7	3,450	798	14,000
8	3,067	1,035	14,000
9	3,457	1,138	14,000
10	2,546	1,008	14,000
11	2,308	1,434	14,000
12	2,109	1,480	14,000

A.2 Data for the Evaluation of the Potential Benefits from Routing Flexibility

Table A.7: Processing Times and Costs of Parts for Problem 1 and 2

Part Type	Demand	Data Type	Operation							
			1		2		3		4	
			1	2	1	2	1	2	1	2
1	936	M/C Time	M5 1.23	M6 1.23	M9 4.13	M5 4.13	M3 4.69	M7 4.69	M4 3.65	M6 3.65
2	904	M/C Time	M9 1.23	M7 1.23	M3 3.55	M4 3.55				
3	1,073	M/C Time	M2 3.85	M7 3.85	M7 2.90	M2 2.90				
4	802	M/C Time	M4 3.35	M9 3.35	M1 3.07	M9 3.07	M7 2.68	M6 2.68		
5	910	M/C Time	M1 4.78	M3 4.78	M4 14.1	M1 14.1	M6 2.14	M2 2.14	M8 3.11	M5 3.11
6	837	M/C Time	M2 1.91	M3 1.91	M8 3.81	M3 3.81	M4 1.95	M6 1.95		

Table A.8: Resource Data for Problem 1 and 2

Machine Type	Machine Cost	Capacity
1	824	5,500
2	866	5,500
3	840	5,500
4	767	5,500
5	711	5,500
6	948	5,500
7	772	5,500
8	732	5,500
9	880	5,500

Table A.9: Processing Times and Costs of Parts for Problem 3

Part Type	Demand	Data Type	Operation									
			1		2		3		4		5	
			1	2	1	2	1	2	1	2	1	2
1	880	M/C Time	M3 3.52	M2 3.52	M9 5.40		M8 5.50	M7 5.50				
2	893	M/C Time	M1 3.53	M9 3.53	M7 5.44		M6 3.03	M7 3.03	M9 4.85	M5 4.85	M10	
3	814	M/C Time	M10 4.18		M8 4.64	M3 4.64	M1 4.63	M2 4.63				
4	916	M/C Time	M7 3.68		M3 2.26	M7 2.26	M9 3.17	M10 3.17	M5 3.66	M1 3.66		
5	866	M/C Time	M10 5.82		M1 2.35		M3 4.48		M7 5.17			
6	978	M/C Time	M1 2.25		M7 4.13	M5 4.13	M4 3.20		M5 5.39	M8 5.39	M8 5.12	
7	928	M/C Time	M7 5.78		M6 5.71	M10 5.71	M9 2.22		M10 2.89	M4 2.89	M2 5.91	
8	913	M/C Time	M5 3.58	M8 3.58	M3 2.67		M10 3.61	M9 3.61				
9	939	M/C Time	M9 5.92	M5 5.92	M5 5.57		M1 3.93					
10	801	M/C Time	M2 5.04		M6 5.67		M5 2.45	M1 2.45	M10 3.13	M9 3.13		
11	932	M/C Time	M7 2.51		M8 3.68		M4 5.94					
12	818	M/C Time	M9 2.42		M10 4.52	M3 4.52	M7 4.33	M4 4.33				

Table A.10: Resource Data for Problem 3

Machine Type	Machine Cost	Capacity
1	2027	831
2	2628	888
3	2769	958
4	2139	739
5	2453	941
6	2496	788
7	2592	919
8	2374	849
9	2869	1000
10	2099	715

Table A.11: Processing Times and Costs of Parts for Problem 4

Part Type	Demand	Data Type	Operation											
			1		2		3		4		5			
			1	2	1	2	1	2	1	2	1	2		
1	842	M/C Time	M7 5.54		M4 5.25	M9 5.25	M6 2.06		M10 5.78					
2	819	M/C Time	M3 5.31		M7 2.37		M5 4.73		M1 3.74	M4 3.74				
3	809	M/C Time	M9 2.76		M8 2.12	M10 2.12	M6 3.67		M4 3.88					
4	971	M/C Time	M1 2.51		M7 5.67	M8 5.67	M10 4.50							
5	846	M/C Time	M4 3.81	M6 3.81	M3 2.35		M8 4.61							
6	875	M/C Time	M3 4.63	M10 4.63	M4 2.68	M8 2.68	M2 5.45		M7 4.22	M2 4.22				
7	858	M/C Time	M9 3.72		M8 5.62		M1 3.17	M7 3.17						
8	923	M/C Time	M1 4.90	M10 4.90	M2 2.21	M3 2.21	M7 2.38							
9	825	M/C Time	M2 3.06		M8 4.18	M3 4.18	M1 3.39	M6 3.39	M7 5.15					
10	998	M/C Time	M6 4.30		M1 2.30		M7 3.86		M2 4.86					
11	861	M/C Time	M3 2.76		M2 5.14	M5 5.14	M9 2.37		M5 4.11	M8 4.11	M4 2.48			
12	803	M/C Time	M6 5.78	M1 5.78	M3 5.49		M8 5.41	M7 5.41						

Table A.12: Resource Data for Problem 4

Machine Type	Machine Cost	Capacity
1	2716	716
2	2395	757
3	2490	960
4	2856	938
5	2556	769
6	2066	792
7	2542	862
8	2564	988
9	2730	890
10	2272	732

A.3 Experimental Design Data

A.3.1 Replicate 2 of Experiment 1

Table A.13: Data of Replicate 2 of Experiment 1

Variable	Value
Part types	11
Machine types	8
Number of period	3
Number of cells	3
Intercell material cost	30
Lower and Upper bounds	2/10
Scenario/period	3

Table A.14: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	6	4-2-1-7-5-3	0.55-0.46-0.63-0.72-0.78-0.48	1
2	5	2-8-6-5-3	0.57-0.76-0.22-0.74-0.36	1
3	4	1-8-6-4	0.45-0.78-0.98-0.14	1
4	3	2-1-7/3	0.14-1.00-0.89/0.77	2
5	3	5-4/6-2	0.26-0.86/0.87-0.62	2
6	3	5-3-1	0.47-0.51-0.19	1
7	3	8-6-4	0.71-0.40-0.68	1
8	2	3-1	0.45-0.51	1
9	2	7-6	0.97-0.19	1
10	2	8-7/8	1.00-0.87/0.71	2
11	2	5-3	0.23-0.41	1

Table A.15: Part Type Demand

Part Type Number	Demand								
	Period 1			Period 2			Period 3		
	Sn 1	Sn 2	Sn 3	Sn 1	Sn 2	Sn 3	Sn 1	Sn 2	Sn 3
1	800	600	800	600	0	0	800	0	900
2	0	500	0	900	800	700	0	600	800
3	900	1,000	600	0	0	0	1,000	0	500
4	600	0	900	700	700	700	700	500	0
5	800	700	500	700	0	0	900	0	600
6	900	0	800	1,000	600	800	600	1,000	0
7	0	500	0	0	0	500	0	900	500
8	1,000	0	700	800	1,000	600	800	800	0
9	0	500	0	0	700	900	0	500	1,000
10	900	0	900	800	700	0	600	0	0
11	0	500	0	0	400	600	0	500	600

Table A.16: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	1,800	360	97
2	1,500	300	141
3	1,300	260	79
4	1,100	220	84
5	2,000	400	41
6	1,700	340	51
7	1,600	320	67
8	1,300	260	51

A.3.2 Replicate 3 of Experiment 1

Table A.17: Data of Replicate 3 of Experiment 1

Variable	Value
Part types	11
Machine types	9
Number of period	2
Number of cells	3
Intercell material cost	20
Lower and Upper bounds	2/10
Scenario/period	2

Table A.18: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	6	6/3-5-4-3-2-1	0.49/0.21-0.77-0.59-0.49-0.28-0.24	2
2	5	2-1-9-8/6-7	0.88-0.17-0.41-0.36/0.11-0.43	2
3	4	8-7-6-5/2	0.32-0.81-0.64-0.23/0.61	2
4	3	5-4-3	0.89-0.20-0.36	1
5	3	3-4-2	0.36-0.87-0.61	1
6	3	3-2-1	0.60-0.97-0.64	1
7	2	6-7/5	0.31-0.48/0.82	2
8	2	6-5/1	0.47-0.37/0.66	2
9	2	1-9/6	0.50-0.20/0.12	2
10	2	4-9	0.77-0.16	1
11	2	9-8	0.48-0.48	1

Table A.19: Part Type Demand

Part Type Number	Demand			
	Period 1		Period 2	
	Scenario 1	Scenario 2	Scenario 1	Scenario 2
1	700	700	0	1,000
2	1,000	700	900	700
3	900	600	0	600
4	800	0	800	500
5	0	800	0	0
6	500	0	700	700
7	0	700	1,000	0
8	900	0	900	600
9	0	600	800	0
10	800	0	0	500
11	0	1,000	1,000	0

Table A.20: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	1,800	720	21
2	1,700	680	112
3	1,400	560	120
4	1,200	480	83
5	1,000	400	65
6	1,900	760	80
7	1,600	640	62
8	1,500	600	98
9	1,200	480	94

A.3.3 Replicate 1 of Experiment 2

Table A.21: Data of Replicate 1 of Experiment 2

Variable	Value
Part types	13
Machine types	10
Number of period	2
Number of cells	3
Intercell material cost	30
Lower and Upper bounds	2/10
Scenario/period	3

Table A.22: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	6	5-4-2-2-1-10	0.47-0.60-0.78-0.56-0.31-0.13	1
2	5	2-10-1-9-7	0.29-0.50-0.71-0.28-0.27	1
3	4	1-9-8-6	0.75-0.74-0.36-0.15	1
4	4	7-5-3-4	0.57-0.18-0.28-0.28	1
5	4	6-4-5-3	0.70-0.80-0.41-0.88	1
6	3	1-9/1-10	0.53-0.79/0.67-0.83	2
7	3	8/2-7-5	0.34/0.77-0.84-0.27	2
8	3	9/3-7-6	0.73/0.46-0.37-0.77	2
9	2	4-2	0.20-0.19	1
10	2	2-10	0.75-0.57	1
11	2	2-1	0.14-0.10	1
12	2	10-9/6	0.41-0.40/0.59	2
13	2	3-2/7	0.63-0.80/0.94	2

Table A.23: Part Type Demand

Part Type Number	Demand					
	Period 1			Period 2		
	Sn 1	Sn 2	Sn 3	Sn 1	Sn 2	Sn 3
1	0	800	500	600	0	0
2	0	0	600	0	0	1,000
3	800	600	900	700	900	500
4	900	700	1,000	700	700	0
5	0	0	0	0	600	600
6	900	700	500	0	700	700
7	1,000	800	500	900	900	500
8	500	500	0	1,000	0	800
9	800	900	0	0	900	800
10	900	0	700	1,000	900	0
11	0	700	800	500	0	800
12	1,000	700	0	600	1,000	900
13	1,000	0	1,000	500	500	0

Table A.24: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	9,000	3,600	78
2	9,900	3,960	108
3	9,500	3,800	61
4	8,400	3,360	38
5	8,000	3,200	92
6	8,900	3,560	53
7	8,600	3,440	30
8	9,500	3,800	94
9	9,100	3,640	48
10	8,000	3,200	58

A.3.4 Replicate 2 of Experiment 2

Table A.25: Data of Replicate 2 of Experiment 2

Variable	Value
Part types	13
Machine types	12
Number of period	3
Number of cells	3
Intercell material cost	50
Lower and Upper bounds	2/10
Scenario/period	2

Table A.26: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	6	2-5-11/4-1-7-10	0.38-0.69-0.86/0.53-0.66-0.49-0.12	2
2	5	4-6-12-3-9	0.83-0.85-0.21-0.51-0.21	1
3	5	5-8-2-4-11	0.91-0.73-0.7-0.42-0.27	1
4	4	2-4-11-1	0.77-0.86-0.35-0.42	1
5	4	12-6-8/1-3	0.71-0.37-0.11/0.79-0.54	2
6	3	11-5/10-8	0.76-0.17/0.23-0.53	2
7	3	11-6/3-8	0.41-0.15/0.60-0.41	2
8	3	1-3-9	0.73-0.41-0.83	1
9	3	1-7-10	0.77-0.91-0.42	1
10	2	2-9	0.39-0.48	1
11	2	7-10	0.78-0.15	1
12	2	4-6/10	0.45-0.67/0.12	2
13	2	5-11/8	0.48-0.59/0.13	2

Table A.27: Part Type Demand

Part Type Number	Demand					
	Period 1		Period 2		Period 3	
	Sn 1	Sn 2	Sn 1	Sn 2	Sn 1	Sn 2
1	900	0	800	600	800	1,000
2	700	500	0	700	900	500
3	0	600	900	800	0	800
4	500	0	0	500	600	600
5	600	0	1,000	600	700	700
6	600	700	0	0	800	1,000
7	0	800	500	700	0	500
8	0	0	600	700	0	500
9	800	900	500	0	0	0
10	900	600	600	0	600	0
11	0	700	700	500	1,000	0
12	900	1,000	0	600	500	1,000
13	1,000	0	700	0	500	0

Table A.28: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	9,400	1,880	75
2	8,300	1,660	75
3	10,000	2,000	75
4	8,800	1,760	32
5	8,500	1,700	130
6	9,400	1,880	93
7	9,000	1,800	90
8	10,000	2,000	128
9	8,800	1,760	48
10	8,400	1,680	63
11	9,300	1,860	121
12	9,000	1,800	107

A.3.5 Replicate 3 of Experiment 2

Table A.29: Data of Replicate 3 of Experiment 2

Variable	Value
Part types	10
Machine types	8
Number of period	3
Number of cells	3
Intercell material cost	20
Lower and Upper bounds	2/10
Scenario/period	2

Table A.30: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	6	7-5-3-2/4-8-6	0.31-0.7-0.33-0.57/0.54-0.73-0.18	2
2	4	5-3-1/7-7	0.66-0.39 0.73/0.19-0.64	1
3	4	6-4-2-1	0.61-0.24-0.22-0.87	1
4	3	7-5-4	0.25-0.61-0.34	1
5	3	2-8-7	0.65-0.63-0.38	2
6	3	8/1-6-4	0.58/0.76-0.12-0.65	2
7	3	3-1-7	0.5-0.36-0.49	2
8	2	5-4/6	0.82-0.51/0.97	1
9	2	2-8	0.61-0.2	1
10	2	5-3	0.91-0.31	1

Table A.31: Part Type Demand

Part Type Number	Demand					
	Period 1		Period 2		Period 3	
	Sn 1	Sn 2	Sn 1	Sn 2	Sn 1	Sn 2
1	600	700	900	0	900	800
2	700	600	0	0	1,000	0
3	700	800	0	1,000	500	800
4	1,000	900	500	800	600	900
5	0	0	600	1,000	600	1,000
6	900	900	0	500	700	900
7	0	1,000	700	600	0	500
8	1,000	500	700	500	0	0
9	0	0	800	700	900	1,000
10	500	0	900	0	0	0

Table A.32: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	9,000	3,000	43
2	8,600	2,867	79
3	9,600	3,200	69
4	9,200	3,067	39
5	8,000	2,667	77
6	9,700	3,233	58
7	8,600	2,867	132
8	8,200	2,733	126

A.3.6 Replicate 1 of Experiment 3

Table A.33: Data of Replicate 1 of Experiment 3

Variable	Value
Part types	13
Machine types	11
Number of period	2
Number of cells	3
Intercell material cost	50
Lower and Upper bounds	2/10
Scenario/period	2

Table A.34: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	6	4/11-2-10-9-6-1/2	0.19/0.82-0.68-0.71-0.42-0.72-0.56/0.68	4
2	5	11/4-8-6-4-2/1	0.60/0.50-0.70-0.42-0.50-0.38/0.67	4
3	5	8/5-6-4-2-10/7	0.51/0.42-0.25-0.42-0.44-0.68/0.17	4
4	4	10/2/6-9-6-4	0.51/0.23/0.18-0.19-0.76-0.40	3
5	4	9/3/7-6-4-3	0.37/0.75/0.14-0.23-0.21-0.76	3
6	3	11/3-9-7/6	0.44/0.39-0.39-0.58/0.24	4
7	3	1/9-11-8/7	0.20/0.33-0.18-0.48/0.78	4
8	3	6/8-4-2/1	0.71/0.27-0.67-0.85/0.65	4
9	2	10/4/8-9	0.65/0.20/0.23-0.53	3
10	2	6/5/9-4	0.58/0.55/0.67-0.74	3
11	2	2/6/11-11	0.52/0.60/0.70-0.61	3
12	2	3/7/5-10	0.69/0.25/0.54-0.58	3
13	2	5/8/3-7	0.38/0.46/0.60-0.8	3

Table A.35: Part Type Demand

Part Type Number	Demand			
	Period 1		Period 2	
	Scenario 1	Scenario 2	Scenario 1	Scenario 2
1	0	700	800	0
2	900	800	900	0
3	1,000	800	0	0
4	500	700	1,000	600
5	1,000	900	800	0
6	700	1,000	0	700
7	0	900	900	800
8	500	1,000	600	500
9	600	500	700	800
10	700	0	0	900
11	0	0	500	600
12	0	0	600	700
13	800	0	0	800

Table A.36: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	2,000	800	66
2	1,800	720	103
3	1,600	640	99
4	1,400	560	79
5	1,100	440	43
6	2,000	800	86
7	1,900	760	61
8	1,600	640	150
9	1,400	560	97
10	1,200	480	29
11	1,000	400	152

A.3.7 Replicate 2 of Experiment 3

Table A.37: Data of Replicate 2 of Experiment 3

Variable	Value
Part types	12
Machine types	11
Number of period	4
Number of cells	3
Intercell material cost	20
Lower and Upper bounds	2/10
Scenario/period	3

Table A.38: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	6	4/1/6-2-11-8-7-10	0.33/0.89/0.53-0.83-0.53-0.87-1-0.77	3
2	4	9/3-6-4-2/7	0.11/0.53-0.33-0.66-0.91	4
3	4	11/5-8-7-4/3	0.13/0.9-0.98-0.18-0.87	4
4	4	10/5-8-5-4/1	0.65/0.85-0.68-0.43-0.43	4
5	4	1/5-10-8-6/7	0.93/0.47-0.63-0.88-0.13	4
6	3	3/1/10-2-11	0.21/0.36/0.88-0.43-0.56	3
7	3	8/11/10-6-4	0.11/0.92/0.82-0.55-0.67	3
8	3	2/10/8-11-9	0.74/0.79/0.73-0.91-0.52	3
9	3	6/3/4-4-2	0.70/0.61/1.00-0.63-0.97	3
10	2	2/5/9-10	0.73/0.63/0.93-0.63	3
11	2	9/7/11-6	0.42/0.95/0.44-0.89	3
12	2	11/1/9-8	0.79/0.44/0.25-0.32	3

Table A.39: Part Type Demand

Part Type Number	Demand											
	Period 1			Period 2			Period 3			Period 4		
	Sn 1	Sn 2	Sn 3	Sn 1	Sn 2	Sn 3	Sn 1	Sn 2	Sn 3	Sn 1	Sn 2	Sn 3
1	1,000	800	600	700	500	1,000	0	1,000	500	1,000	900	0
2	0	800	800	800	600	700	1,000	900	500	700	900	500
3	800	0	500	900	900	800	500	0	0	1,000	0	900
4	800	600	0	600	0	500	0	500	600	1,000	700	600
5	0	900	700	900	500	800	500	700	0	700	1,000	600
6	800	900	600	0	900	0	500	0	600	0	0	0
7	900	0	0	700	1,000	600	900	600	1,000	500	1,000	600
8	0	900	800	900	600	600	600	800	700	700	700	0
9	600	1,000	1,000	0	0	0	0	900	700	0	500	1,000
10	900	700	0	700	500	700	1,000	500	900	600	800	1,000
11	900	1,000	800	1,000	0	0	1,000	600	700	800	800	700
12	700	0	500	0	800	700	700	0	0	0	0	500

Table A.40: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	1,300	780	95
2	1,100	660	157
3	1,900	1,140	54
4	1,800	1,080	116
5	1,500	900	76
6	1,300	780	148
7	1,100	660	111
8	2,000	1,200	42
9	1,700	1,020	124
10	1,600	960	109
11	1,300	780	118

A.3.8 Replicate 3 of Experiment 3

Table A.41: Data of Replicate 3 of Experiment 3

Variable	Value
Part types	11
Machine types	10
Number of period	3
Number of cells	3
Intercell material cost	20
Lower and Upper bounds	2/10
Scenario/period	3

Table A.42: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	5	1/4-2-10-8-9/5	0.17/0.77-0.79-0.14-0.36-0.18/0.38	4
2	4	7/10-6-4-5/9	0.51/0.91-0.1-0.58-0.53/0.93	4
3	3	3/10/7-1-2	0.97/0.85/0.99-0.72-0.56	3
4	3	10/1/8-9-7	0.65/0.60/0.11-0.23-0.48	3
5	3	8/2/9-6-5	0.57/0.66/0.32-0.77-0.95	3
6	3	8/3/10-6-7	0.37/0.96/0.78-0.73-0.87	3
7	2	5/6/1-4	0.24/0.47/0.42-0.83	3
8	2	4/7/3-2	0.61/0.63/0.16-0.66	3
9	2	3/4/2-1	0.83/0.63/0.46-0.6	3
10	2	5/9/4-3	0.13/0.20/0.36-0.55	3
11	2	3/5/6-2	0.81/0.25/0.11-0.98	3

Table A.43: Part Type Demand

Part Type Number	Demand								
	Period 1			Period 2			Period 3		
	Sn 1	Sn 2	Sn 3	Sn 1	Sn 2	Sn 3	Sn 1	Sn 2	Sn 3
1	1,000	500	600	600	800	500	0	1,000	700
2	700	0	900	900	500	0	1,000	600	600
3	1,000	500	900	0	0	700	700	600	0
4	0	1,000	800	700	1,000	0	900	0	600
5	500	600	0	700	0	500	600	1,000	0
6	800	800	1,000	1,000	900	0	500	700	700
7	0	0	0	0	0	900	800	900	1,000
8	900	500	900	800	800	1,000	0	800	700
9	900	700	0	0	1,000	600	1,000	0	900
10	800	1,000	800	800	600	900	0	500	0
11	0	0	700	0	900	1,000	500	0	800

Table A.44: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	1,000	400	103
2	1,900	760	33
3	1,600	640	96
4	1,500	600	126
5	1,200	480	53
6	1,000	400	23
7	1,900	760	121
8	1,700	680	136
9	1,400	560	110
10	1,300	520	50

A.3.9 Replicate 1 of Experiment 4

Table A.45: Data of Replicate 1 of Experiment 4

Variable	Value
Part types	9
Machine types	8
Number of period	3
Number of cells	3
Intercell material cost	30
Lower and Upper bounds	2/10
Scenario/period	2

Table A.46: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	6	6/2-5-3-1-7-4/7	0.13/0.77-0.14-0.6-0.94-0.66-0.65/0.64	4
2	5	2-1/3-7-5-4/8	0.45-0.27/0.66-0.76-0.89-0.16/0.24	4
3	4	2/1-8-7/4-5	0.26/0.92-1 0.85-0.76	3
4	3	3/5/4-1-8	0.85/0.36/0.79-0.34-0.2	3
5	3	6/1/2 4-3	0.62/0.57/0.16-0.54-0.16	3
6	3	2-8-7/6/5	0.94-0.48-0.45/0.60/0.40	3
7	2	5-3/7/6	0.93-0.50/0.36/0.64	3
8	2	2/3/1-8	0.85/0.22/0.81-0.41	3
9	2	1/8/3-7	0.84/0.53/0.82-0.13	3

Table A.47: Part Type Demand

Part Type Number	Demand					
	Period 1		Period 2		Period 3	
	Sn 1	Sn 2	Sn 1	Sn 2	Sn 1	Sn 2
1	1,000	1,000	700	0	800	900
2	900	0	500	0	1,000	600
3	500	0	1,000	1,000	600	700
4	1,000	800	0	700	500	900
5	1,000	600	0	800	0	600
6	1,000	800	800	500	0	0
7	0	1,000	700	700	600	0
8	0	600	900	1,000	800	900
9	600	800	500	900	600	800

Table A.48: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	9,500	5,700	76
2	9,100	5,460	89
3	10,000	6,000	104
4	9,700	5,820	96
5	8,500	5,100	72
6	8,100	4,860	26
7	9,100	5,460	148
8	8,700	5,220	53

A.3.10 Replicate 2 of Experiment 4

Table A.49: Data of Replicate 2 of Experiment 4

Variable	Value
Part types	8
Machine types	9
Number of period	4
Number of cells	3
Intercell material cost	30
Lower and Upper bounds	2/10
Scenario/period	2

Table A.50: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	5	5/1-4-3-2-1	0.31/0.18-0.98-0.17-0.16-0.96/0.14	4
2	4	1/5-9-8-7	0.52/0.23-0.33-0.53-0.85/0.67	4
3	4	2/8-3-1-9	0.18/0.97-0.13-0.98-0.11/0.54	3
4	3	1-9-8/7/6	0.27-0.48-0.10/0.86/0.24	3
5	3	9-8-7/2/9	0.15-0.74-0.65/0.93/0.46	3
6	3	8-7-6/1/4	0.12-0.85-0.39/0.13/0.58	3
7	2	7/9/3-6	0.56/0.32/0.48-0.16	3
8	2	6/5/2-5	0.76/0.45/0.99-0.71	3

Table A.51: Part Type Demand

Part Type Number	Demand							
	Period 1		Period 2		Period 3		Period 4	
	Sn 1	Sn 2	Sn 1	Sn 2	Sn 1	Sn 2	Sn 1	Sn 2
1	600	900	900	0	0	800	500	500
2	1,000	1,000	0	800	700	700	0	700
3	0	0	500	600	500	1,000	1,000	0
4	600	800	900	700	600	800	0	600
5	0	800	0	900	800	0	500	1,000
6	500	0	800	0	0	800	1,000	700
7	1,000	900	700	800	700	900	500	600
8	700	800	1,000	600	600	0	900	0

Table A.52: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	9,100	3,640	50
2	8,000	3,200	125
3	9,700	3,880	145
4	8,500	3,400	179
5	8,100	3,240	31
6	9,100	3,640	86
7	10,000	4,000	108
8	9,600	3,840	55
9	8,500	3,400	50

A.3.11 Replicate 3 of Experiment 4

Table A.53: Data of Replicate 3 of Experiment 4

Variable	Value
Part types	10
Machine types	11
Number of period	3
Number of cells	3
Intercell material cost	30
Lower and Upper bounds	2/10
Scenario/period	2

Table A.54: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	5	1/3-10-8-5-4/2	0.89/0.82-0.53-0.59-0.90-0.58/0.87	4
2	4	1/9-10-9-6/7	0.85/0.66-0.21-0.47-0.71/0.64	4
3	4	4/5-2-11-8/10	0.36/0.17-0.92-0.79-0.61/0.71	4
4	3	6/1-4-2/6	0.63/0.59-0.95-0.44/0.96	4
5	3	10-9-6/4/5	0.14-0.14-0.68/0.46/0.39	3
6	3	1-10-8/11/3	0.74-0.66-0.85/0.26/0.77	3
7	3	5-4-1/8/6	0.32-0.30-0.73/0.44/0.53	3
8	2	10/11/4-8	0.22/0.72/0.94-0.93	3
9	2	6/7/9-3	0.21/0.90/0.29-0.97	3
10	2	4/3/11-2	0.83/0.65/0.25-0.88	3

Table A.55: Part Type Demand

Part Type Number	Demand					
	Period 1		Period 2		Period 3	
	Sn 1	Sn 2	Sn 1	Sn 2	Sn 1	Sn 2
1	800	700	700	0	0	600
2	900	600	700	600	0	0
3	900	800	800	700	700	0
4	900	900	0	700	800	0
5	0	900	0	900	700	700
6	0	800	0	1,000	900	800
7	0	1,000	500	0	1,000	700
8	600	0	500	1,000	800	900
9	700	0	500	0	1,000	1,000
9	700	0	600	0	0	800

Table A.56: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	9,200	5,520	37
2	8,100	4,860	124
3	9,800	5,880	16
4	8,600	5,160	93
5	8,300	4,980	62
6	9,200	5,520	51
7	8,800	5,820	144
8	9,800	5,880	21
9	9,400	5,640	26
10	8,200	4,920	94
11	9,900	5,940	93

A.3.12 Replicate 1 of Experiment 5

Table A.57: Data of Replicate 1 of Experiment 5

Variable	Value
Part types	16
Machine types	14
Number of period	3
Number of cells	3
Intercell material cost	20
Lower and Upper bounds	2/10
Scenario/period	2

Table A.58: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	6	11-7-9-6/4-8-4	0.77-0.87-0.71-0.98/0.47-0.58-0.32	2
2	5	7-10-6-8-5	0.90-0.95-0.85-0.34-0.64	1
3	5	7-3-5-1-4	0.41-0.56-0.32-0.79-0.22	1
4	4	14-2-13-1	0.52-0.78-0.80-0.12	1
5	4	7-3-5-2	0.26-0.38-0.88-0.57	1
6	3	11/6-14-10	0.13/0.60-0.75-0.87	2
7	3	12/9-8-11	0.46/0.78-0.89-0.35	2
8	3	4/2-14-3	0.81/0.56-0.94-0.72	2
9	3	13-1-12	0.17-0.80-0.80	1
10	3	14-2-13	0.81-0.46-0.44	1
11	2	11-14	0.70-0.53	1
12	2	10-12	0.54/0.31-0.10	2
13	2	9/1-11	0.48/0.13-0.87	2
14	2	1/7-11/6	0.32-0.71/0.29	2
15	2	13-10/12	0.95-0.78/0.50	2
16	2	12-8	0.92-0.73	1

Table A.59: Part Type Demand

Part Type Number	Demand					
	Period 1		Period 2		Period 3	
	Sn 1	Sn 1	Sn 1	Sn 2	Sn 1	Sn 2
1	0	800	1,000	0	0	600
2	1,000	0	800	500	500	1,000
3	800	600	0	900	500	1,000
4	0	900	800	600	0	0
5	500	0	800	0	500	1,000
6	900	700	900	900	900	800
7	0	900	800	1,000	600	0
8	1,000	600	600	600	900	500
9	800	600	900	900	700	900
10	900	700	0	1,000	1,000	0
11	800	0	600	0	0	900
12	600	1,000	900	700	700	900
13	900	800	0	1,000	500	0
14	0	0	600	0	0	800
15	600	800	700	700	800	600
16	1,000	800	0	500	500	900

Table A.60: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	1,300	520	13
2	1,200	480	52
3	2,000	800	39
4	1,800	720	54
5	1,600	640	70
6	1,400	560	68
7	1,100	440	31
8	1,000	400	41
9	1,800	720	55
10	1,600	640	43
11	1,400	560	29
12	1,200	480	28
13	2,000	800	51
14	1,800	720	77

A.3.13 Replicate 2 of Experiment 5

Table A.61: Data of Replicate 2 of Experiment 5

Variable	Value
Part types	19
Machine types	13
Number of period	2
Number of cells	4
Intercell material cost	40
Lower and Upper bounds	2/10
Scenario/period	2

Table A.62: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	5	4-13-3-11-2	0.22-0.3-0.82-0.62-0.73	1
2	5	7/1-10-6-9-4	0.90/0.45-0.92-0.84-0.49-0.17	2
3	4	10-13-8-12/5	0.72-0.47-0.43-0.92/0.34	2
4	4	8-3/7-6-1	0.39-0.34/0.35-0.34-0.30	2
5	4	5-13-3-12	0.9-0.28-0.44-0.49	1
6	4	2-11-1-9	0.57-0.93-0.61-0.15	1
7	3	13-8-11	0.15-0.89-0.33	1
8	3	7-10-5/2	0.93-0.70-0.12/0.29	2
9	3	7-10-6/3	0.14-0.73-0.26/0.48	2
10	3	9-4-8/12	0.14-0.13-0.81/0.73	2
11	3	3-11-2	0.85-0.53-0.52	1
12	3	2-10-1	0.34-0.16-0.92	1
13	3	9-12-8	0.32-0.3-0.83	1
14	3	11-6-9	0.32-0.54-0.9	1
15	2	8/4-4	0.91/0.32-0.55	2
16	2	7-2/9	0.61-0.23/0.71	1
17	2	6-1/4	0.91-0.78/0.24	2
18	2	10-13	0.59-0.40	1
19	2	8-12	0.67-0.14	1

Table A.63: Part Type Demand

Part Type Number	Demand			
	Period 1		Period 2	
	Sn 1	Sn 1	Sn 1	Sn 2
1	500	500	900	0
2	0	800	500	800
3	1,000	0	500	600
4	600	700	0	1,000
5	600	500	1,000	0
6	0	900	600	700
7	700	0	600	500
8	700	600	0	0
9	0	1,000	700	0
10	0	0	700	700
11	800	0	0	500
12	800	700	0	1,000
13	1,000	0	800	800
14	900	900	0	600
15	900	800	1,000	1,000
16	500	600	800	900
17	0	1,000	800	700
18	900	800	1,000	0
19	600	600	900	500

Table A.64: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	1,600	960	14
2	1,300	780	23
3	1,200	720	60
4	2,000	1,200	66
5	1,800	1,080	33
6	1,600	960	43
7	1,400	840	39
8	1,100	660	55
9	2,000	1,200	41
10	1,800	1,080	51
11	1,600	960	68
12	1,400	840	55
13	1,200	720	56

A.3.14 Replicate 3 of Experiment 5

Table A.65: Data of Replicate 3 of Experiment 5

Variable	Value
Part types	19
Machine types	18
Number of period	4
Number of cells	4
Intercell material cost	30
Lower and Upper bounds	2/10
Scenario/period	2

Table A.66: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	6	10-18-9-17-8/1-7	0.18-0.14-0.23-0.67-0.97/0.89-0.54	2
2	5	8-16-7-15-6/4	0.86-0.93-0.13-0.32-0.45/0.35	2
3	5	7-15-16-6-5	0.61-0.82-0.57-0.95-0.69	1
4	4	6-14-5-13	0.70-0.32-0.97-0.71	1
5	4	14-4-12-13	0.86-0.91-0.93-0.25	1
6	4	6-14-15-5/11	0.69-0.75-0.60-0.82/0.24	2
7	3	5/2-14-4	0.61/0.59-0.37-0.13	2
8	3	5-13/9-3	0.55-0.21/0.13-0.93	2
9	3	18/7-1-9	0.40/0.69-0.50-0.36	2
10	3	9-18-8	0.73-0.76-0.84	1
11	3	8-17-7	0.86-0.54-0.78	1
12	3	3-12-2	0.83-0.26-0.71	1
13	3	3/6-11-1	0.43/0.43-0.80-0.50	2
14	2	4-12/8	0.33-0.52/0.92	2
15	2	8-16/3	0.73-0.51/0.85	2
16	2	16-7	0.30-0.68	1
17	2	2-10	0.28-0.22	1
18	2	10-1	0.16-0.81	1
19	2	1-9/12	0.13-0.26/0.76	2

Table A.67: Part Type Demand

Part Type Number	Demand							
	Period 1		Period 2		Period 3		Period 4	
	Sn 1	Sn 1	Sn 1	Sn 2	Sn 1	Sn 2	Sn 1	Sn 2
1	0	900	1,000	900	0	800	0	0
2	700	0	0	800	500	0	600	900
3	500	0	900	500	0	500	0	600
4	0	1,000	500	1,000	700	800	0	500
5	800	1,000	0	800	500	0	700	0
6	600	600	0	600	1,000	0	700	1,000
7	800	700	1,000	0	800	500	0	600
8	0	500	600	900	600	900	800	600
9	900	700	600	700	0	500	700	0
10	600	700	500	0	900	600	1,000	700
11	900	0	800	0	700	1,000	0	700
12	800	600	700	1,000	0	800	1,000	0
13	700	800	500	800	0	0	800	1,000
14	900	800	900	500	900	0	1,000	800
15	900	0	800	600	700	500	500	0
16	800	900	0	900	1,000	900	900	1,000
17	0	900	0	700	1,000	700	500	900
18	600	0	1,000	0	800	600	500	900
19	0	1,000	800	0	1,000	1,000	1,000	500

Table A.68: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	1,800	360	15
2	1,600	320	81
3	1,300	260	35
4	1,200	240	61
5	2,000	400	21
6	1,800	360	58
7	1,600	320	38
8	1,400	280	33
9	1,100	220	61
10	1,000	200	59
11	1,800	360	47
12	1,600	320	50
13	1,400	280	34
14	1,200	240	51
15	2,000	400	51
16	1,800	360	63
17	1,600	320	52
18	1,400	280	89

A.3.15 Replicate 1 of Experiment 6

Table A.69: Data of Replicate 1 of Experiment 6

Variable	Value
Part types	17
Machine types	18
Number of period	2
Number of cells	3
Intercell material cost	40
Lower and Upper bounds	2/10
Scenario/period	2

Table A.70: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	5	14-4-13-3-12/9	0.84-0.20-0.56-0.11-0.52/0.22	2
2	5	10-1-9-18-8/13	0.15-0.48-0.89-0.82-0.46/0.30	2
3	4	9-17-8-16	0.44-0.49-0.48-0.61	1
4	4	12-2-3-11	0.20-0.14-0.26-0.47	1
5	4	11-2-10-1	0.45-0.59-0.72-0.71	1
6	3	17-7-15	0.77-0.97-0.58	1
7	3	16-6-15/8	0.66-0.58-0.68/0.82	2
8	3	15-5-6/12	0.44-0.46-0.64/0.62	2
9	3	1-10/7 18	0.54-0.30/0.73-0.29	2
10	3	18-9-17	0.51-0.14-0.17	1
11	2	11-1	0.11-0.73	1
12	2	2-10	0.88-0.25	1
13	2	14-4/16	0.78-0.38/0.90	2
14	2	5-13/6	0.12-0.38/0.92	2
15	2	18-8/11	0.27-0.99/0.84	2
16	2	8-17	0.82-0.79	1
17	2	17-7	0.46-0.33	1

Table A.71: Part Type Demand

Part Type Number	Demand			
	Period 1		Period 2	
	Sn 1	Sn 1	Sn 1	Sn 2
1	0	800	900	0
2	0	900	900	600
3	800	500	1,000	800
4	1,000	500	600	0
5	1,000	600	800	0
6	500	0	700	800
7	700	0	0	1,000
8	0	0	0	0
9	900	700	800	500
10	0	800	1,000	600
11	800	1,000	1,000	700
12	900	600	500	900
13	500	600	700	0
14	500	800	700	800
15	600	0	900	900
16	600	600	0	500
17	800	800	0	500

Table A.72: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	8,400	1,680	16
2	8,200	1,640	48
3	9,000	1,800	53
4	8,900	1,780	43
5	8,600	1,720	43
6	8,400	1,680	60
7	8,200	1,640	77
8	8,000	1,600	50
9	8,900	1,780	71
10	8,600	1,720	63
11	8,500	1,700	38
12	8,200	1,640	39
13	8,000	1,600	42
14	8,900	1,780	54
15	8,700	1,740	72
16	8,400	1,680	34
17	8,300	1,660	51
18	8,000	1,600	61

A.3.16 Replicate 2 of Experiment 6

Table A.73: Data of Replicate 2 of Experiment 6

Variable	Value
Part types	20
Machine types	18
Number of period	4
Number of cells	4
Intercell material cost	50
Lower and Upper bounds	2/10
Scenario/period	2

Table A.74: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	6	1-10-18-9-8/12-17	0.18-0.14-0.23-0.67-0.97/0.51-0.54	2
2	5	7-16-6-15-5	0.86-0.93-0.13-0.32-0.45	1
3	4	6-14-5-13	0.61-0.82-0.57-0.95	1
4	4	14-4-13-3	0.69-0.70-0.32-0.97	1
5	4	17-7-8/4-16	0.71-0.86-0.91/0.81-0.93	2
6	4	16/11-7-15-6	0.25/0.14-0.69-0.75-0.60	2
7	4	2-11-1/6-10	0.82-0.61-0.37/0.46-0.13	2
8	3	10-18-1	0.55/0.22-0.21-0.93	1
9	3	9-18-8	0.40-0.50-0.36	1
10	3	9-17-7	0.73-0.76-0.84	1
11	3	3-12-2	0.86-0.54-0.78	1
12	3	3/5-11-2	0.83/0.50-0.26-0.71	2
13	3	6-14-15/10	0.43-0.80-0.50/0.24	2
14	3	5/1-14-4	0.33/0.56-0.52-0.73	2
15	2	8-16	0.51-0.30	1
16	2	17-7	0.68-0.28	1
17	2	2-10	0.22-0.16	1
18	2	11/9-1	0.81/0.75-0.13	2
19	2	5/2-13	0.26/0.66-0.15	2
20	2	13-4/8	0.77-0.33/0.80	2

Table A.75: Part Type Demand

Part Type Number	Demand					
	Period 1		Period 2		Period 3	
	Sn 1	Sn 2	Sn 1	Sn 2	Sn 1	Sn 2
1	500	600	900	0	1,000	900
2	600	600	1,000	500	1,000	900
3	600	0	0	600	0	1,000
4	0	800	500	700	600	500
5	800	0	600	900	600	700
6	0	700	600	0	0	600
7	800	1,000	700	900	700	700
8	1,000	900	800	500	800	0
9	1,000	0	800	0	1,000	800
10	0	500	0	1,000	900	800
11	500	500	1,000	500	1,000	0
12	600	700	1,000	0	500	1,000
13	0	700	0	600	500	1,000
14	700	0	500	600	0	0
15	700	900	500	0	700	500
16	700	0	0	800	700	500
17	900	800	700	1,000	0	0
18	900	1,000	700	900	800	700
19	0	500	0	1,000	800	700
20	500	1,000	900	1,000	0	0

Table A.76: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	8,700	1,740	55
2	8,500	1,700	53
3	8,300	1,660	63
4	8,100	1,620	47
5	8,900	1,780	42
6	8,800	1,760	55
7	8,500	1,700	52
8	8,300	1,660	36
9	8,100	1,620	45
10	9,000	1,800	72
11	8,700	1,740	26
12	8,600	1,720	42
13	8,300	1,660	50
14	8,100	1,620	64
15	9,000	1,800	92
16	8,800	1,760	27
17	8,600	1,720	34
18	8,300	1,660	25

A.3.17 Replicate 3 of Experiment 6

Table A.77: Data of Replicate 3 of Experiment 6

Variable	Value
Part types	19
Machine types	17
Number of period	3
Number of cells	4
Intercell material cost	40
Lower and Upper bounds	2/10
Scenario/period	3

Table A.78: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	6	1-9-8-17-16-7	0.38-0.69-0.86-0.66-0.49-0.12	1
2	5	7-15-14-5/9-13	0.83-0.85-0.21-0.51/0.77-0.21	2
3	5	4-13-12-3/8-11	0.91-0.73-0.70-0.42/0.87-0.27	2
4	4	10-2/15-1-17	0.77-0.86/0.71-0.35-0.42	2
5	4	12-4-3-11	0.71-0.37-0.11 0.54	2
6	3	9-8-16	0.76-0.17-0.53	2
7	3	8-16-15	0.41-0.15-0.41	2
8	3	7-6-14	0.73-0.41-0.83	1
9	3	14/13-5-4	0.77/0.98-0.91-0.42	2
10	3	11-2-1/4	0.39-0.48-0.78/0.58	2
11	3	1/3-9-8	0.15/0.32-0.45-0.67	2
12	2	16-7	0.48-0.59	1
13	2	6-14	0.27-0.69	1
14	2	14-5	0.79-0.78	1
15	2	13/11-12	0.41/0.90-0.16	2
16	2	3/1-2	0.76/0.95-0.82	2
17	2	11-10/17	0.71-0.38/0.85	2
18	2	16-7	0.66-0.40	1
19	2	6-15	0.32-0.54	1

Table A.79: Part Type Demand

Part Type Number	Demand								
	Period 1			Period 2			Period 3		
	Sn 1	Sn 2	Sn 3	Sn 1	Sn 2	Sn 3	Sn 1	Sn 2	Sn 3
1	0	600	700	800	900	700	1,000	1,000	0
2	600	700	0	1,000	700	500	600	0	600
3	1,000	0	900	1,000	500	900	600	0	1,000
4	800	1,000	0	0	1,000	0	1,000	500	600
5	0	0	800	900	700	800	700	500	600
6	700	700	600	500	600	600	600	700	0
7	1,000	500	1,000	500	900	1,000	500	600	500
8	900	700	900	0	1,000	900	0	600	700
9	700	700	700	600	800	600	700	800	0
10	500	600	500	600	600	500	700	800	500
11	900	0	0	0	1,000	800	0	700	800
12	700	1,000	1,000	0	500	700	1,000	0	500
13	800	800	700	700	700	0	800	900	600
14	1,000	700	600	600	500	500	0	900	800
15	800	500	0	900	0	0	500	700	800
16	0	900	800	700	0	0	900	1,000	0
17	0	0	600	700	800	600	500	900	700
18	500	600	900	800	0	1,000	0	0	500
19	900	1,000	900	900	0	600	600	1,000	900

Table A.80: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	8,700	3,480	18
2	8,400	3,360	42
3	8,300	3,320	69
4	8,000	3,200	27
5	8,900	3,560	52
6	8,700	3,480	31
7	8,500	3,400	49
8	8,300	3,320	20
9	8,100	3,240	31
10	9,000	3,600	41
11	8,700	3,480	83
12	8,500	3,420	75
13	8,300	3,320	54
14	8,100	3,240	47
15	8,900	3,560	41
16	8,800	3,520	65
17	8,500	3,400	48

A.3.18 Replicate 1 of Experiment 7

Table A.81: Data of Replicate 1 of Experiment 7

Variable	Value
Part types	20
Machine types	14
Number of period	3
Number of cells	4
Intercell material cost	20
Lower and Upper bounds	3/10
Scenario/period	3

Table A.82: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	6	8-11/13-7-9-6/8-4	0.89-0.53/0.55-0.59-0.9-0.58/0.18-0.85	4
2	5	7-3-5-1-4/12/14	0.21-0.47-0.71-0.36-0.92/0.71/0.14	3
3	5	9-5-8/5/13-4-6	0.79-0.61-0.63-0.95/0.95/0.23-0.44	3
4	4	2-5-1-3/6/9	0.14-0.14-0.68-0.74/0.23/0.67	3
5	4	9/3-5-8/7-4	0.66/0.97-0.85-0.32/0.29-0.30	4
6	4	14/8-2-13-1/11	0.73/0.58-0.22-0.93-0.21/0.54	4
7	3	6/9-3-5/1	0.97/0.86-0.83-0.88/0.91	4
8	3	1/13/2-4-14	0.96/0.63/0.93-0.34-0.55	3
9	3	2-13-1/6/14	0.64-0.91-0.36/0.26/0.13	3
10	3	11-14-2/4/7	0.11-0.18-0.37/0.69/0.32	3
11	3	12/6-14-11/8	0.49/0.45-0.90-0.56/0.47	4
12	3	14/11-2-12/10	0.72/0.61-0.34-0.53/0.93	4
13	3	1-11/2-13/10	0.66-0.75/0.17-0.18/0.82	4
14	3	10-12-8/1/3	0.40-0.17-0.33/0.40/0.57	3
15	2	11-13/7/2	0.48-0.99/0.95/0.95	3
16	2	10-12/6/9	0.77-0.50/0.91/0.69	3
17	2	13-9/2/7	0.60-0.75/0.34/0.70	3
18	2	12/11/14-8	0.64/0.30/0.32-0.36	3
19	2	10/7/12-7	0.85/0.35/0.97-0.39	3
19	2	2/5/11-5	0.41/0.65/0.71-0.88	3

Table A.83: Part Type Demand

Part Type Number	Demand								
	Period 1			Period 2			Period 3		
	Sn 1	Sn 2	Sn 3	Sn 1	Sn 2	Sn 3	Sn 1	Sn 2	Sn 3
1	0	700	800	600	0	0	0	700	800
2	800	0	0	500	800	600	800	700	600
3	500	700	900	500	900	600	600	0	0
4	1,000	900	600	0	900	0	0	900	800
5	600	0	500	600	0	800	500	500	800
6	0	1,000	0	500	500	800	700	0	900
7	700	500	500	800	700	0	0	1,000	0
8	0	0	700	0	0	800	700	600	900
9	0	600	700	700	600	700	900	600	0
10	800	700	0	900	800	0	0	0	900
11	0	0	0	0	0	500	900	800	600
12	900	600	900	500	800	500	500	0	700
13	900	800	0	500	800	800	0	800	700
14	500	1,000	700	0	0	0	900	1,000	0
15	0	0	800	500	500	700	700	900	800
16	700	1,000	700	700	600	0	600	600	900
17	700	500	600	600	0	900	800	0	0
18	800	500	600	800	500	900	0	500	500
19	700	0	800	0	800	600	800	700	500
20	800	500	0	0	700	500	600	0	0

Table A.84: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	1,900	1,140	70
2	1,700	1,020	79
3	1,500	900	50
4	1,300	780	89
5	1,000	600	44
6	2,000	1,200	34
7	1,700	1,020	50
8	1,500	900	72
9	1,200	720	50
10	1,100	660	84
11	1,900	1,140	45
12	1,700	1,020	10
13	1,500	900	49
14	1,300	780	17

A.3.19 Replicate 2 of Experiment 7

Table A.85: Data of Replicate 2 of Experiment 7

Variable	Value
Part types	16
Machine types	14
Number of period	3
Number of cells	3
Intercell material cost	20
Lower and Upper bounds	3/10
Scenario/period	2

Table A.86: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	6	3-13/8-1-12-14-10/9	0.22-0.30/0.49-0.82-0.62-0.73-0.90/0.22	4
2	5	2/3/1-12-14-10-13	0.92/0.30/0.77-0.84-0.49-0.17-0.72	3
3	4	9-11-14-10/1/2	0.47-0.43-0.92-0.39/0.82/0.59	3
4	4	12/8/6-9-11-7	0.34/0.62/0.49-0.34-0.30-0.90	3
5	4	1/6-9-3-4/5	0.28/0.73-0.44-0.49-0.57/0.28	4
6	4	10-6/3-8/12-5	0.93-0.61/0.24-0.15/0.90-0.15	4
7	3	10/11-6-8/5	0.89/0.92-0.33-0.93/0.88	4
8	3	4-7/4/9-3	0.70-0.12/0.84/0.17-0.14	3
9	3	7/2-3/1-6	0.73/0.49-0.26/0.41-0.14	4
10	3	2/1/14-4-6	0.13/0.17/0.36-0.81-0.85	3
11	2	4-1/7/6	0.53-0.52/0.72/0.43	3
12	2	3-13/6/5	0.34-0.16/0.47/0.32	3
13	2	5/12/4-2	0.92/0.43/0.81-0.32	3
14	2	4-14/11/10	0.30-0.83/0.92/0.64	3
15	2	3/1/2-5	0.32/0.39/0.23-0.54	3
16	2	1/5/6-4	0.90/0.34/0.89-0.91	3

Table A.87: Part Type Demand

Part Type Number	Demand					
	Period 1		Period 2		Period 3	
	Sn 1	Sn 2	Sn 1	Sn 2	Sn 1	Sn 2
1	800	500	1,000	0	1,000	0
2	0	0	700	500	900	800
3	900	800	700	900	600	700
4	800	600	800	0	0	0
5	900	0	0	800	600	700
6	800	600	500	800	600	700
7	600	900	900	900	0	0
8	900	0	0	800	600	600
9	0	700	500	600	900	800
10	600	500	800	900	700	0
11	900	600	0	0	1,000	800
12	0	900	900	700	800	600
13	600	700	900	1,000	500	900
14	700	800	0	0	0	800
15	0	0	900	700	800	600
16	800	800	700	800	600	700

Table A.88: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	1,300	520	20
2	1,100	440	51
3	2,000	800	18
4	1,800	720	73
5	1,600	640	69
6	1,300	520	68
7	1,100	440	24
8	2,000	800	66
9	1,800	720	48
10	1,500	600	52
11	1,400	560	64
12	1,100	440	31
13	2,000	800	71
14	1,800	720	74

A.3.20 Replicate 3 of Experiment 7

Table A.89: Data of Replicate 3 of Experiment 7

Variable	Value
Part types	15
Machine types	15
Number of period	2
Number of cells	3
Intercell material cost	50
Lower and Upper bounds	3/10
Scenario/period	2

Table A.90: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	6	15/7-9-2-3-11-5/4	0.59/0.94-0.30-0.17-0.29-0.34-0.86/0.38	4
2	5	15/77-8-1-2-10/15	0.76/0.38-0.32-0.21-0.85-0.30/0.11	4
3	4	10/3-4-12-13/6	0.60/0.99-0.59-0.73-0.34/0.55	4
4	4	5-13-14/10/6-7	0.50-0.83-0.26/0.73/0.98-0.72	3
5	4	7/5/3-15-1-9	0.84/0.82/0.33-0.87-0.42-0.73	3
6	3	14-7/9/13-8	0.30-0.32/0.36/0.40-0.45	3
7	3	1-10/5/2-3	0.96-0.65/0.22/0.68-0.90	3
8	3	6/12-15-8/7	0.38/0.96-0.40-0.83/0.39	4
9	3	8/4-2-10/1	0.91/0.50-0.15-0.42/0.13	4
10	3	11/7/12-4-13	0.79/0.65/0.55-0.48-0.99	3
11	2	4/3/15-12	0.12/0.55/0.87-0.71	3
12	2	12/7/11-6	1.00/0.83/0.72-0.67	3
13	2	6-14/2/11	0.86-0.14/0.91/0.19	3
14	2	13-7/6/10	0.87-0.58/0.47/0.62	3
15	2	7-15/1/14	0.97-0.88/0.30/0.77	3

Table A.91: Part Type Demand

Part Type Number	Demand			
	Period 1		Period 2	
	Sn 1	Sn 2	Sn 1	Sn 2
1	0	700	0	600
2	900	1,000	500	500
3	0	0	0	1,000
4	800	800	500	500
5	1,000	900	0	800
6	800	800	800	900
7	600	700	800	700
8	700	0	600	700
9	0	700	0	0
10	500	0	500	500
11	700	900	900	0
12	900	0	900	900
13	800	800	1,000	0
14	0	0	700	800
15	800	800	800	0

Table A.92: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	1,800	720	21
2	1,600	640	54
3	1,300	520	51
4	1,200	480	58
5	2,000	800	51
6	1,800	720	55
7	1,600	640	36
8	1,400	560	43
9	1,100	440	35
10	1,000	400	66
11	1,800	720	62
12	1,600	640	26
13	1,400	560	56
14	1,200	480	38
15	2,000	800	10

A.3.21 Replicate 1 of Experiment 8

Table A.93: Data of Replicate 1 of Experiment 8

Variable	Value
Part types	18
Machine types	16
Number of period	3
Number of cells	4
Intercell material cost	30
Lower and Upper bounds	3/10
Scenario/period	2

Table A.94: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	5	4-10-16-7-13/12/8	0.74-0.44-0.98-0.74-0.44/0.28/0.46	3
2	5	14-5-11-1-8/14/11	0.72-0.53-0.48-0.21-0.35/0.94/0.81	3
3	4	14-4-11-1/2/14	0.37-0.73-0.25-0.90/0.20/0.70	3
4	4	7/5-14-4/16-10	0.19/0.53-0.39-0.85/0.75-0.31	4
5	4	3/2-10-16-6/7	0.82/0.28-0.69-0.91-0.56/1.00	4
6	4	15/11-5-11/9-2	0.13/0.16-0.61-0.18/0.28-0.27	4
7	3	8-14-5/11/12	0.28-0.73-0.58/0.84/0.28	3
8	3	11-1/14/16-8	0.87-0.88/0.83/0.28-0.66	3
9	3	12/13-3-9/1	0.61/0.59-0.78-0.60/0.33	4
10	3	15/16-6/3-12	0.45/0.21-0.35/0.54-0.16	4
11	3	2-9/6/2-15	0.58-0.26/0.92/0.21-0.62	3
12	3	16/8/5-7-13	0.91/0.83/0.65-0.64-0.20	3
13	3	3/11/8-10-16	0.86/0.80/0.57-0.69-1.00	3
14	2	14-4/1/10	0.94-0.18/0.51/0.95	3
15	2	11-1/16/13	0.34-0.32/0.28/0.36	3
16	2	7-13/3/15	0.97-0.58/0.42/0.62	3
17	2	5/16/2-12	0.22/0.55/0.17-0.42	3
18	2	2/7/5-8	0.10/0.68/0.33-0.67	3

Table A.95: Part Type Demand

Part Type Number	Demand					
	Period 1		Period 2		Period 3	
	Sn 1	Sn 2	Sn 1	Sn 2	Sn 1	Sn 2
1	600	700	0	600	1,000	500
2	700	800	0	0	900	800
3	0	0	900	1,000	500	700
4	0	0	500	900	700	0
5	700	900	600	500	500	1,000
6	500	1,000	900	600	700	600
7	600	600	600	0	0	0
8	700	900	800	0	0	0
9	900	500	800	500	0	700
10	500	600	0	600	700	900
11	700	0	0	800	900	800
12	600	0	800	500	1,000	900
13	700	0	500	600	700	0
14	0	700	700	1,000	800	0
15	0	1,000	600	500	700	800
16	0	700	700	900	600	1,000
17	800	800	900	0	0	500
18	900	1,000	0	0	0	800

Table A.96: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	9,700	3,880	26
2	8,500	3,400	63
3	8,200	3,280	89
4	9,100	3,640	73
5	8,700	3,480	35
6	9,600	3,840	38
7	9,300	3,720	71
8	8,100	3,240	35
9	9,800	3,920	52
10	8,700	3,480	51
11	8,300	3,320	33
12	9,200	3,680	52
13	8,900	3,560	65
14	9,800	3,920	52
15	9,400	3,760	12
16	8,300	3,320	53

A.3.22 Replicate 2 of Experiment 8

Table A.97: Data of Replicate 2 of Experiment 8

Variable	Value
Part types	17
Machine types	18
Number of period	2
Number of cells	4
Intercell material cost	20
Lower and Upper bounds	3/10
Scenario/period	2

Table A.98: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	6	14/1-4-12-13-3-2/6	0.74/0.81-0.44-0.98-0.74-0.44-0.72/0.33	4
2	5	1/10-9-18-8-17/16	0.53/0.83-0.48-0.21-0.35-0.37/0.40	4
3	4	17/12/5-7-8-16	0.73/0.58/0.53-0.25-0.79-0.19	3
4	4	16-7-15-6/17/10	0.39-0.85-0.31-0.82/0.86/0.87	3
5	4	3-11/12/4-1-2	0.69-0.91/1.00-0.56/0.86-0.13	3
6	4	10/4-1-9-18/16	0.61/0.77-0.18-0.27-0.28/0.55	4
7	3	18/2-9-17/3	0.73/0.77-0.58-0.87/0.11	4
8	3	17/15-18-8/14	0.88/0.71-0.66-0.61/0.33	4
9	3	6-14/2/3-15	0.78-0.60/0.38/0.66-0.45	3
10	3	15/3/7-5-6	0.35/0.75/0.91-0.16-0.58	3
11	3	12-2/1/13-10	0.26-0.62/0.80/0.13-0.91	3
12	2	11-1/14/7	0.64-0.20/0.45/0.98	3
13	2	1-10/18/11	0.86-0.69/0.71/0.18	3
14	2	10/13/6-18	0.61/0.62/0.87-0.49	3
15	2	14/18/10-5	0.18/0.15/0.65-0.34	3
16	2	5/12/13-13	0.32/0.32/0.68-0.70	3
17	2	8/7/14-17	0.58/0.28/0.43-0.22	3

Table A.99: Part Type Demand

Part Type Number	Demand			
	Period 1		Period 2	
	Sn 1	Sn 2	Sn 1	Sn 2
1	1,000	600	600	0
2	0	0	800	800
3	700	700	0	0
4	0	700	900	500
5	600	900	0	0
6	800	800	0	700
7	700	0	1,000	900
8	900	900	500	900
9	1,000	500	500	0
10	500	1,000	700	0
11	600	600	900	900
12	0	800	800	500
13	0	0	0	500
14	700	0	0	600
15	900	800	900	600
16	800	0	1,000	800
17	0	1,000	500	900

Table A.100: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	9,800	3,920	73
2	8,600	3,440	76
3	8,200	3,280	50
4	9,200	3,680	36
5	8,800	3,480	50
6	9,700	3,520	55
7	9,400	3,760	40
8	8,200	3,280	54
9	9,900	3,960	51
10	8,700	3,480	82
11	8,400	3,360	74
12	9,300	3,720	13
13	8,900	3,560	22
14	9,900	3,960	23
15	9,500	3,800	25
16	8,300	3,320	64
17	8,000	3,200	34
18	8,900	3,560	41

A.3.23 Replicate 3 of Experiment 8

Table A.101: Data of Replicate 3 of Experiment 8

Variable	Value
Part types	18
Machine types	18
Number of period	2
Number of cells	4
Intercell material cost	50
Lower and Upper bounds	3/10
Scenario/period	2

Table A.102: Part Type Attribute

Part Type Number	Operation Number	Operation Sequence	Processing Time	Alternate Route
1	6	12-13/4-3-11-2/14-1	0.57-0.12/0.57-0.60-0.69-0.65/0.31-0.73	4
2	5	6-14-5-13-4/9/7	0.26-0.75-0.60-0.38-0.77/0.12/0.98	3
3	5	2-10-1-9/3/12-18	0.43-0.54-0.37-0.56/0.60/0.17-0.61	3
4	4	4/8/6-13-3-12	0.35/0.69/0.16-0.77-0.47-0.21	3
5	4	18-8-9/2/11-17	0.99-0.94-0.83/0.65/0.96-0.36	3
6	3	17/6-8-16/7	0.72/0.52-0.38-0.19/0.73	4
7	3	16/2-7-15/10	0.77/0.26-0.37-0.30/0.33	4
8	3	12/6-2-3/5	0.98/0.75-0.84-0.39/0.53	4
9	3	11/1-2-10/9	0.73/0.60-0.50-0.85/0.85	4
10	3	11/5-1-10/4	0.96/0.38-0.42-0.42/0.18	4
11	3	14/9-4-13/18	0.34/0.13-0.11-0.82/0.77	4
12	2	13/5/16-3	0.36/0.43/0.98-0.30	3
13	2	4-12/17/8	0.85-0.61/0.54/0.11	3
14	2	16-6/4/2	0.54-0.40/0.37/0.27	3
15	2	6-15/8/7	0.71-0.71/0.56/0.48	3
16	2	15/3/2-6	0.84/0.61/0.10-0.87	3
17	2	10/8/6-18	0.67/0.35/0.15-0.86	3
18	2	18/2/1-9	0.23/0.77/0.74-0.33	3

Table A.103: Part Type Demand

Part Type Number	Demand			
	Period 1		Period 2	
	Sn 1	Sn 2	Sn 1	Sn 2
1	900	1,000	500	900
2	1,000	600	600	0
3	600	0	1,000	0
4	0	0	0	500
5	800	500	0	0
6	0	0	0	500
7	600	900	800	700
8	800	600	700	800
9	900	800	800	1,000
10	700	900	600	0
11	900	500	700	0
12	700	0	500	0
13	700	0	0	800
14	0	1,000	0	900
15	0	500	700	1,000
16	0	1,000	500	600
17	900	500	700	900
18	1,000	700	900	500

Table A.104: Machine Type Attributes

Machine Type Number	Machine Cost	Relocation Cost	Operating Cost
1	9,600	1,920	74
2	8,400	1,680	36
3	8,100	1,620	40
4	9,000	1,800	47
5	8,600	1,720	40
6	9,600	1,920	28
7	9,200	1,840	42
8	8,000	1,600	27
9	9,800	1,960	49
10	8,600	1,720	65
11	8,200	1,640	104
12	9,200	1,840	40
13	8,800	1,760	39
14	9,700	1,940	49
15	9,300	1,860	52
16	8,200	1,640	74
17	9,900	1,980	44
18	8,700	1,740	61

A.4 Detailed Results

This appendix shows the detailed results of cellular configurations from the experimental design.

Table A.105: Lower Bound of Replicate 2 of Experiment 1 in Period 1

Cell	M/C Type (Quantity)	Part type										
		1	2	4	5	6	8	11	3	7	9	10
1	1 (1)	1		1								
	2 (1)	1	1	1	1							
	3 (1)	1	1	1								
	4 (1)	1			1							
	5 (1)	1	1		1							
	7 (1)	1										*
2	1 (1)					1	1			*		
	3 (1)					1	1	1				
	5 (1)					1		1				
3	4 (1)								1	1		
	6 (1)			*					1	1	1	
	8 (2)			*					1	1		1

Table A.106: Heuristic's Solution of Replicate 2 of Experiment 1 in Period 1

Cell	M/C Type (Quantity)	Part type										
		1	2	3	4	5	6	8	11	7	9	10
1	1 (1)	1		1	1							
	2 (1)	1	1		1	1						
	3 (1)	1	1		1							
	4 (1)	1			1							
	5 (1)	1	1			1						
	6 (1)			1	1							
	7 (1)	1										*
	8 (1)		1	1								
2	1 (1)					1	1					
	3 (1)					1	1	1				
	5 (1)					1		1				
3	4 (1)								1			
	6 (1)			*					1	1		
	8 (1)			*					1			1

Table A.111: Lower Bound of Replicate 3 of Experiment 1 in Period 1

Cell	M/C Type (Quantity)	Part type										
		2	9	10	11	3	7	8	1	4	5	6
	1 (1)	1	1						*			
	2 (1)	1										
	4 (1)			1								
	9 (1)	1	1	1	1							
	5 (1)					1	1	1				
	6 (1)	*				1	1	1	*			
	7 (1)	*				1						
	8 (1)				*	1						
	2 (1)								1		1	1
	3 (1)								1	1	1	1
	4 (1)								1	1	1	
	5 (1)								1	1		

Table A.112: Heuristic's Solution of Replicate 3 of Experiment 1 in Period 1

Cell	M/C Type (Quantity)	Part type										
		1	4	5	6	10	7	8	9	2	3	11
	2 (1)	1		1	1							
	3 (1)	1	1	1	1							
	4 (1)	1	1	1		1						
	5 (1)	1	1									
	1 (1)	*			*		1	1	*			
	5 (1)						1					
	6 (1)						1	1	1	*	*	
	2 (1)									1	1	
	7 (1)									1	1	
	8 (1)										1	1
	9 (1)					*				1		1

Table A.113: Lower Bound of Replicate 3 of Experiment 1 in Period 2

Cell	M/C Type (Quantity)	Part type									
		2	9	10	11	3	7	8	1	4	6
	1 (1)	1	1						*		
	2 (1)	1									
	9 (1)	1	1	1	1						
	5 (1)					1	1	1			
	6 (1)					1	1	1	*		
	7 (1)	*				1					
	8 (1)	*			*	1					
	2 (1)								1		1
	3 (1)								1	1	1
	4 (1)			1					1	1	
	5 (1)								1	1	

Table A.114: Heuristic's Solution of Replicate 3 of Experiment 1 in Period 2

Cell	M/C Type (Quantity)	Part type									
		1	4	6	3	7	8	9	2	10	11
	2 (1)	1		1							
	3 (1)	1	1	1							
	4 (1)	1	1								
	5 (1)	1	1								
	1 (1)	*		*				1	*		
	5 (1)				1	1	1				
	6 (1)				1	1	1	1	*	*	
	2 (1)								1	1	
	7 (1)				*				1	1	
	8 (1)				*					1	1
	9 (1)								1		1

Table A.115: Lower Bound of Replicate 1 of Experiment 2 in Period 1

Cell	M/C Type (Quantity)	Part type											
		4	7	8	13	6	9	10	11	1	2	3	12
1	3 (1)	1		1	1								
	4 (1)	1				*				*			
	5 (1)	1	1							*			
	6 (1)				1								
	7 (1)	1	1	1	1						*		
	8 (1)			1									
2	1 (1)					1			1				
	2 (1)						1	1	1	*	*		
	10 (1)					1		1					
3	1 (1)									1	1	1	
	3 (1)									1			
	9 (1)										1	1	1
	10 (1)									1	1		1

Table A.116: Heuristic's Solution of Replicate 1 of Experiment 2 in Period 1

Cell	M/C Type (Quantity)	Part type											
		1	2	3	4	9	11	6	10	12	7	8	13
1	1 (1)	1	1	1			1						
	3 (1)	1			1								
	4 (1)	1				1	1						
	7 (1)		1			1							
	9 (1)			1	1								
	10 (1)	1	1										
2	2 (1)	*	*			*	*		1				
	9 (1)							1		1			
	10 (1)							1	1	1			
3	3 (1)											1	1
	5 (1)	*			*						1		
	6 (1)				*							1	
	7 (1)										1	1	1
8 (1)				*						1			

Table A.117: Lower Bound of Replicate 1 of Experiment 2 in Period 2

Cell	M/C Type (Quantity)	Part type											
		3	7	8	4	5	9	12	1	6	10	11	12
1	6 (1)	1		1			*						
	7 (1)		1	1									
	8 (1)	1	1										
	9 (1)	1		1									
2	3 (1)				1	1		1				*	
	4 (1)				1	1	1					*	
	5 (1)		*		1	1						*	
	7 (1)				1			1					
3	1 (1)	*					*		1	1		1	
	2 (1)								1		1	1	
	9 (1)									1			1
	10 (1)								1	1	1		1

Table A.118: Heuristic's Solution of Replicate 1 of Experiment 2 in Period 2

Cell	M/C Type (Quantity)	Part type											
		1	4	9	11	13	6	10	12	3	5	7	8
1	1 (1)	1			1								
	4 (1)	1	1	1							*		
	5 (1)	1	1								*	*	
	7 (1)		1			1							
	10 (1)	1											
2	2 (1)	*		*	*			1					
	9 (1)						1		1				
	10 (1)						1	1	1				
3	3 (1)	*	*			*					1		
	6 (1)									1	1		1
	7 (1)										1		1
	8 (1)									1		1	
9 (1)									1			1	

Table A.119: Lower Bound of Replicate 2 of Experiment 2 in Period 1

Cell	M/C Type (Quantity)	Part type											
		9	11	12	2	3	5	6	7	13	1	4	10
1	1 (1)	1			*						*		
	4 (1)			1							*		
	7 (1)	1	1								*		
	10 (1)	1	1	1							*		
2	1 (1)				1		1					*	
	3 (1)					1							
	5 (1)					1		1		1			
	6 (1)				1		1		1				
	8 (1)					1	1	1	1	1			
	11 (1)					1		1	1			*	
12 (1)				1		1							
3	2 (1)					*					1	1	1
	4 (1)					*					1	1	
	5 (1)										1		
	9 (1)				*								1

Table A.120: Heuristic's Solution of Replicate 2 of Experiment 2 in Period 1

Cell	M/C Type (Quantity)	Part type											
		2	5	7	10	11	12	1	3	4	6	9	13
1	3 (1)	1	1										
	6 (1)	1	1	1									
	9 (1)	1			1					*	*	*	
	11 (1)			1						*	*	*	
	12 (1)	1											
2	4 (1)	*					1						
	7 (1)						1						
	10 (1)						1	1					
3	1 (1)							1		1		1	
	2 (1)				*			1	1	1			
	4 (1)							1	1	1			1
	5 (1)							1	1				
	7 (1)							1				1	
	8 (1)		*	*					1		1		1
	10 (1)							1			1	1	

Table A.121: Lower Bound of Replicate 2 of Experiment 2 in Period 2

Cell	M/C Type (Quantity)	Part type											
		8	9	10	2	3	4	5	7	13	1	11	12
1	1 (1)	1	1			*							
	3 (1)	1											
	7 (1)		1										
	9 (1)	1		1		*							
2	2 (1)			*		1	1						
	4 (1)				1	1	1						
	5 (1)					1					1		
	6 (1)				1			1	1				
	8 (1)					1		1	1	1			
	12 (1)				1		1	1					
3	1 (1)										1		
	2 (1)										1		
	4 (1)										1	1	
	5 (1)										1		
	7 (1)										1	1	
10 (1)										1	1	1	

Table A.122: Heuristic's Solution of Replicate 2 of Experiment 2 in Period 2

Cell	M/C Type (Quantity)	Part type											
		2	5	7	8	10	11	11	1	3	4	9	13
1	1 (1)				1								
	2 (1)					1							
	3 (1)	1	1		1								
	6 (1)	1	1	1									
	8 (1)		1	1					*				*
	12 (1)	1	1		1	1							
2	4 (1)	*						1					
	7 (1)							1					
	10 (1)							1	1				
3	1 (1)								1		1	1	
	2 (1)								1	1	1		
	4 (1)								1	1	1		
	5 (1)								1	1		1	
	7 (1)								1			1	
	10 (1)								1	1			
11 (1)			*							1	1		

Table A.125: Lower Bound of Replicate 3 of Experiment 2 in Period 2

Cell	M/C Type (Quantity)	Part type								
		3	4	6	8	5	9	1	7	10
1	4 (1)	1		1						
	5 (1)		1		1					
	6 (1)	1	1	1	1					*
2	2 (1)					1	1			
	7 (1)		*			1			*	*
	8 (1)					1	1		*	
3	1 (1)	*		*						1
	2 (1)	*							1	
	3 (1)								1	1
	5 (1)								1	1

Table A.126: Heuristic's Solution of Replicate 3 of Experiment 2 in Period 2

Cell	M/C Type (Quantity)	Part type								
		1	5	9	4	7	8	10	3	6
1	2 (1)	1	1	1						
	5 (1)	1							*	*
	6 (1)	1								
	8 (1)	1	1	1						
2	3 (1)	*				1		1		
	5 (1)					1		1	1	
	7 (1)	*	*			1	1			
3	1 (1)					*				1
	2 (1)									1
	4 (1)				*		*			1

Table A.127: Lower Bound of Replicate 3 of Experiment 2 in Period 3

Cell	M/C Type (Quantity)	Part type							
		3	5	6	9	1	2	4	7
1	2 (1)	1	1		1	*			
	4 (1)	1		1				*	
	6 (1)	1		1		*			
	8 (1)		1	1	1	*			
2	3 (1)					1	1		
	5 (1)					1	1		
	7 (1)		*			1	1		
3	1 (1)								1
	5 (1)							1	
	7 (1)							1	1

Table A.128: Heuristic's Solution of Replicate 3 of Experiment 2 in Period 3

Cell	M/C Type (Quantity)	Part type							
		1	2	5	9	4	7	3	6
1	2 (1)	1		1	1				
	5 (1)	1	1						
	6 (1)	1						*	*
	7 (1)	1	1	1					
	8 (1)	1		1	1				
2	1 (1)						1		
	3 (1)	*	*				1		
	5 (1)					1			
	7 (1)					1	1		
3	1 (1)							1	1
	2 (1)							1	
	4 (1)					*		1	1

Table A.131: Lower Bound of Replicate 1 of Experiment 3 in Period 2

Cell	M/C Type (Quantity)	Part type											
		6	12	13	1	2	7	8	11	4	5	9	10
1	3 (1)	1		1								*	
	7 (1)	1	1	1									
	9 (1)	1			*								
	10 (1)		1		*								
2	1 (1)				1		1	1					
	2 (1)				1	1							
	4 (1)				1	1		1					
	6 (1)				1	1							1
	8 (1)					1	1	1					
11 (1)						1		1					
3	4 (1)									1	1	1	1
	6 (1)									1	1		
	9 (1)									1	1	1	1

Table A.132: Heuristic's Solution of Replicate 1 of Experiment 3 in Period 2

Cell	M/C Type (Quantity)	Part type											
		1	2	8	12	7	10	13	4	5	6	9	11
1	2 (1)	1	1										
	4 (1)	1	1	1									
	6 (1)	1	1										
	8 (1)		1	1									
	9 (1)	1											
	10 (1)	1			1								
2	1 (1)	*		*		1							
	4 (1)					1							
	5 (1)				*	1	1						
	7 (1)					1		1					
11 (1)					1							*	
3	3 (1)									1	1		
	4 (1)								1	1		1	
	6 (1)								1	1	1		1
	9 (1)								1	1	1	1	

Table A.135: Lower Bound of Replicate 2 of Experiment 3 in Period 2

Cell	M/C Type (Quantity)	Part type										
		4	8	11	12	5	7	10	1	3	6	
1	8 (1)	1	1		1							
	9 (1)		1		1						*	
	10 (1)	1										
	11 (1)		1	1								*
2	4 (1)	*					1				*	
	5 (1)	*				1		1				
	6 (1)			*		1	1					
	8 (1)					1	1					
	10 (1)					1		1				
3	2 (1)									1		1
	3 (1)										1	1
	7 (1)									1	1	
	8 (1)									1	1	
	11 (1)									1	1	

Table A.136: Heuristic's Solution of Replicate 2 of Experiment 3 in Period 2

Cell	M/C Type (Quantity)	Part type										
		1	3	6	8	11	12	4	5	7	10	
1	2 (1)	1			1							
	3 (1)		1	1								
	4 (1)	1							*			
	7 (1)	1	1									
	8 (1)	1	1									
	10 (1)	1										
	11 (1)	1	1	1								
2	2 (1)				1							
	6 (1)					1						
	8 (1)						1					
	9 (1)				1		1					
	11 (1)				1	1						
3	5 (1)						1	1		1		1
	6 (1)							1	1			
	8 (1)						1	1	1			
	10 (1)						1	1			1	

Table A.137: Lower Bound of Replicate 2 of Experiment 3 in Period 3

Cell	M/C Type (Quantity)	Part type								
		4	8	11	12	5	7	10	1	3
1	1 (1)	1	1	1	*					
	2 (1)	1	1							
	8 (1)	1		1						
	11 (1)	1	1							*
2	5 (1)				1	1	1			
	8 (1)				1	1				
	10 (1)				1	1	1			
3	2 (1)									1
	3 (1)								1	1
	4 (1)								1	1
	6 (1)				*				1	1
	7 (1)	*							1	

Table A.138: Heuristic's Solution of Replicate 2 of Experiment 3 in Period 3

Cell	M/C Type (Quantity)	Part type								
		1	6	9	2	11	12	4	5	10
1	2 (2)	1	1	1						
	3 (1)		1	1						
	4 (1)	1		1						
	8 (2)	1					*			
	10 (1)	1								
	11 (1)	1	1							
2	4 (1)				1			*		
	6 (1)				1	1			*	
	7 (1)	*			1					
	9 (1)				1		1			
	11 (1)					1				
3	5 (1)							1	1	1
	8 (1)							1	1	
	10 (1)							1	1	1

Table A.139: Lower Bound of Replicate 2 of Experiment 3 in Period 4

Cell	M/C Type (Quantity)	Part type								
		2	11	12	1	8	10	4	7	9
1	4 (1)	1			*					
	6 (1)	1	1							
	7 (1)	1								
	9 (1)	1	1	1		*				
2	2 (1)				1		1			*
	7 (1)				1					
	8 (1)			*	1	1				
	10 (1)				1		1			
	11 (1)				1	1				
3	4 (1)							1	1	1
	5 (1)							1		
	6 (1)								1	1
	8 (1)							1	1	

Table A.140: Heuristic's Solution of Replicate 2 of Experiment 3 in Period 4

Cell	M/C Type (Quantity)	Part type									
		1	6	9	2	11	12	4	5	10	
1	1 (2)	1									
	2 (1)	1	1	1							
	3 (1)			1							
	7 (2)	1									
	8 (1)	1				*					
	11 (1)	1									
2	4 (1)		*		1				*	*	
	6 (1)				1		1				
	7 (1)				1						
	9 (1)				1	1		1			
	11 (1)					1	1				
3	5 (1)								1		
	6 (1)									1	
	8 (1)						*		1	1	
	10 (1)	*		*					1		

Table A.141: Lower Bound of Replicate 3 of Experiment 3 in Period 1

Cell	M/C Type (Quantity)	Part type									
		1	3	9	4	5	6	2	8	10	11
1	1 (1)	1	1	1							
	2 (1)	1	1	1				*		*	
	10 (1)	1	1								
2	6 (1)					1	1	*			
	7 (1)				1		1	*			
	8 (1)	*			1		1				
	9 (1)	*			1	1					
3	3 (1)								1		
	4 (1)							1			
	5 (1)					*		1	1	1	

Table A.142: Heuristic's Solution of Replicate 3 of Experiment 3 in Period 1

Cell	M/C Type (Quantity)	Part type									
		1	4	6	2	5	8	11	3	9	10
1	1 (1)	1									
	2 (1)	1						*			
	7 (1)			1	1						
	8 (1)	1	1	1							
	9 (1)	1	1								
	10 (1)	1				*					
2	2 (1)					1	1	1			
	4 (1)				1		1				
	6 (1)			*	1	1		1			
3	1 (1)								1	1	
	3 (1)							1	1	1	
	5 (1)				*	*				1	

Table A.143: Lower Bound of Replicate 3 of Experiment 3 in Period 2

Cell	M/C Type (Quantity)	Part type										
		1	3	8	2	7	8	10	4	5	6	11
1	1 (1)	1	1	1								
	2 (1)	1	1	1								
	10 (1)	1	1									
2	2 (1)						1					
	3 (1)						1	1				
	4 (1)				1	1						
	5 (1)				1	1				*		
3	2 (1)											1
	6 (1)				*					1	1	1
	7 (1)				*				1		1	
	8 (1)	*							1		1	
	9 (1)	*							1	1		

Table A.144: Heuristic's Solution of Replicate 3 of Experiment 3 in Period 2

Cell	M/C Type (Quantity)	Part type										
		1	3	4	6	2	5	7	11	8	9	10
1	1 (1)	1	1									
	2 (1)	1	1									
	7 (1)			1	1							
	8 (1)	1		1	1		*					
	10 (1)	1	1				*					
2	2 (1)								1	*		
	4 (1)					1		1				
	5 (1)					1	1					
	6 (1)				*	1	1		1			
3	1 (1)										1	1
	3 (1)									1	1	
	5 (1)					*						1

Table A.147: Lower Bound of Replicate 1 of Experiment 4 in Period 1

Cell	M/C Type (Quantity)	Part type								
		1	7	8	2	9	3	4	5	6
1	2 (1)	1			*		*			
	3 (1)	1	1	1				*		
	5 (1)	1	1					*		
2	1 (1)	*			1	1				
	4 (1)	*			1					
	5 (1)				1		*			*
	7 (1)	*			1	1				
3	1 (1)							1		
	2 (1)								1	1
	4 (1)						1		1	
	8 (1)			*			1	1		1

Table A.148: Heuristic's Solution of Replicate 1 of Experiment 4 in Period 1

Cell	M/C Type (Quantity)	Part type									
		6	7	8	9	1	2	3	4	5	
1	2 (1)	1									
	5 (1)		1								
	6 (1)	1	1			*					
2	3 (1)			1		*				*	
	7 (1)				1						
	8 (1)	*		1	1			*	*		
3	1 (1)					1	1		1		
	2 (1)						1	1		1	
	4 (1)						1	1		1	
	5 (1)					1	1	1	1		
	7 (1)					1	1				

Table A.149: Lower Bound of Replicate 1 of Experiment 4 in Period 2

Cell	M/C Type (Quantity)	Part type								
		2	3	5	1	4	9	6	7	8
1	2 (1)	1	1					*		
	4 (1)	1	1	1		*				
	5 (1)	1	1							
	8 (1)		1							
2	1 (1)	*		*	1	1				
	7 (1)	*			1		1			
	8 (1)					1	1			
3	3 (1)			*	*					1
	5 (1)				*				1	
	6 (1)				*			1	1	
	8 (1)							1		1

Table A.150: Heuristic's Solution of Replicate 1 of Experiment 4 in Period 2

Cell	M/C Type (Quantity)	Part type									
		6	7	8	9	1	2	3	4	5	
1	2 (1)	1									
	5 (1)		1								
	6 (1)	1	1								
2	3 (1)			1						*	
	7 (1)				1						
	8 (1)	*		1	1	*		*	*		
3	1 (1)					1	1		1	1	
	2 (1)					1	1	1			
	4 (1)						1	1		1	
	5 (1)					1	1	1	1		
	7 (1)					1	1				

Table A.151: Lower Bound of Replicate 1 of Experiment 4 in Period 3

Cell	M/C Type (Quantity)	Part type							
		1	5	8	3	7	2	4	9
1	1 (1)	1							
	3 (1)	1	1	1					
	4 (1)	1	1		*				
	7 (1)	1							
	8 (1)			1	*				
2	2 (1)		*		1		*		
	5 (1)	*			1	1			
	6 (1)	*				1			
3	1 (1)						1	1	
	5 (1)						1	1	
	7 (1)						1		1
	8 (1)						1	1	1

Table A.152: Heuristic's Solution of Replicate 1 of Experiment 4 in Period 3

Cell	M/C Type (Quantity)	Part type							
		3	4	7	8	9	1	2	5
1	1 (1)			1					
	5 (1)	1	1	1					
	8 (1)	1	1						
2	3 (1)				1		*		*
	7 (1)					1			
	8 (1)				1	1			
3	1 (1)						1	1	
	2 (1)	*						1	
	4 (1)	*						1	1
	5 (1)						1	1	
	6 (1)			*			1		1
	7 (1)						1	1	

Table A.153: Lower Bound of Replicate 2 of Experiment 4 in Period 1

Cell	M/C Type (Quantity)	Part type						
		1	4	7	8	2	5	6
1	1 (1)	1	1					
	2 (1)	1						
	3 (1)	1						
	4 (1)	1						
	9 (1)		1					
2	5 (1)				1		*	
	6 (1)		*	1	1			
	9 (1)			1			*	
3	7 (1)							1
	8 (1)					1	1	1
	9 (1)					1	1	

Table A.154: Heuristic's Solution of Replicate 2 of Experiment 4 in Period 1

Cell	M/C Type (Quantity)	Part type						
		1	5	2	4	6	7	8
1	2 (1)	1						
	3 (1)	1						
	4 (1)	1						
	9 (1)		1	*	*			
2	1 (1)				1	1		
	7 (1)				1	1		
	8 (1)		*	1	1			
3	5 (1)	*		*				1
	6 (1)					1	1	
	7 (1)					1		

Table A.155: Lower Bound of Replicate 2 of Experiment 4 in Period 2

Cell	M/C Type (Quantity)	Part type							
		1	3	2	4	5	6	7	8
1	2 (1)	1	1			*			
	3 (1)	1	1						
	4 (1)	1							
2	1 (1)		*	1	1				
	8 (1)			1	1	1		*	
	9 (1)		*	1	1	1			
3	5 (1)	*							1
	6 (1)						1	1	1
	7 (1)						1	1	

Table A.156: Heuristic's Solution of Replicate 2 of Experiment 4 in Period 2

Cell	M/C Type (Quantity)	Part type							
		1	2	3	5	4	6	7	8
1	2 (1)	1		1	1				
	3 (1)	1		1					
	4 (1)	1							
	5 (1)		1						
	9 (1)		1	1	1	*			
2	1 (1)	*		*		1	1		
	7 (1)						1		
	8 (1)		*		*	1	1		
3	5 (1)								1
	6 (1)						1	1	
	7 (1)						1		

Table A.157: Lower Bound of Replicate 2 of Experiment 4 in Period 3

Cell	M/C Type (Quantity)	Part type							
		1	3	2	6	8	4	5	7
1	2 (1)	1	1					*	
	3 (1)	1	1						
	4 (1)	1							
2	5 (1)	*		1		1			
	7 (1)			1	1				
	8 (1)			1	1			*	
3	1 (1)		*		*		1		
	6 (1)						1		1
	9 (1)		*	*			1	1	1

Table A.158: Heuristic's Solution of Replicate 2 of Experiment 4 in Period 3

Cell	M/C Type (Quantity)	Part type							
		1	2	3	5	4	6	7	8
1	2 (1)	1		1					
	3 (1)	1		1					
	4 (1)	1							
	5 (1)	1		1					
	9 (1)			1					
2	1 (1)			*	1		1		
	8 (1)			*	1	1	1		
	9 (1)				1	1			
3	5 (1)								1
	6 (1)							1	1
	7 (1)					*		1	

Table A.163: Lower Bound of Replicate 3 of Experiment 4 in Period 2

Cell	M/C Type (Quantity)	Part type									
		3	7	10	4	6	9	1	2	5	8
1	2 (1)	1		1							
	4 (1)		1		*			*			
	5 (1)	1	1					*		*	
	8 (1)	1	1								
	11 (1)	1		1							
2	1 (1)				1	1					
	3 (1)					1	1	*			
	6 (1)				1		1		*		
3	8 (1)							1		1	
	9 (1)								1	1	
	10 (1)				*			1	1	1	

Table A.164: Heuristic's Solution of Replicate 3 of Experiment 4 in Period 2

Cell	M/C Type (Quantity)	Part type								
		3	8	10	1	4	6	7	2	5
1	2 (1)	1		1						
	3 (1)			1		*				*
	8 (1)	1	1							
	11 (1)	1								
2	1 (1)				1	1	1			
	4 (1)				1	1		1		
	5 (1)	*			1			1		*
	8 (1)				1			1		
	10 (1)				1		1			
3	6 (1)					*			1	
	9 (1)								1	1
	10 (1)		*						1	1

Table A.165: Lower Bound of Replicate 3 of Experiment 4 in Period 3

Cell	M/C Type (Quantity)	Part type								
		1	4	7	5	8	9	3	6	10
1	1 (1)		1	1						
	4 (1)	1	1	1						
	5 (1)	1		1	*				*	
2	3 (1)							1		
	8 (1)	*				1				
	9 (1)				1		1			
	10 (1)	*			1	1				
3	1 (1)	*							1	
	2 (1)		*					1		1
	10 (1)		*					1	1	
	11 (1)							1	1	1

Table A.166: Heuristic's Solution of Replicate 3 of Experiment 4 in Period 3

Cell	M/C Type (Quantity)	Part type								
		3	10	1	6	7	8	4	5	9
1	2 (1)	1	1							
	3 (1)		1							
	8 (1)	1								
	11 (1)	1			*					
2	1 (1)				1					
	4 (1)			1		1		*		
	5 (1)	*		1		1			*	
	8 (1)			1		1	1			
10 (1)			1	1		1				
3	3 (1)			*						1
	6 (1)							1	1	
	9 (1)							1		1
	10 (1)							1	1	

Table A.168: Heuristic's Solution of Replicate 1 of Experiment 5 in Period 1

Cell	M/C Type (Quantity)	Part type												
		1	2	7	13	6	8	11	4	9	10	12	15	16
1	4 (1)	1					*							
	5 (1)		1											
	6 (1)			1										
	7 (1)	1	1		1									
	8 (1)	1	1	1										
	9 (1)	1		1										
	10 (1)		1											
11 (1)	1			1	1									
2	3 (1)						1							
	10 (1)					1								
	11 (2)					1		1						
	14 (1)					1	1	1						
3	1 (1)								1	1		1		
	2 (1)								1		1			
	8 (1)													1
	12 (2)								1		1	1	1	
	13 (2)								1	1	1		1	
	14 (2)								1		1			

Table A.169: Lower Bound of Replicate 1 of Experiment 5 in Period 2

Cell	M/C Type (Quantity)	Part type												
		1	2	3	5	8	6	13	15	16	4	10	11	14
1	2 (1)				1	1								
	3 (1)			1	1	1								
	4 (1)	1		1										
	5 (1)		1	1	1									
	6 (1)		1											
	7 (1)		1	1	1									
	8 (1)	1	1							*				
	9 (1)	1												
	10 (1)		1											
	14 (1)					1								
2	7 (2)	*						1						
	10 (1)						1							
	11 (1)	*					1	1						
	12 (1)								1	1				
	13 (1)								1					
14 (1)						1								
3	1 (1)			*							1			1
	2 (1)										1	1		
	11 (1)												1	1
	13 (1)										1	1		
	14 (1)										1	1	1	

Table A.170: Heuristic's Solution of Replicate 1 of Experiment 5 in Period 2

Cell	M/C Type (Quantity)	Part type												
		1	2	3	5	13	14	6	8	11	4	10	15	16
1	4 (1)	1		1										
	5 (1)		1	1	1									
	6 (1)		1				1							
	7 (2)	1	1	1	1	1								
	8 (1)	1	1											*
	9 (1)	1												
	11 (1)	1					1							
2	2 (1)				*			1						
	3 (1)			*	*			1						
	10 (2)							1						
	11 (1)							1		1				
14 (1)							1	1	1					
3	1 (1)			*			*				1			
	2 (1)										1	1		
	12 (2)												1	1
	13 (2)										1	1	1	
	14 (2)										1	1		

Table A.171: Lower Bound of Replicate 1 of Experiment 5 in Period 3

Cell	M/C Type (Quantity)	Part type												
		9	13	14	15	1	7	8	11	12	16	3	5	10
1	1 (1)	1		1										
	9 (1)		1			*								
	11 (1)		1	1										
	12 (1)	1												
	13 (1)	1												
2	1 (1)									1		*		
	3 (1)							1				*		
	4 (1)					1		1						
	8 (1)					1	1							
	11 (1)					1	1		1					
	12 (2)							1						
14 (1)							1	1		1	1			
3	2 (1)											1	*	
	3 (1)											1	1	
	5 (1)											1	1	
	7 (1)					*						1	1	
	13 (1)													1
	14 (1)													1

Table A.172: Heuristic's Solution of Replicate 1 of Experiment 5 in Period 3

Cell	M/C Type (Quantity)	Part type												
		1	3	7	14	16	5	10	11	13	8	9	12	15
1	1 (1)			1		1								
	3 (1)			1										
	5 (1)			1			*							
	6 (1)					1								
	7 (1)	1	1				*			*				
	8 (1)	1			1									1
	9 (1)	1												
12 (1)				1		1								
2	2 (1)						1	1						
	3 (1)			*			1				*			
	11 (2)	*		*					1	1				
	14 (1)							1	1					
3	1 (1)											1	1	
	4 (1)	*										1		
	12 (1)											1	1	1
	13 (2)						*					1		1
	14 (1)											1		

Table A.177: Lower Bound of Replicate 3 of Experiment 5 in Period 1

Cell	M/C Type (Quantity)	Part type															
		4	7	12	14	2	11	15	16	1	10	17	18	19	6	8	13
1	2 (1)		1	1													
	3 (1)			1													
	4 (1)	1	1		1	*											
	6 (1)	1													*		
	12 (1)			1	1												*
14 (1)		1															
2	7 (1)					1	1		1								
	8 (1)					1	1	1		*							
	16 (1)					1		1	1								
	17 (1)						1										
3	1 (1)												1	1			*
	2 (1)											1					
	9 (1)									1	1			1			
	10 (1)									1		1	1				
	18 (1)									1	1						
4	3 (1)					*									1	1	
	5 (1)	*													1		
	11 (1)													1		1	
	13 (1)	*													1		
	15 (1)													1			

Table A.178: Heuristic's Solution of Replicate 3 of Experiment 5 in Period 1

Cell	M/C Type (Quantity)	Part type															
		1	2	10	11	16	4	6	7	8	12	13	15	19	14	17	18
1	7 (1)	1	1		1	1											
	8 (1)	1	1	1	1												
	9 (1)	1		1													
	16 (1)		1			1											
	17 (1)	1				1											
18 (1)	1		1														
2	3 (1)								1								
	5 (1)						1		1	1							
	6 (1)						1	1									
	13 (1)						1			1							
	14 (1)						1	1	1								
15 (1)		*					1										
3	1 (1)										1			1			*
	3 (1)									1	1	1					
	8 (1)											1					
	11 (1)						*				1						
	12 (1)									1				1			
4	2 (1)									*					1		
	4 (1)		*						*					1			
	10 (1)	*													1	1	
	12 (1)													1			

Table A.179: Lower Bound of Replicate 3 of Experiment 5 in Period 2

Cell	M/C Type (Quantity)	Part type															
		1	9	10	11	18	19	5	7	14	17	2	3	16	6	13	15
1	1 (1)	1	1			1	1									*	
	7 (1)	1			1												
	9 (1)	1	1	1			1										
	10 (1)	1				1					*						
	17 (1)	1			1												
	18 (1)	1	1	1													
2	2 (1)										1						
	4 (1)							1	1	1		*					
	12 (1)							1		1							
	13 (1)							1									
14 (1)							1	1							*		
3	7 (1)											1	1	1			
	8 (1)				*							1					
	15 (1)											1	1		*		
	16 (1)											1	1	1			
4	3 (1)								*				*			1	1
	5 (1)												*			1	
	6 (1)												*				
	8 (1)			*													1
	11 (1)														1	1	

Table A.180: Heuristic's Solution of Replicate 3 of Experiment 5 in Period 2

Cell	M/C Type (Quantity)	Part type															
		1	2	9	10	11	18	3	6	16	13	15	19	5	7	14	17
1	1 (1)			1			1										
	7 (1)	1	1			1											
	8 (1)	1	1		1	1											*
	9 (1)	1		1	1												
	10 (1)	1					1										
	17 (1)	1				1											
	18 (1)	1		1	1												
2	5 (1)							1								*	
	6 (1)							1	1								
	7 (1)							1		1							
	14 (1)								1						*		
	15 (1)			*				1	1								
16 (1)			*				1		1								
3	1 (1)											1		1			
	3 (1)											1	1				
	8 (1)												1				
	11 (1)							*				1					
4	2 (1)																1
	4 (1)		*												1	1	1
	12 (1)												*		1		
	13 (1)														1		
	14 (1)															1	

Table A.181: Lower Bound of Replicate 3 of Experiment 5 in Period 3

Cell	M/C Type (Quantity)	Part type														
		3	4	6	8	1	9	17	18	5	7	12	14	2	11	15
1	3 (1)				1											
	5 (1)	1	1	1	1											
	6 (1)	1	1	1									*			
	13 (1)			1		1				*						
	14 (1)			1	1											
	15 (1)	1	1	1										*		
2	1 (1)						1		1							
	7 (1)	*					1									
	9 (1)					1	1									
	10 (1)					1		1	1							
	18 (1)					1										
3	2 (1)							*		1	1					
	3 (1)										1					
	4 (1)									1	1		1			
	12 (1)									1		1	1			
	14 (1)									1	1					
4	7 (1)					*							1	1		
	8 (1)					*							1	1	1	
	16 (1)	*											1		1	
	17 (1)					*								1		

Table A.182: Heuristic's Solution of Replicate 3 of Experiment 5 in Period 3

Cell	M/C Type (Quantity)	Part type														
		1	9	11	18	2	3	4	6	8	15	5	7	12	14	17
1	1 (1)			1	1											
	7 (1)	1	1	1												
	8 (1)	1		1		*										
	10 (1)	1			1										*	
	17 (1)	1		1												
	18 (1)	1														
2	5 (1)						1	1								
	6 (2)						1	1	1	1						
	7 (1)						1	1								
	13 (1)								1			*				
	14 (1)								1	1						
	15 (1)							1	1	1						
3	3 (1)								1	1						
	5 (1)								1				*			
	8 (1)									1						
	9 (1)	*	*						1							
	11 (1)							*								
4	2 (1)											1			1	
	3 (1)											1				
	4 (1)										1	1		1		
	12 (1)										1		1	1		
	14 (1)										1	1				

Table A.183: Lower Bound of Replicate 3 of Experiment 5 in Period 4

Cell	M/C Type (Quantity)	Part type															
		9	17	18	19	5	7	12	14	1	10	11	15	3	4	8	16
1	1 (1)	1		1	1												
	2 (1)		1			*	*										
	9 (1)	1			1												
	10 (1)		1	1						*							
2	3 (1)							1									
	4 (1)					1	1		1								
	12 (1)					1		1	1								
	14 (1)					1	1										
3	7 (1)									1		1					
	8 (1)									1	1	1	1				
	9 (1)									1	1						
	17 (1)									1		1					
	18 (1)									1	1						
4	3 (1)												*				1
	5 (1)														1	1	
	6 (1)													1	1		
	7 (1)	*												1			1
	13 (1)					*									1	1	
	15 (1)													1			
	16 (1)													1			1

Table A.184: Heuristic's Solution of Replicate 3 of Experiment 5 in Period 4

Cell	M/C Type (Quantity)	Part type															
		1	9	11	18	3	4	16	19	10	14	15	5	7	8	12	17
1	1 (1)		1		1				*								
	7 (1)	1	1	1													
	8 (1)	1		1													
	10 (1)				1												
	17 (1)	1		1													
2	5 (1)					1	1								*		
	6 (1)					1	1										
	7 (1)					1		1									
	12 (1)												*			*	
	15 (1)					1			1								
16 (1)					1		1										
3	3 (1)											1					
	4 (1)										1		*	*			
	8 (1)									1	1	1					
	9 (1)	*	*							1							
	18 (1)	*								1							
4	2 (1)													1		1	1
	3 (1)														1	1	
	10 (1)																1
	13 (1)					*							1		1		
	14 (1)					*							1	1			

Table A.185: Lower Bound of Replicate 1 of Experiment 6 in Period 1

Cell	M/C Type (Quantity)	Part type													
		2	6	9	10	15	16	4	5	11	12	1	7	13	14
1	1 (1)		1	1											
	7 (1)		1	1											
	8 (1)	1				1	1								
	9 (1)	1			1										
	17 (1)				1		1								
	18 (1)	1		1	1	1									
2	1 (1)								1						
	2 (1)						1	1			1				
	3 (1)						1								
	10 (1)	*						1			1	*			
	11 (1)						1	1	1						
	12 (1)	*					1					*			
3	4 (1)										1		1		
	5 (1)		*												1
	6 (1)											1			
	13 (1)										1				1
	14 (1)										1		1		
	15 (1)											1			
	16 (1)											1			

Table A.186: Heuristic's Solution of Replicate 1 of Experiment 6 in Period 1

Cell	M/C Type (Quantity)	Part type													
		1	13	14	2	9	10	15	16	4	5	6	7	11	12
1	4 (1)	1	1												
	5 (1)			1						*					
	12 (1)	1													
	13 (1)	1		1											
	14 (1)	1													
	16 (1)		1										*		
2	7 (1)				1										
	8 (1)				1		1	1							
	9 (1)				1		1								
	13 (1)				1										
	17 (1)						1	1			*				
	18 (1)				1		1	1			1				
3	1 (2)				*	*				1	1			1	
	2 (2)									1					1
	3 (1)	*													
	6 (1)												1		
	7 (1)										1				
	10 (1)				*						1				1
11 (1)									1	1			1		
15 (1)											1	1			

Table A.187: Lower Bound of Replicate 1 of Experiment 6 in Period 2

Cell	M/C Type (Quantity)	Part type													
		4	5	9	11	12	3	10	16	1	6	8	13	14	17
1	1 (1)		1	1	1										
	2 (1)	1	1			1									
	10 (1)		1	1		1									
	11 (1)	1	1			1									
2	8 (1)						1		1						
	9 (1)						1	1							
	16 (1)						1								
	17 (1)						1	1	1						
	18 (1)			*				1							
3	3 (1)	*								1					
	4 (1)									1			1		
	5 (1)										1			1	
	7 (1)										1				1
	12 (1)	*								1				1	
	13 (1)									1					
	14 (1)									1			1		
	15 (1)										1	1			
17 (1)										1				1	

Table A.188: Heuristic's Solution of Replicate 1 of Experiment 6 in Period 2

Cell	M/C Type (Quantity)	Part type												
		1	8	13	14	3	6	10	16	17	4	5	9	11
1	4 (1)	1												
	5 (1)		1		1									
	12 (1)		1											
	13 (1)	1			1						*			
	14 (1)	1		1										
16 (1)			1		*									
2	7 (1)						1			1				
	8 (1)					1			1					
	9 (1)	*				1		1						
	15 (1)		*				1							
	17 (1)					1	1		1	1				
18 (1)							1							
3	1 (1)										1	1	1	
	2 (1)									1				1
	3 (1)	*								1				
	10 (1)										1	1		1
	11 (1)									1	1		1	
18 (1)											1			

Table A.189: Lower Bound of Replicate 2 of Experiment 6 in Period 1

Cell	M/C Type (Quantity)	Part type																
		5	10	16	18	2	6	13	1	9	11	15	17	3	4	14	19	20
1	1 (1)				1				*									
	7 (1)	1	1	1														
	9 (1)		1		1													
	17 (1)	1	1	1														
2	6 (1)					1		1						*				
	7 (1)					1		1										
	15 (1)					1		1										
	16 (1)					1		1										
3	2 (1)										1		1					
	3 (1)										1			*				
	8 (1)	*								1		1						
	9 (1)								1	1								
	10 (1)							*	1				1					
	12 (1)								1		1							
	16 (1)	*										1						
17 (1)								1										
18 (1)								1	1									
4	4 (1)													1	1			1
	5 (1)					*								1	1	1		1
	13 (1)													1	1		1	1
	14 (1)							*						1	1	1		

Table A.190: Heuristic's Solution of Replicate 2 of Experiment 6 in Period 1

Cell	M/C Type (Quantity)	Part type																
		1	9	10	16	18	2	3	6	13	4	15	19	20	5	11	15	17
1	1 (1)	1				1												
	8 (1)	1	1												*		*	
	9 (1)	1	1	1		1												
	10 (1)	1																*
	17 (1)	1		1	1													
	18 (1)	1	1															
2	5 (1)						1	1				*	*					
	6 (1)						1	1	1	1								
	7 (1)			*	*		1		1									
	13 (1)								1									
	15 (1)						1		1	1								
	16 (1)						1		1									
3	3 (1)										1							
	4 (1)										1	1		1		*		
	13 (1)										1		1	1				
	14 (1)						*		*		1	1						
4	2 (1)															1		1
	7 (1)														1			
	12 (1)															1		
	16 (1)														1		1	
	17 (1)														1			

Table A.191: Lower Bound of Replicate 2 of Experiment 6 in Period 2

Cell	M/C Type (Quantity)	Part type																
		6	7	12	13	5	15	16	20	1	8	9	10	18	3	4	14	19
1	2 (1)		1	1														
	6 (1)	1	1		1									*				
	11 (1)		1	1														
	14 (1)				1													
	15 (1)	1			1													
2	4 (1)					1			1									
	7 (1)	*				1		1										
	13 (1)								1									
	16 (1)	*				1	1											
	17 (1)					1		1										
3	1 (1)									1	1			1				
	7 (1)												1					
	8 (1)					*				1		1		1				
	9 (1)									1	1	1	1					
	10 (1)									1								
	17 (1)									1								
18 (1)									1	1	1	1			1			
4	3 (1)														1	1		
	4 (1)															1		
	5 (1)			*										1			1	
	13 (1)													1	1		1	
	14 (1)													1	1	1		

Table A.192: Heuristic's Solution of Replicate 2 of Experiment 6 in Period 2

Cell	M/C Type (Quantity)	Part type																
		5	10	16	18	2	6	13	1	9	11	15	17	3	4	14	19	20
1	1 (1)	1	1				1											
	8 (1)	1		1														*
	9 (1)	1	1	1	1		1											
	10 (1)	1							*									
	17 (1)	1			1	1												
	18 (1)	1	1	1														
2	2 (2)								1	1				*	*			
	5 (1)							1		1								
	6 (1)							1	1	1		1						
	7 (1)				*	*			1									
	11 (1)								1	1	1							
	13 (1)							1										
	14 (1)							1					1					
15 (1)								1										
3	3 (1)												1					
	4 (1)											1	1		1			
	13 (1)											1		1	1			
	14 (1)											1	1					
4	4 (1)																1	
	7 (1)																1	
	16 (1)																1	1
	17 (1)																1	

Table A.193: Lower Bound of Replicate 2 of Experiment 6 in Period 3

Cell	M/C Type (Quantity)	Part type															
		7	8	18	10	11	16	2	4	5	6	12	13	19	1	9	15
1	1 (1)	1	1	1											*		
	9 (1)		1	1													
	10 (1)	1													*		
2	2 (1)	*				1											
	3 (1)					1											
	7 (1)				1		1										
	9 (1)				1										*		
	12 (1)					1											
	17 (1)				1		1								*		
3	2 (1)											1					
	4 (1)							1	1								
	5 (1)							1			1		1				
	6 (1)							1			1		1				
	7 (1)							1		1	1						
	11 (1)	*									1						
	13 (1)								1					1			
	14 (1)								1				1				
	15 (1)								1		1			1			
	16 (1)								1					1			
17 (1)									1								
4	8 (1)														1	1	
	9 (1)													1	1		
	16 (1)									*						1	
	18 (1)		*											1	1		

Table A.194: Heuristic's Solution of Replicate 2 of Experiment 6 in Period 3

Cell	M/C Type (Quantity)	Part type															
		1	8	9	10	15	16	2	5	7	12	13	19	4	11	5	16
1	1 (1)	1	1				1										
	7 (1)				1												
	8 (1)	1		1		1											
	9 (1)	1	1	1	1		1										
	10 (1)	1										*					
	17 (1)	1			1												
	18 (1)	1	1	1													
2	2 (2)								1	1							
	5 (1)							1			1		1				
	6 (1)							1	1	1							
	7 (1)							1	1			1					
	11 (1)								1	1	1						
	14 (1)											1					
	15 (1)							1	1								
16 (1)					*		1										
3	3 (1)												1		1		
	12 (1)														1		
	13 (1)											*	1				
	14 (1)												1				
4	4 (1)												*		1		
	7 (1)														1	1	
	16 (1)														1		
	17 (1)														1	1	

Table A.195: Lower Bound of Replicate 3 of Experiment 6 in Period 1

Cell	M/C Type (Quantity)	Part type															
		1	6	7	19	4	10	11	16	12	17	18	3	5	9	13	14
1	8 (1)	1	1	1													
	9 (1)	1	1														
	15 (1)			1	1												
	16 (1)	1	1	1													
	17 (1)	1				*											
2	1 (1)	*				1	1	1	1								
	2 (1)					1	1		1								
	8 (1)							1									
	9 (1)							1									
3	7 (1)	*							1		1						
	10 (1)					*				1							
	11 (1)						*			1		*	*				
	16 (1)								1		1						
4	3 (1)											1	1				
	4 (1)											1	1	1			
	5 (1)												1			1	
	6 (1)				*									1			
	12 (1)											1	1				1
	13 (1)											1					1
14 (1)												1	1	1			

Table A.199: Lower Bound of Replicate 1 of Experiment 7 in Period 1

Cell	M/C Type (Quantity)	Part type															
		3	4	9	13	7	10	12	14	20	1	6	15	18	5	8	17
1	1 (1)		1		1												
	2 (1)		1	1	1						*					*	
	4 (1)	1															
	5 (1)	1	1											*			
	6 (1)			1	1										*		
	9 (1)	1													*		
	13 (1)	1			1	1						*					
2	2 (1)						1	1		1							
	3 (1)					1			1								
	5 (1)					1				1							
	10 (1)									1							
	12 (1)							1	1								
	14 (1)						1	1							*		
3	8 (1)					*					1	1		1			
	9 (1)									1							
	11 (1)						*			1	1	1	1				
4	4 (1)										*				1	1	1
	7 (1)										*			1			
	13 (1)	*										*			1	1	

Table A.200: Heuristic's Solution of Replicate 1 of Experiment 7 in Period 1

Cell	M/C Type (Quantity)	Part type															
		1	5	19	9	10	13	14	15	3	4	6	7	17	20	8	12
1	4 (1)	1	1		*	*											
	5 (1)		1														
	7 (1)	1	1	1													
	9 (1)	1	1														
2	1 (1)				1		1	1									
	10 (1)							1									
	11 (1)	*				1	1		1								
	13 (1)				1		1		1				*				
14 (1)					1												
3	1 (1)									1	1					*	
	2 (1)									1	1			1			
	3 (1)											1					
	4 (1)									1		1			*		
	5 (1)									1	1	1		1			
	6 (1)									1							
9 (1)									1	1			1				
4	8 (1)	*									*						1
	12 (1)								*							1	1
	13 (1)									*			*		1		
	14 (1)														1	1	

Table A.201: Lower Bound of Replicate 1 of Experiment 7 in Period 2

Cell	M/C Type (Quantity)	Part type															
		2	7	20	4	10	12	13	17	1	5	11	16	19	6	8	15
1	3 (1)	1	1								*						
	5 (1)	1	1	1	*						*						
	9 (1)		1							*	*						
2	1 (1)	*			1			1							*		
	2 (1)				1	1	1	1	1								
	10 (1)						1					*					
	13 (1)							1	1								
14 (1)	*				1	1					*				*		
3	4 (1)									1	1				*		
	6 (1)				*					1		1	1				
	7 (1)	*								1	1			1			
4	8 (1)									*					1		1
	11 (1)				1						*				1	1	1
	13 (1)									*					1	1	

Table A.202: Heuristic’s Solution of Replicate 1 of Experiment 7 in Period 2

Cell	M/C Type (Quantity)	Part type															
		1	5	16	17	19	6	10	12	13	2	4	7	20	8	11	15
1	4 (1)	1	1											*			
	5 (1)		1														
	7 (1)	1	1			1				*							
	9 (1)	1	1	1	1												
	10 (1)			1													
2	1 (1)						1		1								
	2 (1)						1		1	1			*		*		
	11 (1)							1								*	*
	13 (1)				*		1			1							
14 (1)							1	1									
3	1 (1)												1	1			
	3 (1)												1		1		
	5 (1)												1	1	1	1	
	6 (1)	*											1	1			
	9 (1)																
4	8 (1)	*					*										
	12 (1)								*							1	1
	13 (1)	*													1	1	1
	14 (1)												*		1	1	

Table A.203: Lower Bound of Replicate 1 of Experiment 7 in Period 3

Cell	M/C Type (Quantity)	Part type															
		2	7	19	20	1	3	5	6	9	12	13	14	16	17	10	11
1	3 (1)	1	1														
	5 (1)	1	1		1												
	7 (1)	1		1		*											
	9 (1)					*											
2	4 (1)					1	1	1									*
	5 (1)						1	1									
	8 (1)					1		1									
	9 (2)						1	1									
3	1 (1)	*							1			1	1				
	2 (1)								1	1	1	1			1	*	
	10 (1)												1	1			
	12 (1)									1			1	1			
	13 (1)								1	1		1				1	
14 (1)	*							1	1	1							
4	6 (1)		*				*									1	
	11 (1)				*		*								1	1	
	14 (1)														1	1	1

Table A.204: Heuristic's Solution of Replicate 1 of Experiment 7 in Period 3

Cell	M/C Type (Quantity)	Part type																
		3	5	20	6	9	10	11	12	13	17	2	7	14	16	1	18	19
1	4 (1)	1	1													*		
	5 (1)	1	1	1														
	7 (1)			1			*					*				*		*
	9 (1)	1	1															
	10 (1)																	
2	1 (1)				1	1				1								
	2 (1)			*	1				1	1	1							
	11 (1)						1	1						*				
	12 (1)								1									
	13 (1)				1	1					1	1						
	14 (1)				1	1	1	1	1									
3	1 (1)											1						
	3 (1)											1	1	1				
	5 (1)											1	1					
	6 (1)	*					*											
	10 (1)													1	1			
4	8 (1)															1	1	
	9 (1)															1		
	12 (1)													*			1	1
	13 (1)	*														1		

Table A.205: Lower Bound of Replicate 2 of Experiment 7 in Period 1

Cell	M/C Type (Quantity)	Part type													
		1	5	6	8	9	11	12	7	10	14	16	3	4	13
1	1 (1)	1					1								
	3 (1)	1	1	1	1	1		1							
	4 (1)		1		1		1		*						
	5 (1)			1				1							
	7 (1)				1	1									
	8 (1)	1		1											
2	1 (1)		*						1		1				
	4 (1)							1	1	1					
	6 (1)				*			1	1						
	10 (1)			*				1		1					
3	2 (1)											1		1	
	9 (1)		*									1	1		
	11 (1)											1	1		
	12 (1)	*											1	1	
	14 (1)	*										1			

Table A.206: Heuristic's Solution of Replicate 2 of Experiment 7 in Period 1

Cell	M/C Type (Quantity)	Part type													
		6	7	8	9	14	10	11	14	1	3	4	5	12	13
1	3 (1)	1		1	1										
	4 (1)			1		1									
	5 (1)	1													
	7 (1)			1	1										
	8 (1)	1	1												
	10 (1)	1	1												
14 (1)					1										
2	1 (1)						1	1	1						
	4 (1)						1	1	1						
	6 (1)		*		*		1								
3	1 (1)									1			1		
	2 (1)														1
	3 (1)											1	1		
	9 (1)									1	1	1			
	10 (1)									1					
	11 (1)									1	1				
	12 (1)									1		1			1
	13 (1)									1			1		
14 (1)									1	1					

Table A.207: Lower Bound of Replicate 2 of Experiment 7 in Period 2

Cell	M/C Type (Quantity)	Part type													
		5	7	8	9	12	1	2	3	4	6	10	13	15	16
1	3 (1)	1		1	1	1	*								
	5 (1)	1	1												
	6 (1)		1		1										
	7 (1)			1	1				*						
	10 (1)		1					*	*						
	13 (1)					1		*	*						
2	1 (1)	*					1	1							
	9 (1)	*					1		1	1					
	10 (1)								1		*				
	11 (1)								1	1					
	12 (1)						1	1		1					
14 (1)						1	1	1							
3	2 (1)										1	1	1		
	4 (1)			*							1				1
	5 (1)									1			1		1
	6 (1)										1				
	12 (1)									1		1			

Table A.208: Heuristic's Solution of Replicate 2 of Experiment 7 in Period 2

Cell	M/C Type (Quantity)	Part type													
		6	7	8	9	15	10	13	16	1	2	3	4	5	12
1	3 (1)	1		1	1	1									
	4 (1)			1											
	5 (1)	1				1									
	6 (1)		1												
	7 (1)				1	1									
	8 (1)	1	1												
	10 (1)	1	1												
2	1 (1)								1		1				
	2 (1)								1		1				
	6 (1)								1						
	12 (1)									1					
3	1 (1)								*	*		1		1	
	2 (1)											1		1	1
	3 (1)											1		1	1
	9 (1)											1	1	1	
	10 (1)											1			
	11 (1)											1	1		
	12 (1)											1			
	13 (1)											1			1
	14 (2)											1	1	1	

Table A.209: Lower Bound of Replicate 2 of Experiment 7 in Period 3

Cell	M/C Type (Quantity)	Part type													
		5	8	15	16	3	10	14	1	2	6	9	11	12	13
1	3 (1)	1	1	1											
	4 (1)		1		1		*	*							
	5 (1)	1		1	1						*				
2	1 (1)	*				1	1				*				
	9 (1)	*	*			1									
	11 (1)					1		1							
	14 (1)					1									
3	1 (1)								1				1		
	2 (1)											1			1
	3 (1)								1	1	1	1	1	1	
	4 (1)											1			
	6 (1)						*					1			
	10 (1)									1	1				
	12 (1)								1	1	1				1
	13 (1)								1	1				1	
14 (1)								1	1						

Table A.210: Heuristic's Solution of Replicate 2 of Experiment 7 in Period 3

Cell	M/C Type (Quantity)	Part type													
		8	9	15	10	11	13	14	16	1	2	3	5	6	12
1	3 (1)	1	1	1											
	4 (1)	1													
	5 (1)			1								*	*		
	6 (1)			1											
	7 (1)	1	1												
2	1 (1)								1						
	4 (1)				1	1		1	1						
	6 (1)				1										
	12 (1)						1								
3	1 (1)				*	*	*			1			1		
	2 (1)											1			
	3 (1)									1	1		1	1	1
	9 (1)									1		1			
	10 (1)										1			1	
	11 (1)							*				1			
	12 (1)									1	1			1	
	13 (1)									1	1				1
	14 (2)									1	1	1			

Table A.211: Lower Bound of Replicate 3 of Experiment 7 in Period 1

Cell	M/C Type (Quantity)	Part type												
		4	6	10	11	7	12	13	1	2	5	8	9	15
1	4 (1)			1	1	1								
	7 (1)	1	1	1										
	12 (1)				1									
	13 (1)	1		1										
	14 (1)	1												
2	1 (1)					1								
	3 (1)					1								
	5 (1)	*				1			*					
	6 (1)						1	1						
	11 (1)						1	1	*					
3	1 (1)									1	1		1	1
	2 (1)									1	1		1	
	3 (1)									1		1		
	7 (1)										1		1	
	8 (1)		*								1		1	
	9 (1)									1	1			
	15 (1)									1	1	1	1	

Table A.212: Heuristic's Solution of Replicate 3 of Experiment 7 in Period 1

Cell	M/C Type (Quantity)	Part type												
		10	11	12	13	1	2	5	6	8	9	4	7	15
1	4 (1)	1	1											
	6 (1)			1	1									
	12 (1)	1	1	1										
	14 (1)				1									
2	1 (1)					1	1			1				
	2 (1)					1	1	1		1				
	4 (1)					1				1				
	7 (1)								1	1				
	8 (1)						1		1					
	9 (1)					1		1						
	11 (1)					1	1							
	12 (1)									1				
15 (1)					1	1	1		1					
	1 (1)											1	1	
	3 (1)					*						1		
	5 (1)										1	1		
	7 (1)										1		1	
	13 (1)	*									1			
	14 (1)								*		1			

Table A.213: Lower Bound of Replicate 3 of Experiment 7 in Period 2

Cell	M/C Type (Quantity)	Part type												
		1	2	5	7	8	12	4	6	13	15	3	10	11
1	1 (1)		1	1	1									
	2 (1)	1	1		1									
	3 (1)	1		1	1									
	6 (1)					1	1							
	7 (1)					1	1							
	9 (1)	1		1										
	11 (1)	1	1											
15 (1)	1	1	1		1									
2	5 (1)	*						1						
	6 (1)								1					
	7 (1)							1		1				
	8 (1)		*						1					
	13 (1)							1	1					
14 (1)							1	1	1	1				
3	4 (1)											1	1	1
	10 (1)											1		1
	12 (1)											1	1	1
	13 (1)											1	1	1

Table A.214: Heuristic's Solution of Replicate 3 of Experiment 7 in Period 2

Cell	M/C Type (Quantity)	Part type													
		3	10	11	12	13	1	2	5	6	8	15	4	7	14
1	4 (1)	1	1	1			*								
	6 (1)				1	1									
	10 (1)	1													
	12 (1)	1	1	1	1										
	13 (1)	1	1												
14 (1)					1				*						
2	1 (1)						1	1							
	2 (1)						1	1							
	6 (1)														
	7 (1)									1					
	8 (1)						1		1	1	1				
	9 (1)						1		1	1					
11 (1)						1									
12 (1)															
15 (1)						1	1	1		1	1				
3	1 (1)						*		*					1	
	3 (1)													1	
	5 (1)												1	1	
	7 (1)												1		1
	13 (1)												1		1
14 (1)												1			

Table A.215: Lower Bound of Replicate 1 of Experiment 8 in Period 1

Cell	M/C Type (Quantity)	Part type															
		2	6	7	11	17	18	1	5	12	13	9	10	11	8	14	15
1	2 (1)			1													
	5 (1)	1	1														
	8 (1)			1													
	11 (1)	1	1														
	12 (1)				1	1	1										
	14 (1)	1		1													
2	4 (1)						1										
	7 (1)								1								
	10 (1)						1	1		1							
	16 (1)						1	1	1	1							
3	3 (1)										1						
	7 (1)						*				1		1				
	13 (1)						*	*		1							
	15 (1)				*						1	1					
4	1 (1)	*									*				1	1	
	8 (1)	*								*							
	11 (1)												1			1	
	14 (1)												1	1			

Table A.218: Heuristic's Solution of Replicate 1 of Experiment 8 in Period 2

Cell	M/C Type (Quantity)	Part type														
		1	4	13	3	7	8	14	15	5	11	6	9	10	12	16
1	4 (1)	1	1													
	7 (1)	1	1													
	10 (1)	1	1	1												
	14 (1)		1													
	16 (1)	1		1												
2	1 (1)				1				1			*				
	4 (1)				1			1								
	8 (1)					1	1							*		
	11 (1)			*	1		1		1							
	14 (1)				1	1	1	1								
	2 (1)									1	1	*				*
3	6 (1)								1				*			
	10 (1)								1							
	16 (1)								1							
4	3 (1)					*						1				
	5 (1)										1					
	7 (1)													1	1	
	11 (1)										1					
	12 (1)	*										1	1			1
	13 (1)													1		
	15 (1)									*		1		1		1

Table A.219: Lower Bound of Replicate 2 of Experiment 8 in Period 1

Cell	M/C Type (Quantity)	Part type														
		3	8	10	14	15	17	18	1	11	16	5	6	12	4	7
1	5 (1)	1		1		1					*					
	6 (1)			1	1											
	7 (1)	1	1				1							*		
	8 (1)	1	1					1								
	17 (1)						1									
	18 (1)				1	1		1								
2	4 (1)		*					1				*			*	
	10 (1)								1							
	12 (1)							1	1							
	13 (1)							1	1	1						
	14 (1)							1								
3	1 (1)										1	1	1		*	
	9 (1)											1				
	11 (1)										1		1			
	16 (1)	*										1			*	
4	2 (1)								*		*				1	1
	3 (1)								*						1	
	6 (1)									*						1
	15 (1)			*										1		1

Table A.220: Heuristic's Solution of Replicate 2 of Experiment 8 in Period 1

Cell	M/C Type (Quantity)	Part type															
		5	7	12	1	11	16	3	4	9	10	6	8	14	15	17	18
1	2 (1)	1	1														
	3 (1)	1	1														
	9 (1)			1								*					
	12 (1)	1			1												
2	3 (1)				1												
	5 (1)						1	*			*				*		
	6 (1)				1												
	12 (1)				1	1											
13 (1)				1	1	1											
3	2 (1)									1							
	6 (1)								1	1	1						
	8 (1)							1									*
	15 (1)							1	1	1							
16 (1)							1	1									
4	1 (1)	*		*								1					
	4 (1)				*							1					
	7 (1)						*		*							1	
	10 (1)					*							1				
	14 (1)				*												
	17 (1)				*								1			1	
	18 (1)											1	1	1	1		1

Table A.221: Lower Bound of Replicate 2 of Experiment 8 in Period 2

Cell	M/C Type (Quantity)	Part type														
		7	9	10	14	15	4	12	17	1	11	13	16	2	6	8
1	3 (1)	1	1								*					
	5 (1)			1		1										
	6 (1)			1	1	1					*					
	9 (1)	1														
18 (1)	1			1	1											
2	7 (1)						1		1							
	11 (1)							1			*					
	15 (1)		*	*			1									*
	17 (1)						1		1							
3	1 (1)							*		1		1			*	
	4 (1)									1					*	
	10 (1)										1					
	12 (1)									1	1		1			
13 (1)									1	1		1				
4	8 (1)													1		1
	9 (1)													1	1	
	10 (1)													1		
	16 (1)						*							1		
18 (1)													1	1	1	

Table A.224: Heuristic's Solution of Replicate 3 of Experiment 8 in Period 1

Cell	M/C Type (Quantity)	Part type														
		7	14	16	1	2	10	11	12	3	5	8	9	13	15	17
1	2 (1)	1	1	1												
	7 (1)	1														
	10 (1)	1														
	16 (1)		1													
2	1 (1)				1		1									
	3 (1)				1				1			*				
	4 (1)						1		1							
	5 (1)					1	1		1							*
	9 (1)					1			1							
	11 (1)				1											
	12 (1)				1											
	13 (1)				1	1			1							
14 (1)				1	1											
3	1 (1)									1			1			
	2 (1)									1	1	1	1			
	8 (1)										1					
	10 (1)									1			1			
	12 (1)									1		1				
	17 (1)										1					
18 (1)									1	1						
4	4 (1)													1		
	6 (1)			*											1	1
	8 (1)														1	
	18 (1)													1		1

Table A.225: Lower Bound of Replicate 3 of Experiment 8 in Period 2

Cell	M/C Type (Quantity)	Part type																
		6	13	14	1	2	4	11	12	8	15	16	17	3	7	9	10	18
1	4 (1)			1	1		*	*	*									
	8 (1)	1	1						*									
	16 (1)	1		1														
2	3 (1)				1		1		1	*								
	5 (1)					1												
	11 (1)				1													
	12 (1)				1		1							*				
	13 (1)				1	1	1	1	1									
14 (1)				1	1		1											
3	2 (1)								1		1							
	6 (1)	*				*			1	1	1	1						
	18 (1)											1		*				
4	1 (1)													1		1	1	1
	2 (1)				*									1	1	1		
	7 (1)													1				
	9 (1)														1			1
	10 (1)													1	1	1		

Table A.226: Heuristic's Solution of Replicate 3 of Experiment 8 in Period 2

Cell	M/C Type (Quantity)	Part type																
		7	14	16	1	2	4	9	10	11	12	13	3	8	18	6	15	17
1	2 (1)	1	1	1														
	7 (1)	1																
	10 (1)	1																
	16 (1)		1															*
2	2 (1)							1										
	3 (1)				1						1			*				
	4 (1)				1	1			1	1		1						
	5 (1)				1	1			1									
	11 (1)				1		1											
	13 (1)				1	1	1				1	1						
14 (1)				1	1					1								
3	1 (1)				*				*				1					
	2 (1)												1	1	1			
	6 (1)			*									1					
	9 (1)						*								1			
	10 (1)												1					
	12 (1)				*		*					*	1					
	6 (1)					*										1	1	1
	8 (1)															1	1	
	18 (1)												*					1

Vita

Anan Mungwattana was born in Bangkok, Thailand. He graduated from Kasetsart University with the degree of Bachelor of Engineering, major in Industrial Engineering in March 1991. He received his Master degree in Industrial Engineering from Auburn University in June 1995. He completed his Ph.D. in Industrial and Systems Engineering at Virginia Polytechnic Institute and State University in September 2000. Following his Ph.D., he returned to Thailand. Currently, he is teaching at the Department of Industrial Engineering, Kasetsart University.