MINICELL CONFIGURATION FOR MASS CUSTOMIZATION MANUFACTURING

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The objective of this research is to develop a method to design a manufacturing system for mass customization. Mass customization is the production of individually customized products and services at near mass production efficiency. Most literature on the subject focuses on developing products that can be manufactured through mass customization. A new approach to design a cell-based system for mass customization manufacturing is presented in this research.

The options offered for customized products' features and their process plans are used to design the proposed multi-stage minicell configuration. A new type of cells called minicells—small manufacturing cells dedicated to process a part of the operations required for an option family—are the building blocks in the new system. The processing operations for the options are divided into multiple stages and option families and minicells are formed within them to create the multi-stage configuration.

A multi-chromosome genetic algorithm is developed to design a minicell configuration for a given expected product variant demand. An approach is presented to find a flexible minicell configuration that can handle variations in product mix and volume for a particular problem, using the genetic algorithm and simulation. Alternate minicell designs and the performance of the system with such designs are evaluated to assist in choosing the most appropriate minicell configuration. In addition, this research presents two

approaches to laying out the minicells within the stages after the cells have been designed, in order to minimize the total distance traveled.

The minicell configuration is an attempt to combine the benefits of cellular manufacturing and job shops to meet the requirements of mass customization. The proposed design is more flexible than traditional cellular manufacturing systems particularly in dynamic demand—volume and mix—environments seen in mass customization. Forming options families and minicells helps benefit from group technology concepts while still retaining some of the flexibility offered in job shops. With the minicell configuration, the desired performance—makespan and flow time—can be achieved without a significantly influencing machine requirements.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. INTRODUCTION

The manufacturing industry has evolved over the past several decades in response to changing customer needs. Previously the primary source of competitive advantage for manufacturing companies in many industries used to be related with the price. Therefore all manufacturing strategies were driven by approaches to reduce the cost of products. Customer demand was met by producing standardized products to stock in large volumes by applying mass production techniques. This enabled manufacturers to benefit from economies of scale and achieve lower unit costs.

Technological advances, in manufacturing as well as information, have provided the impetus for changes in many paradigms, including customer expectations. Customers have become more demanding and want products that can meet their specific individual requirements. The standard products previously produced in large batches are not sufficient to meet this variety demanded. Given the increased competition, both locally and globally, companies must also now respond faster to get and keep customers. While demanding quick response from manufacturers, customers are no longer willing to pay a large premium for individualized products.

Companies have long pursued differentiation strategies in selected niche markets as a means to serve the specific needs of selected groups of customers. But with changing customer expectations, differentiation now has to concentrate on the needs of the individual customer in the chosen market. Thus customization is turning out to be essential to maintain competitive advantage in many industries.

1.1. Mass Customization

Mass customization is the production of individually customized products and services at near mass production efficiency [67]. Conventionally, product customization came with a cost and consumers had the option of either purchasing standard products that were mass produced at low cost or paying a premium to purchase customized products. Mass producing customized products at a low cost, which seemingly is a paradox, is the goal of mass customization.

The term mass customization was coined by Davis [20] in his 1987 book *Future Perfect*. The concept was then considered to be impossible, constrained by the technology that existed during the era. Pine [67, 69] later popularized the concept of mass customization as a manufacturing strategy and described the manufacturing aspects of mass customization by mapping the progression from mass production.

Today, manufacturers in many industries are faced with very high product variety and much smaller batches, which can approach one unit. Many firms find that they are no longer able to compete on the basis of standardized products and services alone [48]. According to Kotler [50] the concept of ‘mass markets is dead—segmentation has now progressed to an era of mass customization’. Therefore it is no longer possible for companies to produce only standardized products and retain a competitive advantage. As pointed out by Westbrook and Williamson [99], Mass customization represents a new frontier in a world of saturating markets and slow growth. It is arising as an

organizational strategy in direct response to the turbulence created by the decline of mass markets and technological advances that have led to shorter product life cycles [32].

As Pine points out “firms have thrown away the old paradigm of mass production…they have found their way to a new paradigm by creating *variety and customization through flexibility and responsiveness*” [67] (emphasis original). The availability of new flexible manufacturing technologies and of e-commerce, which gives manufacturers a platform for taking orders from a mass audience for customized products, have enabled production systems to deliver higher variety at a lower cost, making mass customization a promising strategy [18].

Mass customization involves going back to traditional craft production, but now in a much larger scale. It also eliminates the customer’s dilemma of having to choose between a standardized product that is mass produced at low cost vs. a customized product at an extra premium. With mass customization, customers can now have a customized product without having to pay the extra price.

Mass customization is also characterized by a make-to-order inventory strategy where production is not begun until the customer order has been received. Therefore producing to forecasts and holding finished items in inventory is no longer necessary. The fact that mass customization significantly reduces the finished goods inventory and improves the liquidity of corporate funds has made it even more appealing to manufacturers.

In August/September 2003, “Manufacturing Engineer” devoted an entire issue to the discussion of implementing mass customization and IEEE Transactions on Engineering Management is planning on a special issue on mass customization manufacturing systems. In addition an International Journal of Mass Customization is being launched and the call for papers for the first issue has already been made. All these further demonstrate the growing interest in mass customization as a competitive strategy.

Customization can vary from being merely cosmetic or postponed assembly to collaborative customization with customer involvement beginning at the design stage. Hewlett-Packard postpones the differentiation of its DeskJet printers for the European and Asian markets to distribution centers rather than at the factory in Singapore by having an external country-specific power supply that is added after the printer has been assigned to a customer. As a result the company has been able to reduce manufacturing, shipping, and inventory costs by 25% [25]. This is the most rudimentary form of customization with assembly and/or packaging postponement.

At the other extreme is complete customization of the finished product, where customer involvement begins at the product design stage. Customers of the National Bicycle Industrial Company (NBIC) of Japan can design their own bicycles, which are then manufactured and delivered within two weeks [48, 49]. Between these two extremes one can find many companies adopting strategies with varying degrees of customization. Adidas for example sells custom-made shoes and Andersen Windows manufactures windows to fit the customer’s specific requirements [101]. Airborne USA of Ohio [4]

manufactures high-end customized bicycles to individual specifications using standard parts sourced from others.

1.2. Problem Background

The limitations to implementing mass customization can broadly be classified as being related to the product and to the technology. Not all products are appropriate for customization. For example commodities (such as oil or wheat) may not require differentiation by customization [69]. Collecting product-related information from customers to identify attributes to be customized and incorporating this information into product specifications is an extremely complex and costly process which is another drawback to implementing mass customization [3].

Whether a company chooses to transform from a mass production system to mass customization (e.g., Melbo men's suits [101]) or to apply both strategies simultaneously with separate factories (e.g., the NBIC case [48, 49]), implementing mass customization calls for a different type of production system. As pointed out by Pine, et al. [69], mass production and mass customization require different organizational structures, values, management roles and systems, learning methods, and ways of relating to customers.

Having made the strategic choice to pursue mass customization, companies are then faced with the tasks of designing a system to manufacture the products and then managing the system to operate efficiently. *Flexibility*—in organizational activities and in the use of technology—is the key for successful mass customization as opposed to

standardization which is the practice in mass production. The difficulties encountered in making the switch from a system that is based on homogeneity to one that is more agile and responsive to customer needs is probably the biggest drawback to implementing mass customization.

A highly flexible manufacturing system that can be adapted swiftly to accommodate changes in customer demand is required. Short turnaround times between receiving customer orders and product delivery is another requirement in mass customization manufacturing. All these capabilities need to be built into the system while still maintaining low cost of production.

1.2.1. Manufacturing System Alternatives

Manufacturing strategies have evolved over the past several decades to accommodate market changes. The process-oriented job shop environments that existed during the craft production era were replaced by mass production assembly lines.

Mass production grew out of the need to spread the benefits of advancing technology in the early part of the 20th century; the low costs achieved made products more accessible to a greater population. In mass production, a brainchild of Henry Ford, identical items were produced in large quantities using assembly lines, enabling greater efficiency and lower unit cost. Ford's production line was designed to produce a high volume with, little-or-no variety. Thus the popular slogan—the customer could get "any color, as long as it's black."

As customers began to demand variety and were prepared to pay the extra cost, manufacturers opted for product differentiation strategies as a means to achieve competitive advantage. The highly specialized production lines were not efficient when more product variety was introduced.

Cellular manufacturing is based on the concept of group technology where like items are combined to benefit from the similarities. By combining products with similar manufacturing requirements into families to share the same equipment and workforce, companies were able to benefit from scale economies while also providing some product variety.

These manufacturing concepts, in terms of the product variety and volume of production they can support, are shown in Figure 1. The figure is adapted from Steudel and Desruelle [85] and modified to include mass customization. The figure also indicates the variation in efficiency and flexibility for the different systems. Production lines are suited to high volume production with little variety. At the other extreme, job shops are suited to producing a wide variety of products in very small quantities. Cellular manufacturing was developed to produce moderate quantities of a moderate variety of parts.

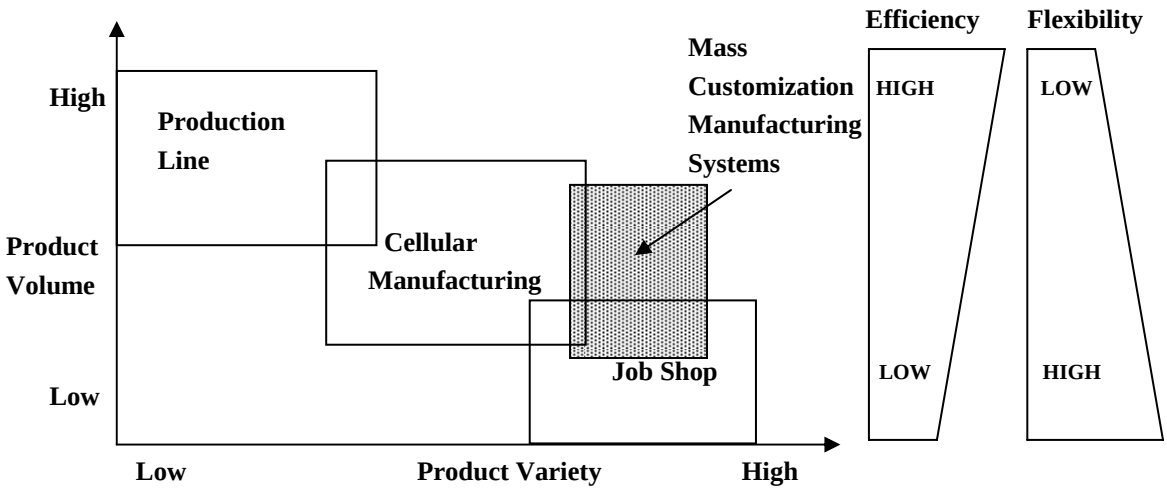


Figure 1: Product Volume-Variety Relationship for Different Manufacturing Systems

As shown in Figure 1, mass customization deals with large variety of products made in smaller quantities, a scenario currently encountered by manufacturers in many industries. The high product variety requires a very flexible manufacturing environment such as that in a job shop. However the total product volume in a mass customization system would be much higher than in a normal job shop. On the other hand, to achieve the low cost and a rapid response, a more cost efficient and agile configuration is required. A production line can provide the cost advantage, but not the agility to respond fast to customer requirements. Manufacturing cells on the other hand provide the capability to achieve a higher variety than production lines, but at a higher cost than with mass production. Mass customization requires an even more flexible production system to manage the product variety and dynamic demand.

1.2.2. Mass Customization Manufacturing

Being an efficient mass producer does not assure success as a mass customizer. This is illustrated by Toyota's early efforts at customization [69]. In the early 1990s, the company attempted manufacturing and delivering a made-to-order car within three days, but had to retreat due to soaring production costs. One of the reasons for Toyota's trouble was attributed to the lack of organizational preparation for the strategy. This reiterates that mass production and mass customization are two different paradigms; they require numerous operational and organizational changes [2, 69].

Mass customization requires a manufacturing system that has the flexibility to deliver the variety of products demanded by customers. The system also requires the to capability to adapt to the highly dynamic product mix. Agility and responsiveness is essential to transform customer orders into finished products within a short time. These system requirements must be delivered without adding significantly to the cost.

No existing manufacturing system provides all these capabilities necessary to successfully implement mass customization. The most favorable system would be one that gives the flexibility of a job shop combined with the cost advantages that can be enjoyed using production lines. Cellular manufacturing attempts to provide the best of both these systems to a certain extent, but at the cost of lower product variety than is desired in mass customization. Therefore the flexibility of manufacturing concepts used in cellular manufacturing need to be further refined to meet the conflicting objectives of mass customization.

Researchers are progressing on developing approaches to formulate product families that can be derived from a common platform to achieve economies of scale in mass customization. Though many authors discuss the importance of configuring appropriate manufacturing systems prior to implementing mass customization there is a lack of scholarly effort on designing such a system.

Thus, as rightly emphasized by Da Silveira, et al. [18], the flexible manufacturing technologies must be configured into production systems that can take orders from a mass audience and deliver high variety at a lower cost to make mass customization a promising strategy. Therefore, achieving competitive advantage using mass customization depends to a great extent on how well flexibility and responsiveness—emphasized by Pine [67]—can be incorporated to the manufacturing system.

1.2.3. Analysis of Existing Approaches

Many innovative approaches to cell design and cellular manufacturing strategies have been discussed in the literature recently. Hyer and Wemmerlov [36] highlighted the need to explore the use of integrated, multi-stage cell designs to meet the rapid responsiveness and the demand for higher customization, which they expect will become important in the future. The use of various other types of manufacturing cells—virtual, dynamic, linked, fractal, holographic, and network cells—have been proposed to meet the requirements of high-variety, low-volume production.

Virtual cells are logical groupings of machines which have to be changed each time there is a variation in the product mix. On the other hand, dynamic cells are reconfigured physically each time a change in the product mix occurs.. Linked cells integrate all operations, from order receiving to production, and are useful in achieving reduced lead time and in-process inventory.

Fractal cells are mini factories that are replicated to achieve the required capacity. While more flexible than a single large factory, the fractals can be constrained by long lead times and in-process inventory as product families assigned to the fractals become large. Holographic cells require considerable planning and coordination to operate successfully because they result in a manufacturing system with a variety of cells distributed throughout the floor. They could be useful in providing more alternatives to route products through the system. Network cells, which are groups of several processors required for a part of the operations on a product family, can be useful in delivering greater flexibility.

These are different approaches to cell formation that have been put forward in the literature to meet various requirements. Most of them are based on the concept of forming cells for product families. Dedicating cells to product families in a mass customization environment, where the product mix as well as quantity demanded is highly dynamic, could be inefficient. However, the ability to virtually or physically reconfigure cells can contribute to increasing the flexibility of the manufacturing system. Further, dividing the processes into smaller units to form micro factories and distributing

the machines is also important to increase flexibility. Thus, easily reconfigurable, modular manufacturing systems are necessary to deliver the requirements of mass customization. However, the system must be designed to accommodate the platform-based product structure that is often used in mass customization to achieve scale and scope economies. Therefore, a manufacturing system design within which the concepts used in the aforementioned cell types can be used is necessary for mass customization.

Mixed-model production lines are more flexible and adaptable compared to single model lines (dedicated lines for a single product) or multi-model lines (multiple products processed in batches). Mixed-model lines are used to manufacture a sequence of different products (ideally with a batch size of one unit) and may be useful in a mass-customization environment since that is also typically characterized by lot sizes of one unit. The challenge in using mixed-model production arises from the differing work content of the products that result in uneven flow of work.

Agile manufacturing is the ability to respond quickly and effectively to current market demands, as well as being proactive in developing future market opportunities [30]. It involves a structured application of the principles of previous manufacturing concepts to build the capability to respond to changes in customer requirements faster and adapt accordingly. Lean manufacturing on the other hand is geared to reducing waste and eliminating non-value adding activities to improve an organization’s performance [64]. Mass customization manufacturing can benefit from incorporating agile manufacturing features and lean thinking in system design.

These innovative ideas appear to have considerable potential in delivering different aspects of the system requirements for mass customization; no current single approach is sufficient to provide all the capabilities needed. However, none of them have been explored in depth for applicability to mass customization and have to be studied in greater detail, separately and possibly integrated in some manner, to evaluate their usefulness to provide the flexibility and efficiency required in a mass customization manufacturing environment.

1.3. Research Objectives

The objective of this research is to formulate a procedure to design a mass customization manufacturing system. The design and operation of a manufacturing system for mass customization is a complex process that requires decisions at all levels of management in an organization. At the tactical managerial level, the most crucial tasks involve developing the systems and structures needed for the successful implementation of mass customization. This research aims to develop procedures to design a system that can deliver the requirements for successful mass customization. Successful system design requires evaluating the performance of feasible configurations at the operational level and feedback to modify the design. Therefore, though developing procedures to operate and manage the proposed system is not an objective in this research, its performance is evaluated in developing a robust design.

As discussed previously, most literature on mass customization focuses on discussing the importance of the strategy, issues that have to be addressed prior to implementation, and

developing classification schemes. Some work has already been done on designing platform-based product structures for mass customization manufacturing. However, no research has focused on designing manufacturing systems for mass customization whether transforming from mass production, custom manufacturing or directly adopting the strategy.

This research aims to fill that void by developing methods that can be used in the design of a mass customization production system. The manufacturing system chosen by a company will depend on the type of mass customization that is practiced. For example, the structure and processes required by a collaborative manufacturer who engages in pure mass customization—customer is involved right from the design stages—would differ from those required in assemble-to-order customization.

Evidence from empirical studies on mass customizers and a consideration of companies currently engaged in mass customization reveal that most companies practice standardized customization [52]. This is a form of mass customization where customers are allowed to choose between different options for the products' features—the options themselves being mostly standardized while a few may be custom manufactured to individual specifications. The final assembly is carried out to configure the customized product (e.g.: Dell computers [43], Bally Engineered Structures [67], Airborne bicycles [4], NBIC [48, 49]). The procedures developed in this research focus on designing manufacturing systems for companies involved in standardized customization.

1.3.1. Methodology

The existing strategies used in traditional cellular manufacturing are extended and adapted to meet the system requirements for successful mass customization. Traditional cell formation progresses by first forming product families and then identifying part families for each of them, resulting in a separate cell for each part family. With mass customization, often there is only a single basic product; the portfolio is made up of numerous variants of the basic product. The variants differ from each other in terms of the options available for each feature. Most options often would require similar processes but with different materials, tooling, and/or setup.

The assortment of product variants in mass customization, each with slightly different options, could generate large manufacturing cells if considered as a single family. Large cells make manufacturing scheduling difficult and result in long lead times and large in-process inventory, contrary to what is required with mass customization.

An alternative to using the traditional cells is to form smaller cells by considering the options rather than every product variant. The result would be smaller cells dedicated to producing option families as opposed to large cells for product families. These small cells, formed by using an option-machine matrix, are defined as minicells. Therefore, a product variant may have to be routed through several minicells, depending on the options chosen, to complete processing.

A minicell is formed by grouping the machines and operators required to process a sub-set of operations of an option family. Therefore, the larger traditional cell that is dedicated to one product family is now split into several minicells as shown in Figure 2.

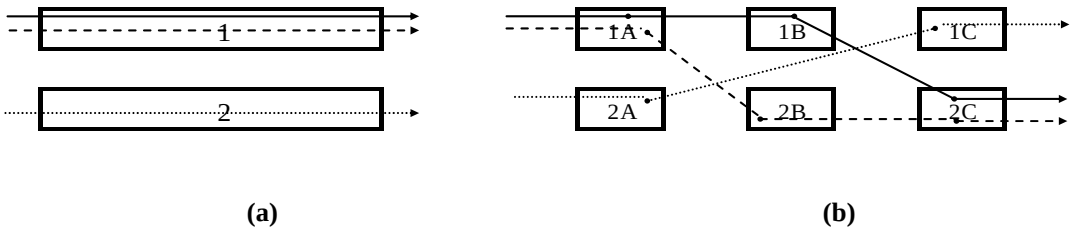


Figure 2: (a) Traditional Manufacturing Cells, and (b) Minicells

As shown in Figure 2(a) all parts in a family pass through the cell from start to finish with traditional cellular manufacturing. With the minicell configuration, the large cell is replaced by several minicells (Figure 2(b)) that break the process into multiple stages, so options can be routed to each necessary minicell. Therefore, the minicells are similar in operation to network cells. However, the platform-based product structure—different features and multiple options for each feature—is used as the basis for developing the minicells which are organized into several stages.

The aim of traditional cell formation strategies is to develop self-contained cells that can completely process a product family. The multi-stage minicell structure, to the contrary,

requires products to be routed to several smaller cells. Therefore, as a result of the inter-cell transfers required, an increase in the amount of material handling is likely. Hence the layout of minicells within each stage, considering the routing of product variants across the configuration and the demand for each option, becomes an important issue.

This research sets out to develop methods that can be used in the design of a multi-staged, minicell configuration such as that described. Important decisions in designing the system involve determining the number of stages in the configuration, forming option families and minicells within each stage, determining the type and number of machines that must be assigned to each minicell, and the layout of the minicells within the stages. The objective of the research is to develop procedures that can be used to find solutions to each of these issues.

1.3.2. Benefits

With the minicell configuration, machines that were confined to one large cell can now become available to several option families. Modularizing the production process by diving into smaller units permits selecting minicells based on a product variant's processing requirements—virtually reconfiguring. This will increase the product variety that can be offered compared to a system with a traditional cell arrangement. Minicells are smaller and would have lesser machines than in typical traditional cells. Also the option families formed will be much smaller than product families. Smaller minicells with option families are easier to manage and can help reduce waiting time and in-

process inventory particularly when there is a high variability—in terms of quantity and mix—of demand.

The minicell configuration is an attempt to exploit the advantages of both cellular manufacturing and job shops. The system benefits from group technology because options are grouped into families based on the similarity in their processing requirements and assigned to minicells. The ability to batch process items helps reduce setup times. Smaller transfer batches and bypassing minicells whose operations are not required could help achieve lower lead times to improve system responsiveness. Skipping machines, or even minicells, when no processing is required in them can also contribute to reducing delivery times. Further, with minicells, machine groups are not dedicated to whole families of products: they are divided and distributed among smaller cells increasing availability to a wider variety of products, as in job shop configurations. This helps increase the flexibility of the system that is necessary to produce a larger variety of products in mass customization.

2. LITERATURE REVIEW

This section presents a summary of the research that has been done in mass customization and related topics that are of relevance to this research. Initially a summary of literature on the origins, features, empirical studies, and classification systems of mass customization are presented. This is followed by a review of studies on different manufacturing strategies including cellular manufacturing and agile manufacturing. Various approaches to facility layout and the application of these methods to different manufacturing situations that are presented in the literature are also discussed.

2.1. Mass Customization

Mass customization was introduced by Davis [20] in 1987 through his book *Future Perfect*. As Davis explains, if the technology made possible customizing each product in a batch of products while still processing the batch as a whole, as one would with mass production, '*each is understood to be both part (customized) and whole (mass) simultaneously*' [20] (italics added). This thinking led to the new strategy known as mass customization.

Mass customization is the production of customized products/services to meet individual specifications at low-cost and with shorter lead times. Customization has been practiced long before mass production was used to fabricate similar items in large volumes at a low cost. However, traditional customization always came with an extra cost and waiting. Mass customization, on the other hand, is concerned with providing customized offers at no (or little) extra cost without long waiting times. It is a synthesis of the two long

competing systems of management: the mass production of individually customized goods and services [67].

Davis [20] mapped the progression of the once disintegrated local markets to its current individualized state. Initially the disintegrated small local markets were consolidated to benefit from economies of scale brought about by the technological advances. However, as customer need for variety increased in later years they were forced to revert to segmenting the large markets. The segmentation continued to progress with the increase in customer demand for variety and more specific products. The market segmentation has now progressed to a state of mass customization to focus on the individual customer [50].

The demand in small local markets was traditionally met by custom products made through craft production. Mass production techniques were later used to achieve greater efficiencies in the mass markets. The evolution of markets thereafter and strategies used by manufacturers can be explained by reviewing Porter's [70] generic strategies. The generic strategies, shown in Figure 3, outline the strategic options open to an organization to achieve sustainable competitive advantage.

		Competitive Advantage	
		Low cost	*Higher cost*
Competitive Scope	*Broad*	Overall Cost Leadership	Differentiation
	Narrow	Cost Focus	Differentiation Focus

Figure 3: Porter's Generic Strategies [70]

The source of competitive advantage—low cost or higher cost—explains the approach taken by companies to distinguish their products from competition. The competitive scope explains the market segments to which the source of competitive advantage is applied. Thus, a company could seek to offer its products to a large market at the lowest cost (overall cost leadership) or make its products different from competitor's ones (differentiation) and charge higher prices. Alternatively, these two strategies can be applied to a smaller segment of the market—narrow scope—to meet the specific needs of that market.

The differentiation focus strategy, according to Porter [70], aims at customers in a small niche of the market to meet the specific needs of its customers at a premium. However, mass-customized markets go one step further to reach the individual customer within the selected niche to attain a level of differentiation that is as varied as the clientele itself.

Porter's avenues to competitive advantage lie along the dimension of cost; according to him, differentiation can not be achieved while maintaining low cost.

Mass customization is about achieving differentiation with low cost which, according to Porter, would be 'being stuck in the middle' with no clear strategy. However, scholars have demonstrated the need for the concurrent application of differentiation and low cost strategies to achieve competitive advantage [66] and mass customization presents the fusion of the two approaches, now with extended differentiation to focus on the individual customer.

Achieving competitive advantage through mass customization, a concept presented in the late 1980s, was then considered to be impossible, constrained by the technology that existed during the era. Davis predicted that when the technology became available, it would provide the 'speed and specificity' required to deliver the customized products in mass scale at no greater expense [20]. Mass customization however did not gain popularity until Pine [67] further expounded and popularized the concept as a manufacturing strategy.

According to Pine [67], the increased market turbulence due to factors such as changing needs, wants, and demographics of customers, technological shocks, and economic changes caused the breakdown of the mass production paradigm. The new way of thinking emerged out of the need to outperform mass production and gain stability under the changing circumstances. Thus companies were forced to rethink product and process

designs in order to meet the low-cost, high-quality, customized products that were demanded. The problems were compounded by fragmented and dynamic demand as opposed to the stable conditions manufacturers were previously accustomed to. Pine [67] described the above changes by mapping the evolution from one paradigm to another in greater detail.

These thoughts on mass customization and its implications on US manufacturing were further elaborated through a series of articles that later appeared in the Harvard Business Review [68, 69, and 28]. These articles illustrated the market changes that took place during the era, the limitations of existing manufacturing philosophies in meeting them and the need for mass customization. The studies clarified that the two paradigms of manufacturing are fundamentally different from each other and that they require completely different operating structures and principles [69].

2.2. Empirical Studies on Mass Customization

Empirical studies illustrate the mass customization of different products across various industries. Findings also reveal the existence of different types of mass customizers employing varying degrees of customization. Though mass customization is equally important for products as well as services, most studies on the subject have focused on companies in the manufacturing sector.

Kotha [48, 49] conducted in-depth case studies of the National Bicycle Industrial Company (NBIC) of Japan to examine the implementation of a mass customization

strategy in a company that earlier relied primarily on mass production revenues. The company converted its pilot plant to mass customize bicycles, a concept not heard of for bicycles at that time in Japan, within a four month period.

The customer agreed upon the specifications required at the retail store which were then communicated to the factory electronically. The bicycle was manufactured to specifications within two weeks of receiving the order for a price of approximately 20-30% above comparable mass produced bicycles. Some parts—the frame and fork [54]—were custom made to specifications and the bicycle was assembled using these and other standard components. This case illustrates the application of pure customization for certain parts of the product while the final product itself is custom built from standard components.

The early efforts of Hewlett-Packard (HP) at customization are described by Feitzinger and Lee [25]. HP DeskJet printers were fitted with a country-specific external power supply at the distribution center instead of at the point of production, which had been the case earlier. This saved the company from holding large inventory, differentiated by the type of power supply, for different markets [25]. The company's strategy for customization was to delay the differentiation of the products to the later stages in the value chain. Contrary to the case of NBIC, there was no customer involvement in determining product specifications; the choice of power supply merely depended on where the customer lived.

Pine [67] showed several examples of mass customization in many industries e.g.: newspapers, eye glasses, and men's suits. He also described the case of Bally Engineered Structures, an electronics company that designs and manufactures lighting control devices, where every order is customized to individual specifications, but mass produced from standard components.

Another classic example of a company mass customizing using modular components is Dell computers. The customized manufacturing of Dell computers at the manufacturing facility in Austin, TX is explained by Kepzyk [43]. Customer orders are received mostly through the company website or over the telephone. Each order is accompanied by a 'traveler form' with details of specific components required and the service tag that will later be assigned to the finished product. Actual production is started by assembling the chassis, motherboard, and memory which are then moved to the 'kit' area. Other internal components are added to the tray in the kit area and the order is routed to final assembly. The entire process is completed in less than 24 hours [31] and the customer gets a computer whose customizable features have been modified to meet his/her requirements. The case of Dell illustrates another company that uses standard mass-produced components to achieve mass customization.

Several others explored the customization efforts by other companies [69, 32, and 99]. Many other examples of mass customization from shoes (Nike [2]), bicycles (Airborne [4]), to replacement windows (Andersen [101]) can be found. These case studies demonstrate the importance, feasibility, and different forms of mass customization.

2.3. Mass Customization from an Organizational Perspective

As evidenced by the empirical examples a company's efforts at mass customization could take various forms. It can vary from mere cosmetic differentiation to total customization where the customer is involved in the process from the point of design. Different classification schemes have been put forward to describe and illustrate the approaches to mass customization. Most classification systems are based on the level of customer involvement in the activities along the value chain while some also consider the extent of modularization/standardization in the production process or the amount of information technology integration in the customization.

2.3.1. Value Chain-based Classifications

An initial attempt to classify mass customizers was presented by Pine [67] in his seminal writings on the subject. He identified five approaches to offering individually customized products or services: customizing services (for standardized products and services), creating new customizable products and services, providing point-of-delivery customization, providing quick response throughout the value chain, and modularizing production of components for customizing end products and services.

The five approaches defined by Pine are linked to the value chain of an organization, and are sequenced from the option requiring the least amount of organizational change to the most. Pine's approaches to mass customization and their association to the different stages in the organizational value chain are presented in Figure 4.

Pine describes steps that a company can follow, starting from the simplest to the most complex, to transform from mass production to fully fledged mass customization. He recommended customizing the services provided around existing products or services (by customization of the marketing and delivery activities) as the stepping stone to mass customization for mass producers seeking to change the paradigm. Developing customizable products or services and manufacturing them through standardized production is the second approach suggested. The sale, in this case, has to be customized through appropriate marketing strategies.

The production of standardized products and services to be customized by delaying final fabrication at the point-of-delivery was another approach presented. The most involved approach to deliver customization, according to Pine, is to produce modular interchangeable components that can be mixed and configured to increase variety. This, he believed, provided the opportunity to benefit from scale economies while allowing for the economies of scope required in mass customization.

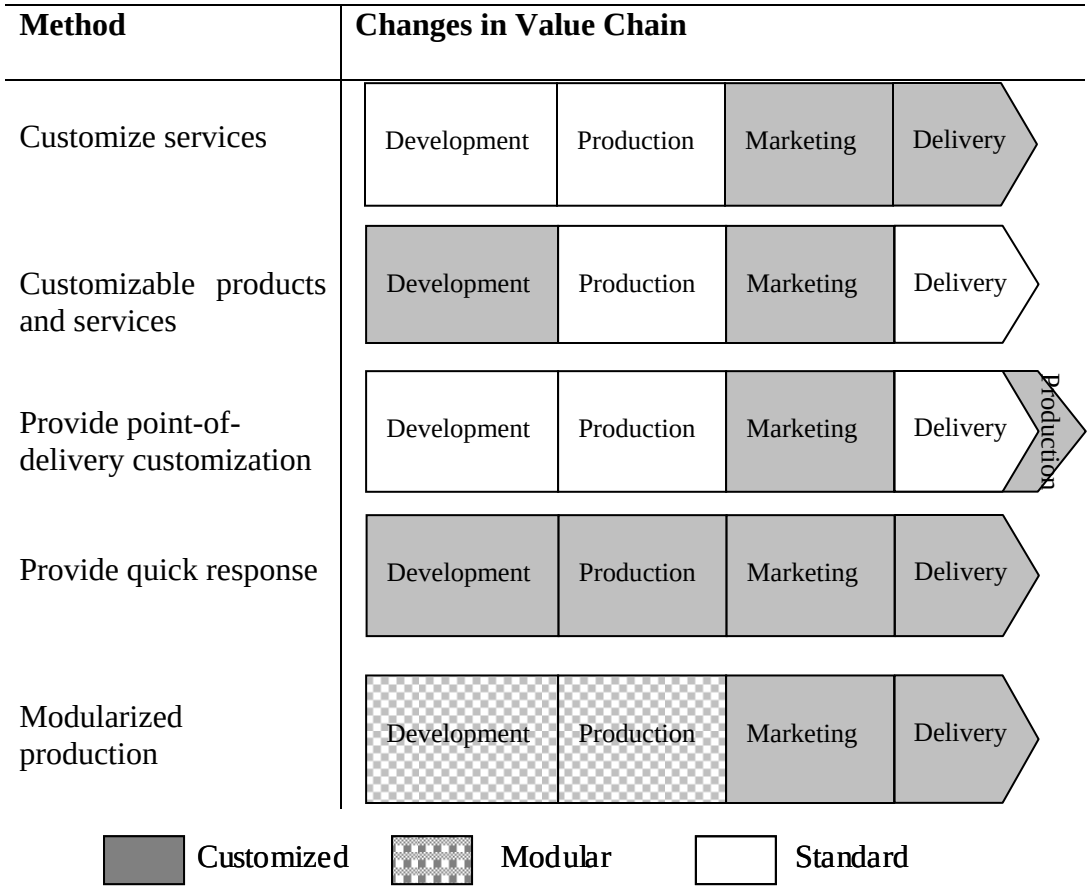


Figure 4: Pine's Approaches to Mass Customization [67]

Lampel and Mintzberg [52] describe standardization and customization as extremes of a continuum of strategies. Five manufacturing strategies are identified: pure standardization, segmented standardization, customized standardization, tailored customization, and pure customization. They mapped the strategies in relation to the organizational value chain and the point at which customization is undertaken. They advocate that customization should begin with those activities closest to the market and then progress upwards as shown in Figure 5.

Similar to Pine [67], Lampel and Mintzberg [52] too considered a four-stage classification of the value chain activities in identifying approaches to mass customization. However, Pine emphasized on customizability through marketing and delivery, and modularized production. Lampel and Mintzberg [52] present a more systematic approach to transforming organizational activities starting from the customer's end.

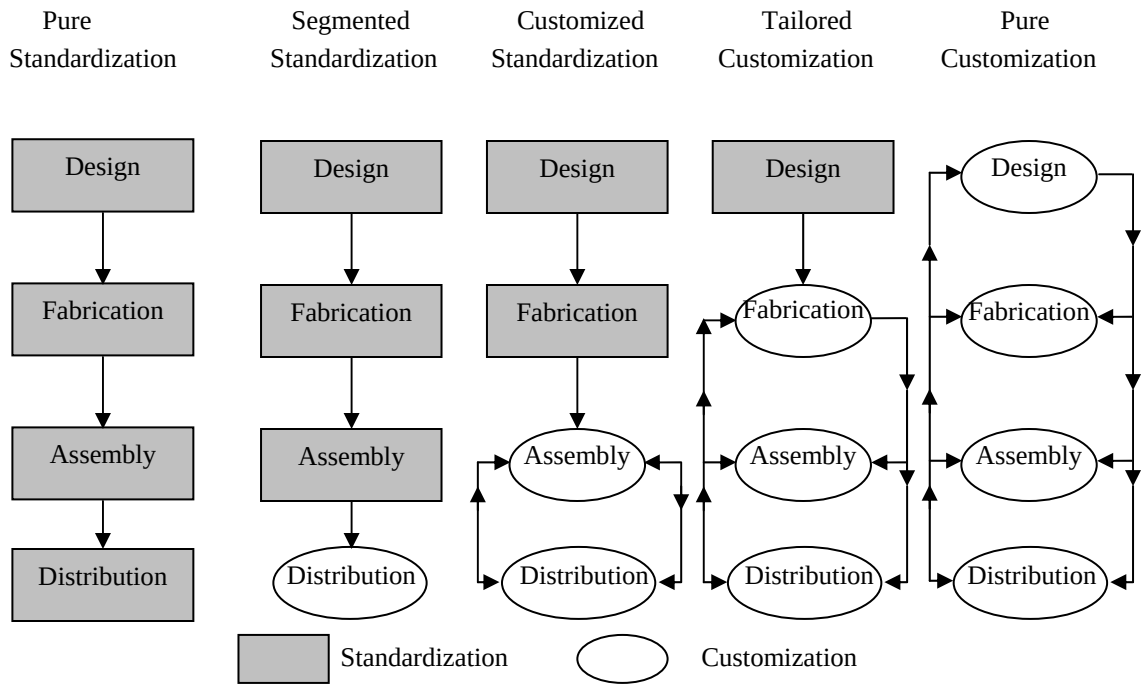


Figure 5: Lampel and Mintzberg's Continuum of Strategies [52]

Pure standardization operates on the mass production paradigm: identical products manufactured and offered to customers with no allowance for customer choice. In segmented customization, choices are offered to customers while maintaining standardized design and manufacturing operations. With standardized customization or customized standardization—terms the authors use interchangeably—products are made to order using standardized components. A standard design is used to customize production and delivery of the final product with tailored customization. In pure customization, all operations in the value chain are customized to suit individual customer requirements. Lampel and Mintzberg [52] argue that the trend in industry has shifted towards standardized customization, not pure customization.

A slightly different approach to classification is presented by Gilmore and Pine [28]. The four approaches to customization, derived mostly through empirical observations, are defined as collaborative, adaptive, cosmetic, and transparent customization.

Collaborative customization, the form that most closely resembles pure mass customization, is said to occur when customers are engaged in the purchase beginning from the design stage. In adaptive customization a standard product that can be customized by the user to suit individual requirements is offered. Cosmetic customization is the differentiation of a standard product mainly through packaging. The fourth approach, transparent customization, is more subtle and difficult to distinguish in many cases. This form involves providing “individual customers with unique goods or services without letting them know explicitly that those products and services have been

customized for them" [28]. The approaches to mass customization elaborated in Pine's initial classification are implicit in this model as well.

Ross [75] presented five different approaches to mass customization with customization taking place at different points in the value chain. Core customization is where customers can modify core elements of the product. With the 'pushing high variety' strategy, market needs are understood and integrated in manufacturing products to respond faster to the changing demands. In post-product customization, a third party converts the standard product to a customized product (e.g.: customizing software for business applications).

Ross [75] uses the term mass retail customization to describe the form of customization where the product is modified at the point of retail (e.g.: eye glasses). Finally, with self customization, products that customers can change at any time to meet their preferences are produced. Most of the strategies presented by Ross require little or no changes to the design and manufacturing operations for customization.

Alford, et al. [5] present a mass customization classification scheme for the automotive industry, which is also based on a value chain viewpoint (Figure 6). Three types—form, optional, and core customization—are identified based on the extent of customer involvement in distribution, manufacturing and design activities, respectively.

Similar to the Lampel and Mintzberg [52] classification, customization is started off with the customer end of the supply chain. In the simplest type, form customization, the form

of the automobile is changed at the dealer, for example through terms of sale. They classify the low volume, specialist vehicles where customers get involved in the design as core customization. The popular type of automobile customization where customers get to choose from various feature options and purchase a vehicle to their liking is termed optional customization. This classification is very similar to the previous taxonomies which imply a value chain standpoint but in this case considered from the automobile industry perspective.

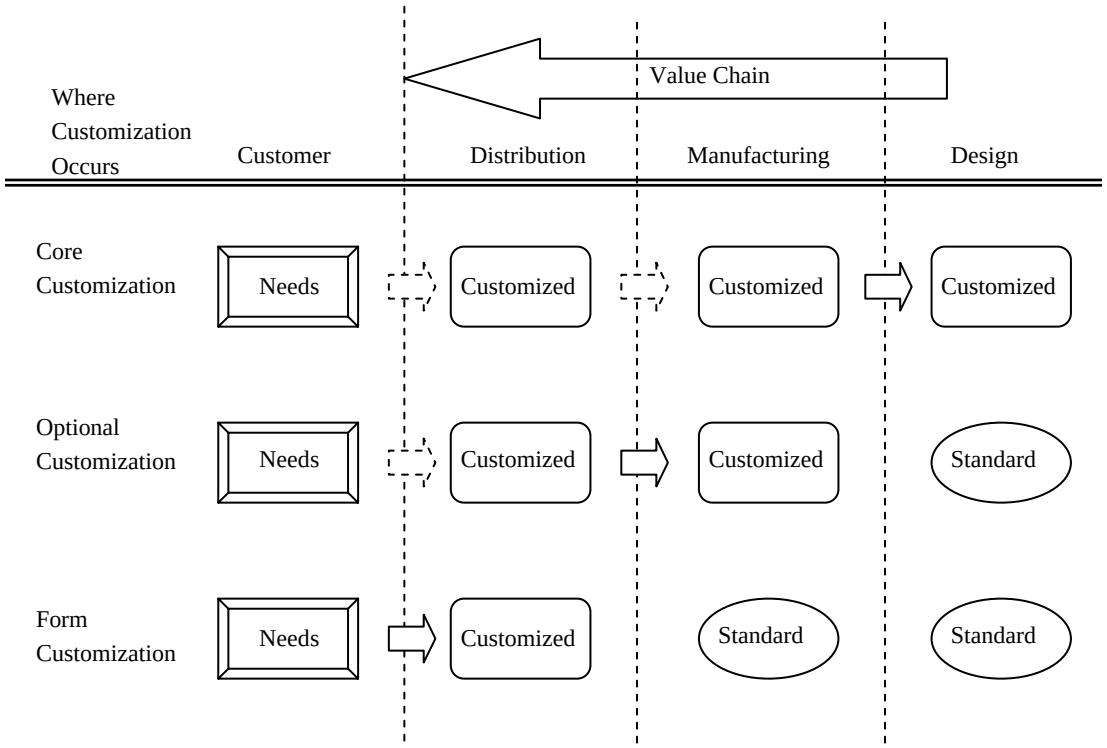


Figure 6: Automotive Customization Schemes [5]

Da Silveira, et al. [18] identified eight generic levels for mass customization through an extensive review of value chain-based classification schemes, including some discussed here. Their levels vary from pure customization, where products are designed individually for each customer, to pure standardization.

A value chain perspective is implicit in all of the above classification schemes; the type of customization is based on the point of customer involvement in the value chain.

2.3.2. Other Classification Schemes

Moving away from this convention, Duray, et al. [24] presented a taxonomy that is based on two dimensions; the point of customer involvement and the type of modularity used by the producer. Their matrix configuration is shown in Figure 7.

<table>
<tr><th rowspan="2">Point of Customer Involvement</th><th colspan="4">Type of Modularity</th></tr>
<tr><th>Design</th><th>Fabrication</th><th>Assembly</th><th>Use</th></tr>
<tr><td>Design</td><td colspan="2" rowspan="2">1
Fabricators</td><td colspan="2" rowspan="2">2
Involvers</td></tr>
<tr><td>Fabrication</td></tr>
<tr><td>Assembly</td><td colspan="2" rowspan="2">3
Modularizers</td><td colspan="2" rowspan="2">4
Assemblers</td></tr>
<tr><td>Use</td></tr>
</table>

Figure 7: Matrix Grouping of Mass Customization Configurations [24]

Fabricators have customers involved in the process as early as design and fabrication stages which are also modularized. This form resembles Pine's [67] collaborative customization and the pure customization strategy of Lampel and Mintzberg [52] with respect to customer involvement. Assemblers, on the other extreme of the model, do not get customers involved until the latter stages; modularity is only applied in the assembly and use stages. The authors categorize customization through interchangeable parts, or standardized customization as it was termed by Lampel and Mintzberg [52], in this category as there is no customer involvement in design/fabrication. They validated the conceptual model through empirical data relating to a group of mass customizers and identified the types of processes, process control, design technology, manufacturing techniques, and administrative software technologies used by each type of customizer.

MacCarthy, et al. [54] present five fundamental modes of operation for mass customization based on their findings from the application of existing classification schemes to case studies. They emphasize that a good classification should be capable of grouping organizations that use similar approaches while distinguishing those different and assert that existing classification schemes are not capable of serving their purpose to the fullest. They consider the Gilmore and Pine [14] classification to be the most straightforward. Their mode of classification, which is developed by building on the existing, is shown in Table 1. It must be noted that the MacCarthy, et al. [26] scheme follows a process orientation, rather than the more common value chain approach.

Table 1: Fundamental Modes for Mass Customization [26]

Fundamental Mode	Features
Mode A	Catalogue mass customization: pre-engineered catalogue of variants, produced using standard processes
Mode B	Fixed resource design-per-order mass customization: customer specific product is engineered, produced through standard processes
Mode C	Flexible resource design-per-order mass customization: customer specific product is engineered, produced through modified processes
Mode D	Fixed resource call-off mass customization: customized product designed, manufactured through standard processes. Repeat orders anticipated.
Mode E	Flexible resource call-off mass customization: same as D, but order fulfillment activities modifiable.

A more recent classification scheme that integrates the role of information technology in delivering mass customization is presented by Piller [66]. His framework which classifies approaches to mass customization based on the degree of customer integration with manufacturing operations and the degree of digitizability (extent to which functions relevant to a customer can be fulfilled by the use of information technology only) of customized components is shown in Figure 8.

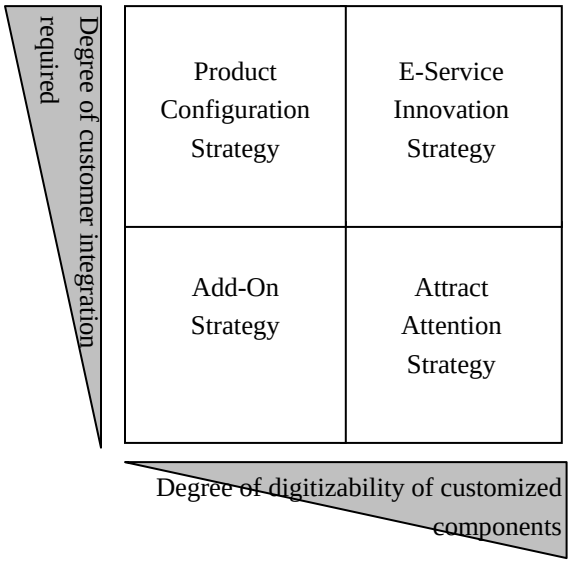


Figure 8: Mass Customization Strategies [66]

Products and services which offer little customization or about which customers have enough knowledge to choose from alternative configurations are grouped under the Add-on strategy. On the other hand, those with an opportunity for better customization by increasing digitization are grouped under the ‘attract attention’ category.

Instances that require high customer integration but where the customization process is not fully digitizable fall into the product configuration strategy. He classifies consulting services and other information goods (e.g.: online health centers), which require high degrees of customer integration and digitizability as E-service innovation strategies. Through this classification, Piller attempts to emphasize the importance of information in

delivering mass customization and its potential in exploring more opportunities for customization without adding significantly to the cost.

The classification schemes present an overview of the manufacturing system requirements for delivering mass customziation. The continuum of strategies ranging from pure customization to more simpler approaches such as assemblers [24] or form customization [5] require manufacturing system configurations with varying degrees of flexibility.

The most flexible systems are required for pure customization: the system must have the capability to manufacture products designed to customer specifications within a short time. Such capability can be built by the use of highly automated flexible manufacturing systems (FMS). While such systems will be resourceful in fabricating a multitude of product variants to customer specifications, they are very costly due to the technology required and their use is not as widespread. On the other hand, approaches to mass customization in which customization is achieved at a point closer to the customer such as in delivery/distribution is less demanding with respect to manufacturing system flexibility. It is only necessary to produce an assortment of products that can be customized later, for example by adding/removing parts or by packaging.

In standardized customization products are customized by using standard components: customization is achieved by providing a variety of options for the components/features from which customers can choose from. With all products made-to-order, the different

options for the features must be manufactured after the customer orders have been received. The manufacturing system will need to be configured to provide this flexibility together with low lead time. FMS can be configured to manufacture the different options and can be used in standardized customization as well. However, given their high cost, such systems are still not widely used by many companies. Alternatively, if processors other than FMS are used, configuring a manufacturing system to give the flexibility *and* responsiveness required for mass customization will be challenging.

2.3.3. Limitations/Challenges to Mass Customization

Examples of mass customization in various industries are widespread and interest in the field has been growing over the past several years. However, there are many challenges to successfully implementing the strategy highlighted through research as well as empirical evidence.

The greatest challenge to implementing mass customization probably is determining the most suitable manufacturing configuration that gives the required process flexibility at a low cost [53, 67]. As has been emphasized by many, mass production and mass customization require completely different organizational structures and processes. Flexible manufacturing techniques provide the capabilities required to provide high product variety within a short time. Large volume standardized production help achieve low cost through economies of scale. Mass customization manufacturing systems require high flexibility achieved at a low cost; a fusion of two opposite approaches, which is no simple feat.

Zipkin [101] supports this view stating that process flexibility required to fabricate customized products is a major limitation to implementing mass customization. He emphasizes the need for highly flexible manufacturing technologies and also suggests that mass customization should be approached cautiously because developing such technologies is expensive and time consuming.

As Pine, et al. [68] describe, breaking away from the traditional, long-lasting, manufacturing configuration to build a dynamic structure that gives the flexibility is difficult. Empirical studies of companies engaged in mass customization reveal that the inflexibility of factories is one of the greatest barriers to implementing mass customization [3].

Approaching the issue from an automobile manufacturing perspective, Agrawal, et al. [2] too emphasize the need for many operational changes in the organization to achieve the flexibility required for mass customization and the difficulties in transforming the system. For example, customers may like to choose the color of their cars; but paint shops are run in batches to reduce cost and wastage [2]. The mass customization manufacturing system needs to have the flexibility to provide the customers with the choice of color—a very trivial option from the customer's perspective–without adding significantly to the cost.

As MacCarthy and Brabazon [53] argue the process of engaging the customer is one other challenge to mass customization because customer behavior is less well understood. Mass customization is all about providing the customer with exactly what he or she

wants. However, getting information from customers for customization is difficult. That is, ‘to give customers exactly what they want, you first have to learn what that is’ [101]. Customization is a necessity to meet varied customer demand; but it should not proliferate to a level where customers are overwhelmed with, or do not want, that many options to choose from or customize [69]. For example, Nissan once had 87 different varieties of steering wheels for customers to choose from; but most disliked having to select from that many options [69, 52].

In an exploratory study conducted among several British firms, understanding customer wants was one of the two most frequently cited difficulties to implementing mass customization [3]. Therefore, a systematic approach to communicate effectively with customers and gain accurate and reliable product information is essential [53].

Another major hurdle to successful mass customization is overhauling the supply chain to provide the quick responsiveness without increasing the cost. The traditional supply chain was structured around a push production philosophy of manufacturing to stock and subsequent distribution. But with mass customization, there has been a change in paradigms; inventory is not made-to-stock but made-to-order. Thus ‘there is no supply chain anymore; instead, a *demand chain* is created’ [28] (italics original). Many studies have attempted to understand the needs of and determine approaches to reconfigure the supply chain to increase responsiveness [93, 51].

In Ahlstrom and Westbrook's survey of companies supply chain management was listed as one of the top two difficulties to implementing mass customization [3]. Zipkin [101] emphasized the importance of better logistics networks, integrating e-commerce, for better direct-to-customer distribution.

Mass customization also requires more responsive suppliers for effective inventory management and order fulfillment [53]. Postponed differentiation strategies to achieve mass customization call for reconfiguring the supply chain to place some traditional production operations further down in the distribution channel [25, 93].

Information technology plays an enormous role in making mass customization feasible. It provides the platform to receive customer orders and transfer them to the production floor within a short time. However, managing the customer relationship to get the required information from customer and integrate it in the manufacturing process are other problems in mass customization. Many studies have focused on these issues.

In addition to the above, the changes in information technology capabilities required [3], the need for dynamic teams as opposed to the less flexible cross-functional teams [91], developing managerial skills and abilities, are also found to be difficulties encountered by companies seeking to pursue mass customization.

The focus of this research is developing a manufacturing system for mass customization to provide the flexibility required to deliver high product variety at low cost. Therefore,

the other issues discussed above, though very important to the implementation of mass customization, are beyond the scope of this research. Hence, the following sections will focus on manufacturing related studies on mass customization.

2.3.4. Mass Customization Manufacturing

Customizing products in times of high market turbulence requires *dynamic stability*; firms designed to serve a wide range of customers with changing product demand (dynamic) while building on existing process capabilities, experience, and knowledge (stability) [67]. Whether transforming from a mass production system, or building a new mass customization facility, a more fundamental reconsideration of operational systems is required for a strongly customer-focused mass customizer [53].

Traditional manufacturing operates on the premise of economies of scale–achieving low-cost through large volume production of similar items. To the contrary, mass customization has to focus on economies of scope—applying the same processes to manufacture a greater variety of products (or services) faster and at a low cost [67].

Therefore, being an efficient mass producer does not assure success as a mass customizer. This is because the two systems require different organizational structures, values, management roles and systems, learning methods, and ways of relating to customers [67]. Unsuccessful efforts at mass customization by many companies due to the lack of appropriate systems can be found in the literature [69, 52].

However, this does not signify that a company can not employ mass production and mass customization strategies simultaneously. Kotha [48, 49] presented one of the earliest case studies on mass customization manufacturing by describing the case of the Japanese bicycle manufacturer. The company had two factories; one mass producing standard bicycles and the other for mass customization. While not much information is available on how the mass customization facility was designed and implemented, a learning relationship between the two factories has been reported [23, 48, and 49].

According to Feitzinger and Lee [25] one of the organizational design principles for effective mass customization is using modular processes. Process modularity is the standardization of process modules to enable frequent and easy re-sequencing or to allow for new modules to be added quickly depending on changing product requirements [91]. Therefore unlike the long and dedicated production lines often used in mass production systems, smaller, easily reconfigurable, process modules or micro factories [53] are necessary to customize products.

Through the synthesis of available literature and four case studies, Spring and Dalrymple [84] addressed some manufacturing issues in mass customization. They demonstrated the importance of the relationship between the degree of design activity and volume of manufacture to classify customized products. The degree of design activity is based on whether the products are custom-built from options or if they involve some custom-designed elements. From this classification, they attempt to identify different problem-solving situations in the customization process and proposed criteria to support

management decision making; however, they did not address the formulation or implementation of a manufacturing strategy to enable product customization.

Tu, et al. [91] studied the relationship between the ability of a company to implement time-based manufacturing practices (TBMP) and corporate success at mass customization. Examples of TBMP are shop-floor employee involvement in problem solving, reengineering setups, preventive maintenance, cellular manufacturing, and pull production. They conclude that TBMP form part of the foundation for achieving customization by providing the flexibility, responsiveness, and efficiency that the system requires.

In an exploratory study conducted among British companies, the most widely used approaches to product customization were found to be assembling products from core components, doing materials processing, and increasing inventory [3]. However, they provided no additional information explain the meaning of ‘materials processing’ in this context.

Duray [23] used a classification scheme developed in a previous work by Duray, et al. [24], based on the extent of customer involvement in organizational activities and modularity, to conduct an exploratory study and evaluate the progression of companies from standard or custom manufacturer to mass customizer.

Building on the previous findings of Kotha [48, 49], Duray found that companies practicing mass customization continued to produce non-mass customized products (standard or custom) in the same plant [23]. The findings of Duray are not conclusive as to if standard and custom producers use significantly different approaches for mass customization.

Qiao, et al. [73] assert that fixed and centralized control would not work in mass customization manufacturing. They propose three steps to overcome this situation. First, a generalized production line platform (GPLP) is suggested to make the physical reconfiguration simpler. A GPLP is a collection of basic workbenches fitted with fixtures and tooling required, which can be reorganized according to production requirements. The GPLPs are formed into functional modules each for a typical manufacturing capability which are then combined and reconfigured as demanded. This supports Pine's [67] thinking that investing in general-purpose processes, rather than specialized systems, is more beneficial in achieving flexibility and responsiveness.

Though many facets of customization have been studied, there is a notable lack of literature linking customization to other broader issues relating to manufacturing [83, 84]. Many have conducted exploratory studies to identify the manufacturing practices of mass customizers. While some insights can be gained from these studies to develop manufacturing systems for mass customization, no studies have addressed this issue directly.

As pointed out by Lampel and Mintzberg [52] smaller modules or micro factories are necessary to produce customized products. These modules must comprise of general, multi-purpose machines that can be used for a variety of operations to achieve the flexibility required with mass customization [91]. Such systems must also incorporate pull production techniques and eliminate non-value adding operations to achieve the responsiveness required [67]. However, none of these issues have been addressed jointly in the literature with respect to mass customization manufacturing.

2.4. Manufacturing Systems for Mass Customization

Various manufacturing system alternatives that may have the potential of delivering some of the requirements of mass customization manufacturing are described in the literature. While some of these strategies can be useful in system design others are more applicable in operations planning for mass customization manufacturing. They include cellular manufacturing (CM), agile manufacturing (AM), and lean manufacturing systems. The literature on these different systems is reviewed in the following sections.

2.4.1. Cellular Manufacturing

Mass customization manufacturing has a lot to gain by extending the concepts used in CM. Group technology is the philosophy of combining like items to benefit from their similarities; CM is the application of this thinking to manufacturing.

Burbidge [15] defined group technology as the formation of small organizational units which complete all the products assigned to them, through one or few major processing

stages. He asserted that these organizational units should have all the machines and other processing equipment required to complete the processing of the family of parts. Thus CM exploits the similarities in the design and manufacturing processes of products [100] to create and operate manufacturing cells dedicated to the production of a set of product families [80]. According to Steudel and Desruelle [85], in a manufacturing cell machines of dissimilar functional type are grouped together and dedicated to processing a family of similar parts.

Most of the definitions of manufacturing cells imply a mere physical clustering of machines and equipment to produce similar parts. Hyer and Brown emphasize that a cell is more than a physical layout by defining them as a dedication of resources to a similarly processed family and the tight connection of tasks and people in terms of time, space, and information [38]. Their definition illustrates the integration of the elements within the cell—machines, workers and products—along three dimensions that are vital to its operation. Suer and Ortega [89] too included workers in their definition of manufacturing cells.

The objective of traditional cell design has been to group machines into self-contained units where all processing for the product family can be completed within cells avoiding inter-cell material transfers. Such designs are useful in low-to-medium volume, low-to-medium part variety production [61]. However the disadvantage of creating manufacturing cells is that it reduces the flexibility to route products through the shop floor compared to a job shop environment. Also since the machine cells are formed by

grouping products that require similar processing, constant changes in the product mix may require reconfiguration in order to benefit from group technology concepts [61]. Many innovative approaches to cell design and CM have been presented in the literature recently to meet this need for higher responsiveness and product variety.

2.4.1.1. Virtual Cells

Virtual cells were devised as a means to improve the manufacturing performance in turbulent environments. According to Prince and Kay [71], virtual cells are 'not identifiable as a fixed physical grouping, but as data files and processes in a controller'. Hence they are logical groupings of machines that are reorganized to meet demand variation [92]. With virtual cells, the physical layout of the machines is not changed as the product mix or demand changes. Instead they are regrouped logically by identifying machines that have the potential to form manufacturing cells. This information is then used for product routing and scheduling purposes.

The virtual cells are particularly useful when large machines are used and it is difficult to relocate them to form traditional cells. The logical dedication of machines to product families enables lower setup times compared to that in a job shop [92]. The virtual cell configuration can be adapted to changes in the product mix because the machine layout does not require reorganization. However they do not provide the benefit of reduced material handling because the machines are not arranged in close proximity to each other. Also since the cells exist only virtually, a high level of information and communication between the machines in the system is required for efficient operations [58].

Due to the ease of reconfiguration this type of cells may appear to have potential for use in mass customization manufacturing. However, with mass customization the product mix changes so frequently and the cell assignment will have to be changed repeatedly resulting in a loss of the benefits of virtual cells. Though many analytical studies on the design and operation of virtual cells and their usefulness can be found, little research has been done on comparing the performance of virtual cells with other manufacturing systems [92]. There is also a lack of empirical evidence to demonstrate the superior performance of virtual cells in high-variety, dynamic product mix situations.

2.4.1.2. Dynamic Cells

Dynamic cells evolved in an effort to combine the benefits of virtual cells and traditional cells. They are similar to virtual cells because the machines are reconfigured to respond to changes in the product mix [46]. However, with dynamic cells the machines are physically rearranged each time the system is reconfigured [58]. Therefore dynamic cells have the advantage of reduced material handling due to adjacent location of machines, as is the case with traditional cells, and the flexibility to accommodate changes in product mix as with virtual cells.

The performance of dynamic cellular manufacturing systems has been studied by many to evaluate their performance relative to traditional cells [58, 57, 22, and 46] and job shop [58, 22, and 46] configurations. Analytical models are used to illustrate that dynamic cells outperform both types of systems with respect to several performance measures.

However, there is little evidence in the literature to show the successful application of dynamic cells.

Dynamic cells are useful in manufacturing environments with movable, small machining devices where the mobility can be exploited to form dynamic cells by economically relocating them [74]. However, in most manufacturing environments, other than when assembly operations are performed or in industries such as jewelry manufacture or electronics, the processors used to fabricate products are larger and less mobile. In such situations dynamic cells are less beneficial due to the time and effort required to reconfigure the machines each time there is a change in the product mix.

From a mass customization perspective, the optimal manufacturing system needs to have the agility to respond quickly to customer requirements in addition to having the flexibility to accommodate the varying product mix. The high variability in the product mix in mass customization would require frequent reconfigurations of the dynamic cells, just as for virtual cells. In addition, if the processors used in the shop floor are not lightweight and mobile, the reconfiguration is costly and time consuming and will only add to the time required to manufacture customized products.

2.4.1.3. Linked Cells

Black [11, 13] introduced a new type of cells termed linked cells which are composed of manufacturing cells and assembly cells that are linked together with a pull system for material and information control. The basic building block, in this type of cells as well, is

a cell created based on the GT concept; however, cells performing different operations, manufacturing and assembly, are combined into one integrated unit [11].

The operation of linked cells is somewhat analogous to flow lines because products are processed one unit at a time. This is also comparable to multi-model assembly lines which can manufacture a variety of products with similar processing requirements and therefore low changeover times between products. However, because the processes are completely automated, a linked cell manufacturing system could be considered an alternate form of a FMS. Research on analytical or empirical studies on the subject is limited with the exception of the work done by Black [11, 13] and Davis and Mabert [19].

Lower throughput times and faster delivery could be achieved with linked cells. However, this is only possible if products assigned to a given linked cell require similar processing and the changeover and setup time between products is very low. Else, single unit processing in linked cells will increase throughput time.

Mass customization manufacturing involves producing a large variety of products, each with different options and, therefore, different processing requirements. Using a linked cell manufacturing system to handle a large variety of products will be inefficient unless they require similar processing: this is unlikely with mass customization manufacturing. An alternative would be to consider using separate linked cells for different families of customized products. However, due to high variation in demand for different product

variants, dedicating linked cells for each family may not be economical. The concept of integrating manufacturing and assembly operations into a single cell, however, can be used to advantage in designing a mass customization system to reduce the lead time and material handling.

2.4.1.4. Holographic Cells

These types of cells were initially introduced by Montreuil, et al. [60] for use in volatile environments with a dynamic product mix. Each holographic cell (or holonic cells as referred to by Askin, et al. [6]) is composed of one or a few similar or complementary machines [56]. The different holographic cells composed of different machine(s) are then replicated, as necessary, and distributed throughout the factory floor. The objective is to strategically locate the cells so that dynamic routing of products is possible. Thus, to whichever part of the factory a particular product is assigned, all the required machines would be available in several holographic cells in proximity. It is anticipated that this type of configuration would increase the flexibility particularly when there is little information available on product mix and demand ahead of time [94].

The holographic cell based factory is indeed a job shop with the machines distributed in different regions, instead of being functionally organized. As pointed out by Montreuil and Lefrancois [60], to be successful, a holographic cell based factory requires considerable planning and coordination. Further, as a result of having to visit several holographic cells to complete processing of a particular product, the amount of material handling involved with these types of cells would be higher than with traditional cells.

Marcotte and Montreuil [56] presented a metaheuristic for holographic factory layout. Askin, et al. [6] studied the behavior of holonic cells in relation to fractal cells (discussed below) and proposed a methodology to design these cells. Marcotte and Montreuil [55] compared different types of cells, including holographic cells, to evaluate their usefulness under stochastic demand conditions.

The widespread use of holographic cell based configurations is still to be seen [60]. Though they contribute to achieving higher flexibility, holographic cells require considerable effort in terms of planning and implementation.

2.4.1.5. Fractal Cells

Fractal cells were developed to benefit from the high flexibility offered by job shops while trying to curtail the amount of material handling required in traveling between machines/workstations. Venkatadri, et al. [94] define fractal cells as a set of workstations that are capable of processing most, if not all products that enter the shop floor. Thus the job shop is divided into fractal cells such that each cell contains a mix of machines of various types contained in the entire shop [62]. While each fractal cell has the capability to handle all (or most) of the products, each has the responsibility of processing an equal fraction of the total demand [60]. Each fractal cell can be considered a mini-factory. The fractal cells are not always independent in which case the need for inter-cell as well as intra-cell material transfers is required to complete processing of products.

Venkatadri, et al. [94] explained a methodology for designing the fractal cells by considering cell creation and cell layout simultaneously. Montreuil and Lefrancois [60] have elucidated some issues related to the design and operation of fractal cells compared to various other types of cells. Askin, et al. [6] also proposed some approaches to design fractal cells. They compared process, fractal, and holographic cells using queuing theory and concluded that fractal cells with a nearly square arrangement of machines are best only when material movement is low and facilities are large.

Forming mini-factories which are replicates of the job shop will contribute to maintaining the flexibility that was possible with the latter. The cells also have the advantage of being able to handle a varying product mix just as job shops. However, when the number of products and variants offered for each product are high, as is with mass customization, the fractals will have to be made larger to build the capability to manufacture all of them. Unless duplicated, the capacity assigned to each fractal will again lead to problems of long waiting times and in-process inventory, which are typical with job shop configurations.

2.4.1.6. Network Cells

The notion of network cells, where each cell is assigned a specific set of responsibilities, was first introduced by Schnoberger [60]. A network cell has the responsibility for a set of products and a set of processes required for those products [60]. Products are routed to one or more network cells depending on the processing requirements. The amount of

inter-cell flows with network cells is higher than with traditional cells but lower compared to a job shop.

Network cells are designed to benefit from the similarities in products, thus reducing setup time and in-process inventory. With network cells machines are not grouped together and dedicated to product families for complete processing: only certain operations required for those products are performed in each cell. This allows the machines to be made available to a wider range of products increasing the flexibility of the system. Hence network cells appear to have the potential to deliver some of the requirements of mass customization manufacturing.

A traditional product structure where each product has a set of features/components is used in developing the network cell configuration. In mass customization manufacturing, often there are only a few products: however the portfolio explodes in size due to the variety of options offered for each feature. This distinction in product structures will necessitate a different approach to designing network cells if used for mass customization manufacturing. Nevertheless, the concept of dividing the processing operations required for products between multiple cells and routing products as necessary appears to be the correct path to pursue cell design for mass customization.

2.4.2. Agile Manufacturing

Agile manufacturing (AM) was first introduced by the 21st Century Manufacturing Enterprise Strategy published by the Iacocca Institute in 1991. According to the report a

new competitive environment was emerging and companies with the capability to rapidly respond by delivering customized high quality products were to have a competitive advantage over others [44]. The need to integrate flexible technologies with a skilled and empowered work force was also emphasized in the same report.

Dictionary definitions of agility include being ready to act, nimble, and quick. Gunasekaran and Yusuf [29] define agile manufacturing as the 'capability of an organization, by proactively establishing virtual manufacturing with an efficient product development system, to (i) meet the changing market requirements, (ii) maximize customer service level and (iii) minimize cost of goods, with an objective of being competitive in a global market and for an increased chance of long-term survival and profit potential'. Brown, et al. [14] consider agile manufacturing as the 'ability to respond quickly and effectively to current market demands, as well as being proactive in developing future market opportunities'.

Previous approaches to manufacturing (production line, cellular, and job shop) each have its own distinct operating rules and principles. However, AM is not a unique manufacturing strategy by itself. Rather it involves the application of existing manufacturing strategies, the building blocks, to bring about improvements in quality, productivity, and customer service [30]. AM therefore is a more structured application of principles of previous manufacturing concepts to build manufacturing flexibility so that companies can respond to changes in customer requirements faster and adapt accordingly.

DeVor, et al. [21] present a review of the research to date on agile manufacturing since its introduction through the Iacocca Institute's report. Gunasekaran and Yusuf [29] present a detailed review of the scope of agile manufacturing and provide a framework to understand the strategies and technologies that are imperative for its successful implementation. They use four dimensions to explain the agile manufacturing paradigm; flexible technologies, flexible people, market focus, and strategic objectives. Based on existing literature, the most relevant and important strategies and technologies for developing agile manufacturing are presented. It is important to note that automated production techniques (flexible manufacturing (FM) systems, CAD/CAM, robots, AGV's etc) are classified as imperative for implementing agile manufacturing by the authors.

Empirical studies that demonstrate the benefits of implementing agile manufacturing are lacking. Bessant, et al. [10] present the 'agile wheel', a synthesis of behavioral practices, developed through their interaction with several small/medium enterprises to describe the best practices for developing organizational agility. They present agile strategy, agile processes, agile people, and agile linkages as the four main dimensions in the wheel. This is analogous to the four-way classification put forward by Gunasekaran and Yusuf [29]. According to the Bessant, et al. model, flexible facilities are essential to attain agile processes. The empirical model is based on work with smaller firms which the authors believe have greater potential with AM.

Gunasekaran and Yusuf classify mass customziation as a characteristic of agile enterprises together with others such as quick response manufacturing, learning

organization, integrated value chain, reconfigurability, flexible organization, and physically distributed manufacturing environment [29]. Many others have considered mass customization to be part of agile manufacturing or, in some instances, synonymously.

Ahlstrom and Westbrook [3] attribute the large investment required for process technologies in mass customization as a limitation for smaller companies to implement it. On the other hand, Bessant et al [10] state that large firms ‘tend to form the greatest parentage of firms pursuing mass customization and agile manufacturing is believed to have a greater potential for small enterprises. However, these arguments are unfounded if, according to literature available, achieving agility requires flexible and automated manufacturing technologies that call for high capital investment. Thus smaller enterprises would probably have more difficulty in financing the structural changes required to achieve agility. Therefore, describing the differences between the paradigms of mass customization and AM can not be merely limited to size.

Many studies on AM cite the need for flexible and automated manufacturing systems for attaining agility [29, 35]. Huang [35] emphasizes that agile system characteristics can be achieved only with automated manufacturing systems. AM is a more structured application of the existing practices to achieve greater responsiveness to market requirements. As pointed out by Pine [67], flexible technologies are not by themselves mass customization; there is more to mass customization than AM. However, mass

customization manufacturing can benefit by incorporating AM features in system design to attain the agility required to meet customer requirements.

2.4.3. Lean Manufacturing

The term lean production was first introduced by Womack, Jones, and Roos in their book *The Machine that Changed the World* in 1990. They brought to light the superior performance of Japanese automobile manufacturers compared to their European and American counterparts. Murman, et al. [64] define lean thinking as 'the dynamic, knowledge driven, and customer focused process through which all people in a defined enterprise continuously eliminate waste with the goal of creating value'.

Lean manufacturing is not a novel production technique. It is a concept that can be applied to any shop configuration—job shop, cellular, or product—to improve organizational performance [17]. A lean organization is more flexible and adaptive because there are lower levels of inventory and due to the elimination of all non-value adding activities and all other types of waste.

The pull production system required to deliver products on a make-to-order basis with mass customization requires maintaining low in-process inventory. Receiving customer orders and transforming them to finished products within the shortest possible time calls for rapid responsiveness in order processing, product design, and manufacturing. Therefore, irrespective of the configuration chosen for the manufacturing system, the

application of lean principles to achieve a more efficient organization will be essential for mass customization.

2.5. Cellular Manufacturing Design

CM is a mature and well-developed subject area that is very rich in literature. The most relevant in the context of this research are those relating to cell formation, cell layout, and cell scheduling. Cell formation (CF) involves identifying product families and machine cells in which each of those families will be manufactured. Determining the optimal location of these cells within the manufacturing facility to minimize the cost of material handling is done in cell layout (CL). Once the product families are assigned to the machine cells, the jobs assigned to each machine cell must be scheduled to achieve the desired performance objectives. This is the purpose of cell scheduling (CS). The most important literature pertaining to each of these areas is reviewed in the following sections.

2.5.1. Cell Formation

Most studies on CM over the past several decades have heavily focused on developing CF strategies. The approaches suggested vary from very simple clustering algorithms that only consider products and their machine requirements to more versatile methods that incorporate processing times, machine utilization, and processing flexibility.

Comprehensive reviews of cell formation strategies are provided in [45, 80, 81, 42 and 97] among others. King and Nakornchai [45] and Wemmerlov and Hyer [97] classified

the CF methods into four broad categories. Selim et al. [80] and Shafer [81] used five and six groupings, respectively, to classify the CF methods. The taxonomies by Kaparthi and Suresh [42], Selim, et al. [80], and Shafer [81] included a separate category for artificial intelligence based approaches to CF such as genetic algorithms, artificial neural networks, and fuzzy logic. Shafer's [81] classification framework shown in Figure 9 summarizes the various approaches to CF that have been presented. Detailed literature reviews on CF strategies can be found in the sources mentioned above.

Shambu, et al. [82] assert that conversion to CM reduces the flexibility to cope with dynamic product mixes and demand rates. Their comparative evaluations are relative to functional layouts. This finding provides an important insight for designing manufacturing systems for mass customization. CM manufacturing systems have greater flexibility to deal with product variety than mass production systems [38, 98]; however they are less flexible than functional layouts [82]. This means that production systems for mass customization, while maintaining the advantages of processing similar items together (which is the objective of CM), should try and incorporate features of functional layout based configurations to increase the flexibility that is essential to provide high product variety.

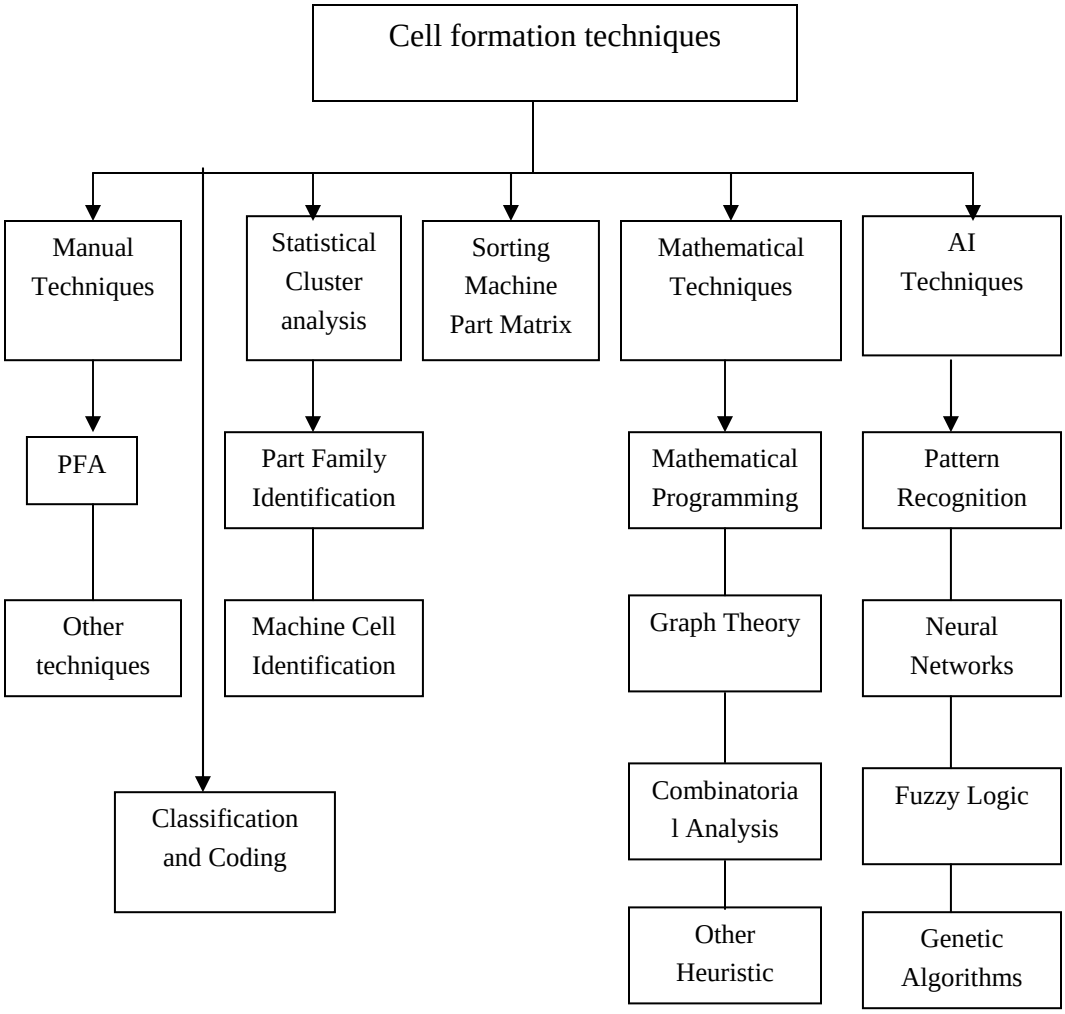


Figure 9: Classification Framework for Cell Formation Strategies [81]

Forming cells to manufacture all different variations of a particular product, or a family of products, would result in exceptionally large cell sizes in mass customization because of the high variety in terms of the number of options offered for each product feature. The number of different machines required would probably be very high, given the

processing requirements for all product variations. Empirical studies have revealed that the multi-machine concept in traditional cells, where employees have to be cross-trained on several machines, reduced productivity and was met by operator resistance [98].

According to Hyer and Brown [38, 37] large cells sizes require more operators and large groups are found to be disadvantageous for effective communication reducing the performance of the group as a whole. Based on empirical findings, they report that manufacturing cell performance decreased as the number of different products assigned to a cell increased, though there isn't a universal size for the ideal number [38].

2.5.2. Cell Layout

A key to exploiting the benefits of CM involves the efficient layout of cells and machines within them. Different approaches to layout cells and machines have been investigated. Cell layout strategies to minimize inter-cell movement and those designed to handle changing product mixes are more important in the context of the mass customization system design problem addressed in this research.

Layout designs for CM have been addressed by [8, 33, and 34] among others. Bazargan-Lari and Kaebernick [8] present an approach to cell and machine layout integrating it with CF. The application of this method is illustrated through a case study in [9]. Ho and Moodie [34] propose an integrated model for CF and layout when flexible routing is required in a multi-cell environment.

Strategies for layout when cells other than the conventional type are used have also been studied. Holographic cell layouts are addressed in [38, 41], fractal layouts in [4, 41, 65], and network layouts in [41, 42]. Badurdeen and Masel [6] investigated heuristic procedures for minicell layout in a multi-stage configuration. They used the volume of transfers between cells to determine the layout that gives total minimum inter-cell travel distance over a given period of time.

2.5.3. Cell Scheduling

While there has been an increasing interest in other areas of CM, less attention has been paid to cell loading in the literature. Through a series of articles Suer, et al. [87, 88, 90] have presented empirical studies for manufacturing cell loading.

Shambu, et al. [82] provide a comprehensive review of the scheduling rules used in CM. Manufacturing cells are groupings of machines for processing a product family. Depending on the routing of products within a cell, they can vary from being a pure flow shop—all products follow the same sequence—to a job shop where each product has its own flow path [95]. Therefore, the nature of scheduling principles used in each manufacturing cell would depend on the type of routing used within. However, in general, most traditional manufacturing cells are organized as flow shops where products attend all the machines in the same sequence.

Therefore, scheduling techniques used in flow shops can be used to determine the processing sequence of jobs in manufacturing cells. Various techniques have been

presented to schedule jobs in flow shop configurations to achieve different objectives. Johnson [41] presented a heuristic procedure to minimize makespan in a flow shop with two machines. Campbell, Dudek, and Smith [16] (CDS) later extended this algorithm for application in multiple machine flow shops. Other metaheuristic such as genetic algorithms and simulated annealing have also been used for flow shop scheduling [39, 63, 65]. Scheduling techniques used in multi-stage flow shops are relevant when products have to flow through more than one manufacturing cell to complete processing. Different methods have been tested for scheduling in multi-stage flow shops which are more complex [95]. Wemmerlov and Vakharia [96] compared the application of CDS and as well as other techniques (e.g.: First Come First Serve, SLACK) for scheduling in five-stage dynamic flow shops.

Several studies have explored approaches for distributed scheduling to support mass customization in the European shoe industry [8, 68]. These studies present a hierarchical, decentralized approach where lower level units are given the autonomy to schedule manufacturing jobs within a wider framework that is administered at the factory level.

3. METHODOLOGY

In the previous section literature pertaining to mass customization, limitations to successful mass customization manufacturing including the lack of appropriate manufacturing configurations, and different manufacturing system alternatives that may have potential to deliver the mass customization requirements were reviewed. Based on existing system alternatives and mass customization manufacturing requirements, a novel approach to design manufacturing cells is proposed. The two primary goals of this research are to develop methods to design minicells and determine approaches to lay them out. The concept of minicells that appear to be promising in delivering the needs of mass customization manufacturing, how these cells differ from traditional cells, and the approach that is proposed to develop a minicell-based configuration are discussed in this section.

For the purpose of the design it is assumed that customization is offered by fabricating the options required for some features—tailored customization—and assembling the remaining options from standard parts—assemble-to-order customization. The procedure described in this section addresses designing a manufacturing system to produce the options that are fabricated after receiving customer orders. The assembly operations required to produce the final product by combining the fabricated parts and purchased parts—for the remaining options—is not addressed.

3.1. Minicell Configuration for MC Manufacturing

Conventionally, a product's structure can be represented as shown in Figure 10(a), with each distinct product having a set of features. Traditional cell formation progresses by first forming product families based on machine requirements and then identifying part families for each of them, resulting in a separate cell for each part family. Most techniques use the product-machine matrix, which represents all the product types and machines required to make them, to form product families and machine cells. The objective is to form self-contained cells in which products can be processed completely avoiding inter-cell material transfers.

In mass customization, often there may be only one or a few products: the assortment is made up of a large number of variants of these products. The product variants differ based on which one of the mutually-exclusive options is chosen for each feature. Thus the product structure in mass customization can be represented as shown in Figure 10(b). When a large number of options are offered for each feature, the total number of product variants will be very high and developing cells that contain all of the processes for products can result in large cells. Large cells are difficult to manage and could be less flexible, contrary to what is required with mass customization. The limitations of having too large cells have also been pointed out by many in the literature [36, 37]. Also, the demand for product variants can exhibit a high variability over time and a single fixed cell will not have sufficient flexibility to accommodate major changes in the workload.

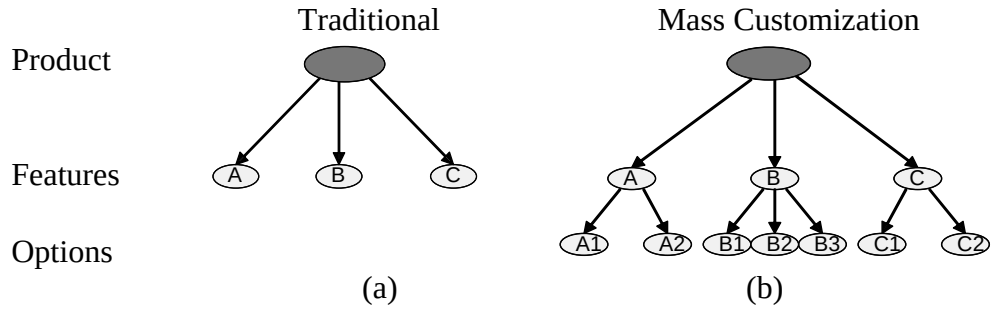


Figure 10: (a) Traditional and (b) Mass Customization Product Structures

Many options are common to several product variants. Hence the demand for options is less fragmented than for the product variants. Therefore, an alternative to the traditional cells is to form smaller cells by considering the options rather than every product variant. The result would be smaller cells dedicated to producing option families as opposed to large cells for product families. These small cells, formed by using an option-machine matrix, are referred to as minicells. Therefore, a product variant may have to be routed through several minicells, depending on the options chosen, to complete processing as shown in Figure 2 previously on page 31.

All parts in a family pass through the cell from start to finish with traditional CM. With the minicell configuration the system is divided into stages. The options within each stage are grouped to form option families and minicells. Each minicell, therefore, is a grouping of machines and operators required to process a sub-set of operations for an option family.

The large traditional cell is now replaced by several minicells (Figure 2 (b)) and each option is routed to one minicell in each stage depending on the processing required. Machines that were confined to one large cell can now become available to several option families, thus increasing the flexibility of the system. This will increase the product variety that can be offered compared to a system with a traditional cell arrangement without a large increase in the number of machines. However, a product variant may require routing to several minicells within a stage depending on the options necessary.

3.2. Designing a Minicell Configuration

The tasks involved in designing the minicell configuration are illustrated in Figure 11. All but the last stage in the flow diagram involve steps required for minicell system design. Once a robust configuration has been developed, the minicells are laid out in the final step. Each of these phases in the design process is described in detail below. *S* denotes the number of alternate configurations designed. *Z* is the number of predicted demand scenarios for which the performance of each of these configurations is evaluated to select the robust design.

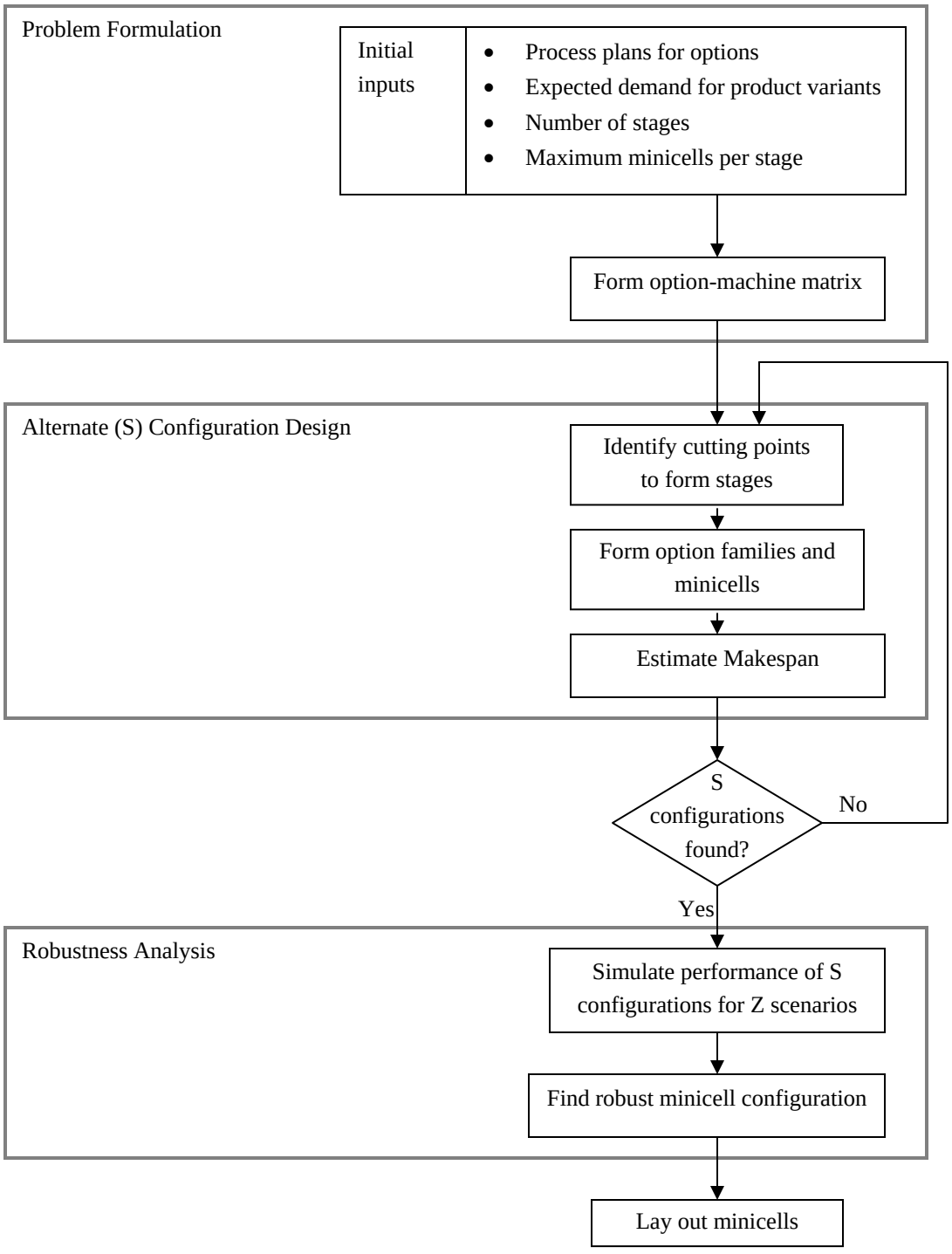


Figure 11: Minicell Configuration Design Process

3.2.1. Minicell System Design

The aim of traditional cell formation strategies is to develop self-contained cells that can completely process a product family. The multi-stage minicell structure, to the contrary, requires products to be routed to several smaller cells. Therefore, an approach different from that used to form traditional cells needs to be developed for minicells.

Minicell formation uses an option-machine matrix as opposed to the product-machine matrix used in traditional cell formation. Traditional cells are designed to process product families. With minicells, options—not products—are grouped to form option families which are then assigned to separate minicells. Hence the use of the option-machine matrix instead of the product-machine matrix.

Stages are created by separating the operations required to process the options into multiple segments—selected after evaluating the effect on performance—while ensuring the sequential flow between them. Option families and minicells are then formed within each stage. The separation into stages breaks the operations into smaller groups, thus enabling the formation of smaller minicells within them. The smaller minicells will improve the flow of product variants through the system compared to using the larger traditional cells and reduce the flow time for processing the customized products.

With the multi-stage configuration, every option may require visiting one minicell in each stage, except when the option does not require processing in the stage. Also all options belonging to one family, and therefore the same minicell, in one stage may not

belong to the same family in other stages. At the end of processing in a minicell, the product variants that were assigned will be separated into sub-families and routed to other minicells for processing.

The approach taken to address each of these issues is discussed in the following sections. The assumptions made as well as challenges to be overcome are also detailed where relevant.

3.2.2. Option-Machine Matrix for Minicells

Most traditional cell formation techniques proceed by starting with the product-machine matrix. Starting with this matrix the products and machines are clustered together to form independent groups of product families and machine cells in which they will be processed. As the number of products increases the size of these cells could also increase.

Instead of using the product-machine matrix, minicell formation utilizes an option-machine matrix which is much smaller in size. Rather than considering machine requirements for each product variant, the total options offered for all features of the product variants is considered. Because some options are common to more than one product variant, this approach reduces the size of the matrix to be handled.

For example, in a situation where a product type has three features and four options for each feature, a total of 64 ($=4^3$) different product variants can be offered. This compares to only 12 options (=4x3) that would be listed in an option-machine matrix.

Information for developing the option-machine matrix for a given problem can be derived from the bills of materials and process plans. All the different options available for the various features are obtained from the bills of materials for the product variants. The process plans for the options will provide information on machines required, and processing sequence, as well as the setup and operation time on each.

The flow of parts in the multi-stage minicell configuration is assumed to be sequential. Thus parts flow from one end to the other in the production system, so there is no back tracking; however bypassing stages will be allowed. Permitting back tracking would make scheduling more complex. It could also increase the time spent by products waiting to be processed in machines. To avoid back tracking, the machines in the matrix must be organized such that they are ordered in the processing sequence. Further, the rearrangement of the columns (assuming the machines are assigned to the columns of the matrix) is prohibited to preserve this sequence.

To ensure processing sequence is not violated for all options, the machines in the matrix may need to be duplicated in some situations. Additional machines may also have to be added to maintain unidirectional flow and avoid back tracking to previously visited machines.

3.2.3. Number of Stages for Minicell Configuration

With the minicell configuration the manufacturing system will be divided into multiple stages with several minicells in each stage. The options will have to be routed across one

or more stages depending on processing requirements. A particular option family would have to be routed to no more than one minicell in each stage. However, given the option requirements for a particular product variant, visits to multiple minicells within a stage may be necessary before a product variant could be completely processed.

The number of stages in the system is one of the parameters required in minicell configuration design. The number of stages chosen could affect the allocation of machines between stages and, therefore, the number of machines required, the makespan to process jobs in the system as well as the amount of material handling. Too many stages will increase the amount of material handling required: too few stages will make the system less flexible as minicells tend to increase in size.

3.2.4. Cutting Points to Form Stages

The option-machine matrix is divided into smaller sub-matrices to reflect the stages in the configuration after the machines have been ordered in the processing sequence.

Determining the optimal locations to separate this matrix and create the stages is an important decision in the minicell system design process. The cutoff points chosen will influence the option families and minicells formed within each stage. This, in turn, will affect the total machine requirements as well as the performance of the minicell configuration. Also, it may be possible to create different configurations that could result in the same machine requirements but perform differently and vice versa. Therefore,

determining the effect of the cutoff points on system performance is important for selecting the cutoff points for the design.

3.2.5. Minicells and Option Families

Once the number of stages for the configuration has been decided, the next step involves combining options to create option families and grouping machines to form minicells within each stage.

Numerous approaches for traditional cell formation have been put forward in the literature (see section 2.5.1). These methods use the product-machine matrix or other information from process plans for the product and parts required for those products. The traditional cell formation techniques cannot be applied directly for minicell formation due to several reasons. With minicell formation, the column sequence in the option-machine matrix must be preserved to maintain sequential flow across stages. Therefore, cell formation techniques that proceed by diagonalizing the product-machine matrix (e.g.: King's algorithm [45]) can not be used in this case.

Minicells are groups of machines dedicated to processing all or part of the requirements for an option family. Therefore, minicell formation requires evaluating the processing needs for options, not for products or parts as is the case with traditional cell formation. Further, since the proposed configuration consists of multiple stages, the traditional techniques must be applied separately to each stage. Thus, for example, if a similarity

coefficient-based method were to be used to form minicells in a stage, the similarity of options in terms of the processing needs in that stage need to be considered.

3.2.6. Performance Evaluation

One of the main requirements for successful mass customization is the ability to deliver customized products quickly. Two criteria are pertinent in reducing the delivery times. To shorten the time between receiving a customer order and product delivery, the time it spends within the manufacturing system—flow time—must be minimized. Secondly, all product variants assigned for processing at a particular moment—for example hour, day, or week—should all be completed within the shortest possible time. This requires minimizing the makespan which is the time taken to complete an entire batch of items. Minimizing flow time and makespan are conflicting objectives and optimizing one of them may require compromising the other. On the other hand, reducing the cost of customized products is also important in order to be competitive in a mass customization environment. By adding more machines, and operators, lower flow times and makespan can be achieved. However, this will increase the cost of production.

In this research, makespan is used as the performance measure to select alternate minicell system designs. These minicell designs are later evaluated to find the most robust design that has the flexibility to accommodate the dynamic demand scenario encountered in mass customization. All the three performance measures—makespan, flow time, and machine count—are studied for the robustness analysis. The three measures are also used

to when comparing the performance of minicells with other configurations such as traditional cells.

For each minicell design, the machine requirements to process the expected demand for product variants is determined. Then, the makespan to process the predicted demand using that capacity is found. Makespan is considered to be more important for mass customization because, with longer delivery times, customers can be lost to competition even if the customized products are priced lower (by keeping machine count low). System designers can later evaluate minicell designs using benefit/cost analysis to study the impact of reducing the machine requirements.

The minicell design for a problem is evaluated by first conducting capacity planning to determine machine requirements to process an expected product variant demand, and then estimating makespan to process the predicted demand for product variants.

3.2.7. Robust Minicell Design

As described previously, evaluating a minicell system design requires analyzing the performance of the system for variable product mix and dynamic demand conditions—one of the main characteristics of mass customization manufacturing. Developing a design that consistently delivers superior performance may not be practical given the high variability. This could be achieved if frequent reconfigurations were permitted. However, system reconfiguration can be costly and can result in lost production time.

For successful mass customization, the manufacturing system designed must have the flexibility to provide desired performance under the dynamic conditions. Changes in product variant demand can take two forms: (1) changes in the predicted demand experienced in the short-term and (2) variation in the expected demand over the long-term. Both these situations must be evaluated in designing a robust minicell configuration for a particular problem.

In the short-term, the flexibility of the minicell designs is analyzed by evaluating their performance for different predicted demand scenarios. A system design which on average performs better than other designs, over a variety of predicted demand scenarios, is more desirable than one that gives superior performance under one scenario. Such a design would provide the flexibility to accommodate day-to-day variation within a given range of demand for product variants reducing the need for frequent reconfigurations. In this research simulation is used to analyze the performance of alternate minicell configurations and the design with overall best performance is selected as the most robust.

In the long-term, the system may have to be reconfigured to accommodate changes in expected demand. Different approaches to minicell system reconfiguration are possible and the most appropriate strategy must be chosen based on the cost that must be incurred and the potential benefit.

3.2.8. Scheduling in Minicells

In this research, the makespan for processing the demand is taken as the primary performance measure for evaluating minicell system design. This, together with the machine capacity, is used in scenario-based simulation to evaluate alternate designs. Therefore, an effective scheduling strategy to determine minimum makespan in the given minicell configuration is required.

Developing strategies to schedule jobs in a minicell configuration to minimize makespan is a complex task that would qualify for a separate study by itself. Therefore, this research does not address that issue in depth. However, scheduling the jobs in the minicells is necessary to evaluate the performance of the proposed new configuration. Therefore, a strategy currently used to schedule jobs in traditional manufacturing cells is modified and adapted for the minicell configuration.

Processing operations within a manufacturing cell can be compared with those in a flow shop since product variants visit multiple machines. Therefore, methods used to schedule jobs in a flow shop can be extended for application in cellular manufacturing, and therefore, to minicells.

Various approaches to flow shop scheduling have been put forward in the literature; some applicable to two machine situations and others for use with multiple machines. In the proposed minicell configuration, each minicell could have several machines. Therefore any scheduling procedure used must accommodate this requirement. The heuristic

procedure described by Campbell, Dudek, and Smith (CDS) [95] for flow shop scheduling is one technique for minimizing makespan that can be used for scheduling in minicells. This heuristic is chosen because it can be applied to multiple machine flow shops and is also more straightforward than some other scheduling techniques.

When each stage is considered a separate flow shop, the multi-stage configuration proposed for mass customization manufacturing resembles a multi-stage flow shop. However, in the minicell configuration, each stage could have multiple minicells; the result is a nested multi-stage flow shop configuration, making scheduling more complex. Therefore, existing methods cannot be used directly for scheduling in minicells.

Alternate forms of the CDS heuristic as well as other methods have been presented for scheduling jobs in multi-stage flow shops. Wemmerlov and Vakharia [96] compared the application of CDS and other heuristics. Application of any scheduling strategy for only the first minicell in the first stage, and applying the same sequence for all subsequent minicells—the approach used by Wemmerlov and Vakharia [96]—can contribute to higher makespan and flow times. The strategy ignores the possibility of prioritized processing of jobs in later minicells depending on when they are completed in the previous minicells.

To simplify scheduling in the minicell configuration, it is assumed that all jobs are available at the same time for processing in the first minicell in the initial stage, i.e.: ready time equals zero—a requirement for applying CDS. However, for the subsequent

minicells the start times will depend on the completion time in the previous minicell. Every minicell in the configuration is assumed to be a separate flow shop. Therefore, system designed is equivalent to a multi-stage flow shop with multiple flow shops within each of the stages.

Given such a configuration, one approach that can be applied to schedule jobs in the later stages of the minicell configuration is to apply a first-come-first-served (FCFS) rule. Thus the job that is first completed in stage 1 will be assigned to the relevant minicell in stage 2 first, followed by the second job completed and so forth.

3.2.9. Minicell Layout

Once a satisfactory minicell system design has been developed, the final step in the process involves determining the optimal layout of the minicells. Given a multi-stage configuration, the number of possible layouts increases exponentially with the number of stages and minicells within each stage. For a system with n stages and m minicells in each stage, the number of possible layouts is equal to $(m!)^n$.

With the sequential-flow, multi-stage configuration two types of material flows are possible: inter-stage transfers between the minicells in different stages and intra-stage transfers between minicells within a stage. The latter may become necessary if the options chosen for a particular product variant require processing in more than one minicell in any stage. Also, when two adjacent stages are considered, material flows can occur from all minicells in one stage to one, several, or all minicells in the subsequent

stage: the volume of transfers between the minicells in two stages would depend on the demand for options assigned to those minicells. However, if stages are bypassed a product would flow from one stage to another further down the line. Therefore, given the minicell configuration, determining the layout of minicells within stages will be significant for system performance.

The optimal layout of minicells would be one that minimizes the cost of total material handling. The impact of the number of stages, number of minicells within each stage, and the amount of material transfers between the minicells must be evaluated to determine the optimal layout for minicells.

3.3. Conclusions

This section described the minicell concept and an outline of the design process for developing multi-stage minicell configurations for mass customization manufacturing. The next step involves formulating tools that can be used to design such a configuration. The tasks involved and the methods used for each task are shown in Table 2.

Table 2: Methods used for Minicell System Design

Task	Method
Selecting cutoff points for stages	Genetic Algorithm
Minicell formation	Genetic Algorithm
Scheduling in minicells	Campbell, Dudek, and Smith Heuristic & FCFS
Minicell layout	Mathematical Model Genetic Algorithm

Extensive preliminary experimentation was conducted to gain insight for minicell system design. An outline of the testing and important findings from this experimentation is discussed in Section 4. The genetic algorithm (GA) and heuristic procedure developed for minicell system design is described in Section 5. Further experimentation using the GAs for minicell system design is explained in Section 6. Different strategies evaluated for scheduling in the minicell configuration and results obtained are discussed in Section 6. The mathematical model and GA developed for minicell layout are described in Section 7.

4. PRELIMINARY EXPERIMENTATION

An example of a customized bicycle with different features and multiple options for each feature was created for initial experimentation in this research. Customized bicycle manufacturing was chosen following a visit to a company that is engaged in customized fabrication of high-end bicycles. The company adopts a platform-based approach to product design where each product variant has several customizable features and a variety of options for each feature. This familiarity made identifying options for each feature, processing requirements for each option, and determining the sequence of operations to fabricate them straightforward, thus making the example more realistic. The processing time and the demand for every option were randomly generated.

This processing information—machines and routing information—for all the options available was used to form the option-machine matrix. The machines in the matrix were ordered in the processing sequence based on the routing.

For the preliminary experimentation, a similarity-coefficient-based method was applied to form option families and minicells. However, in this case the method was used to evaluate the similarity in processing needs of the options within a stage contrary to its use in traditional cells where all operations required for products from start to end are considered. A modified form of Jaccard's similarity coefficient (MJSC) [86], which works better than the original Jaccard's similarity coefficient [40], was used to form option families and minicells. The MJSC for a pair of options is computed as shown in equation [1].

$$MJSC = \frac{Y_{ij}}{Y_{ii} + Y_{jj} - Y_{ij}} \qquad [1]$$

Where,

Y_{ij} = number of machine types processing both options i and j

Y_{ii} = number of machine types processing option i

Y_{jj} = number of machine types processing option j

For example, consider the option-machine matrix shown in Figure 12. The options are indicated by numbers and machines by uppercase letters. A value of '1' in a cell indicates that the machine is required by the corresponding option. Zeros have been omitted for clarity.

		Machines																					
		A	B	C	D	E	F	G	H	I	J	K	L	O	P	Q	R	S	T	U	V	W	X	Y
Options	1	1	1	1	1					1			1						1			1	1	
	2		1								1				1		1			1		1	1	
	3	1	1								1				1		1			1		1	1	
	4		1			1		1			1				1		1			1		1	1	
	5	1	1	1						1				1			1		1			1	1	1
	6	1								1				1			1		1			1	1	1
	7	1				1	1			1				1			1		1			1	1	1
	8	1			1	1				1			1					1	1			1	1	1
	9			1								1				1	1				1	1	1	1
	10			1								1				1	1				1	1	1	1
	11			1		1			1			1				1	1				1	1	1	1

Figure 12: Option-Machine Matrix

If the first four machines (A-D) constitute the first stage, within this stage the following can be observed: options 1 & 2 and 2 & 5 have one machine in common and, options 1 & 5 have three common machines. Therefore, the MJSC values for these pairs of options are 0.25 (=1/4), 0.33 (=1/3), and 0.75 (=3/4), respectively.

A matrix of MJSC values is generated to tabulate the similarity of each option with every other within the stage considered. Option families are then formed by Single Linkage Clustering (SLINK) [78] using a threshold MJSC value. If the MJSC between two options is greater than or equal to the threshold value, those options are combined to form a family. For example, in the above case, if the threshold value was set at 0.65, options 1 & 5 would be grouped to form an option family. Then, according to SLINK, the MJSC between the family 1-5 and option 2 will be the higher of 0.25 (MJSC between 1 and 2) and 0.33 (MJSC between 2 and 5), i.e., 0.33. The procedure is repeated for all stages to determine the option families and minicells.

The threshold values determine the degree of similarity necessary to combine two options into one family. The greater the threshold value chosen, the higher the similarity between options assigned to a particular family.

4.1. Number of Stages in Minicell Configuration

Initially, the MJSC was applied to the entire option-machine matrix, without separating into stages, to evaluate cell formation. In most cases the result was a single large cell containing all options. A similar configuration was found when traditional cells were formed for the same problem using a product-machine matrix. The machine requirement for the configuration was determined based on the demand for product variants and processing times for options.

Large cells reduce the flexibility because batch sizes can get large when having to process a larger number of options and this can result in longer lead times and higher in-process inventories. These are some limitations of traditional cellular manufacturing that have to be overcome in mass customization manufacturing. Therefore creating minicells without dividing the processes into stages did not appear to provide the system desired in this research.

Alternatively, the effectiveness of dividing the option-machine matrix into multiple stages was evaluated. Creating multiple stages involves determining the optimal cutoff points to separate the original option-machine matrix into smaller matrices.

Different configurations were analyzed for several option-machine matrices to evaluate the impact of multiple stages on the number of minicells and machine requirements; the makespan to complete the jobs was not evaluated at this point in the preliminary experiments. The cutoff points in each case were determined by examining the option-machine matrix and selecting candidate points such that minicells with higher densities (the ratio of the number of 1's in the minicell to the total number of 0's and 1's in the minicell) can be formed.

An analysis of all the results indicated that the total number of machines required varied slightly depending on the number of stages in the configuration. However, there was no identifiable relationship between the number of stages and the total machine requirements.

Nevertheless, in all instances, it was possible to find a multi-stage configuration with a total machine requirement as low as when the entire option-machine matrix was considered together without dividing into stages. These findings were encouraging because it reinforced the initial expectation that a multi-stage minicell configuration can be found without significantly increasing the machine requirements.

4.2. Selection of Cutoff Points between Stages

Experimentation was also conducted to gain insight into the effect of varying the cutoff point—number of machine types assigned to each stage—when the same number of stages is maintained.

The cutoff point analysis was done by selecting a few different locations in the option-machine matrix arbitrarily for a given number of stages. Changing the cutoff point resulted in slight variations in the total machine requirement for all cases experimented. The machine requirements for different configurations of the option-machine matrix illustrated in Figure 12 is shown in Table 3. The results supported the initial expectation that cutoff point selection has a bearing on the resulting multi-stage minicell configuration formed and its operation.

Table 3: Machine Requirements for Different Configurations

Configuration Number	Machine Requirement	
	Three Stages	Four Stages
1	157	158
2	159	157
3	156	158
4	158	158

In an effort to understand this variation better and identify the best locations to separate the matrix into stages, further experimentation was conducted. Starting with a two stage configuration, the cutoff point was varied from one end of the matrix to the other. Thus if there were n machines in the option-machine matrix, $n-1$ cutoff points were used to form alternate two-stage configurations. The minicells within each stage were formed based on the MJSC values and machine requirements were estimated for each case. This analysis was repeated with several problems for three-stage and four-stage configurations.

For the different problems tested, the machine requirement varied slightly depending on the location of the cutoff point. Every problem had a cutoff point(s) at which the total machine requirement was a minimum. There were also some regions in the matrix within which the total machine requirement remained constant irrespective of where the cutoff point was chosen. However, there were no distinct characteristics at or around those cutoff points in the option-machine matrix that made their identification possible without going through the iterative analysis.

4.3. Minicell Formation

In all the above analyses, the option-machine matrix was used to form minicells by using the MJSC values together with SLINK. The effectiveness of different types of cell formation techniques has been reviewed in the literature. With SLINK, the similarity of an option family with other options outside the family depends on the member who has the largest similarity with the exterior option. This may lead to less similar options being combined into one family. More stringent clustering techniques, such as CLINK [78] or ALINK [79] can be used to avoid this. However, the objective of the preliminary experimentation was to evaluate minicell formation, and therefore a simple clustering procedure was chosen.

Minicell formation using MJSC was sometimes found to generate remainder minicells that consist of a single option. For example, consider the minicell formation for a 0.65 threshold value shown in Figure 13 in a six-stage configuration. Remainder minicells are created for option 8 in stages two and four and they require only a single machine in either case. Such remainder minicells are more frequent when higher threshold values are chosen, leaving options out of any minicell unless they have high similarities with other options. In such situations, to avoid the excessive duplication of machines and reduce material handling, the remainder minicells can be grouped with other minicells within the same stage.

Options	Machines																						
	A	B	C	D	E	F	G	H	I	J	K	L	O	P	Q	R	S	T	U	V	W	X	Y
1	1			1					1			1						1			1	1	
2				1						1				1		1			1		1	1	
3				1						1				1		1			1		1	1	
4				1	1		1			1				1		1			1		1	1	
5	1								1				1			1		1			1	1	1
6	1								1				1			1		1			1	1	1
7	1				1	1			1				1			1		1			1	1	1
8	1			1	1				1			1	1					1			1	1	1
9			1								1				1	1				1	1	1	1
10			1								1				1	1				1	1	1	1
11			1		1		1	1			1				1	1				1	1	1	1

Figure 13: Remainder Minicells in the Configuration

The options in the remainder minicells can be combined with the options in whichever minicell they are most similar to. This is only recommended for remainder minicells with a single option and when all the machines required for that option are contained within another minicell. Therefore, in the matrix shown in Figure 13, option 8 can be grouped with option 7 in stage 2 and added to the family 5-7 in stage 4. Minicells having the responsibility to process a family of options should be kept separate even if they only require a single machine.

Maintaining separate minicells that process multiple options, but have only a single machine, could contribute to increasing the flexibility of the system. If there is excess capacity in any other minicells to which the options in a single-machine minicell can be assigned to, it can be done so whenever necessary. Also, these minicells could be used for processing the options that were originally assigned to them. This strategy allows for

alternate routing of options within the minicells. Given the dynamic product mix and demand in mass customization, having such flexibility will greatly improve system performance.

For example, consider the minicell with options 2, 3, and 4 in stage 1 in the option-machine matrix in Figure 13. The machine required for these options is also contained in the minicell with options 1 and 8. Thus if there is excess capacity in the latter minicell, options 2, 3, or 4 could be assigned to it. This provides an alternate routing for these options and increases the flexibility of the system to cope with changes in product demand. However, combining the two option families is not recommended as this will reduce the flexibility of the minicell system.

4.4. Scheduling in Minicell Configuration

As described previously, the multi-stage configuration studied in this research resembles a multi-stage flow shop. However, the proposed design is more complex, as there could be several minicells within a stage, each a separate flow-shop by itself.

Wemmerlov and Vakharia [96] proposed a strategy for applying the CDS heuristic to multi-stage flow shops. In this method, they applied CDS to schedule jobs in the first stage of the flow shop. The sequence of processing obtained through this procedure is then maintained for all subsequent stages in the flow shop.

An alternate strategy for scheduling in the minicell configuration is to use the CDS heuristic together with a FCFS strategy. With this method, CDS will be applied to the first minicell in the first stage to determine the optimal schedule. Based on the completion time, jobs are scheduled on the second minicell (or first minicell of the next stage) on a first-come-first-served basis. Thus, the job that exits the first minicell first is scheduled on the second minicell first, followed by the second job that comes out and so on.

Experimentation was conducted to compare the effectiveness of using the CDS heuristic, as proposed by Wemmerlov and Vakharia [96], and the CDS heuristic together with a FCFS strategy as described above. These two methods will be referred to as ‘CDS only’ and ‘CDS & FCFS’, respectively.

The procedure is illustrated below for one problem where the customized product has three features; twelve different product variants can be offered by combining the options available for these features. The option-machine matrix for the example is shown in Figure 14. In this case, the matrix indicates the processing time for options in the respective machines (in minutes) instead of binary values to indicate machine requirements. The daily demand for the product variants is shown in Table 4.

		Machines					
Options		A	B	C	D	E	F
	11	0.97		0.08	0.23	1.62	
	12	0.5		0.5			0.41
	13				0.51		1.79
	14	0.05	0.12	1.54		1.37	1.43
	15	1.04	1.62			0.18	
	16	1.91	1.38	1.67	1.13		0.71
	17			0.2			1.36

Figure 14: Option-Machine Matrix for Example

The combination of options that define a particular product variant can be identified by its product identification number. For example, the product variant 11.14.16 is made by combining options 11, 14, and 16 for the three features.

Table 4: Product Variant Demand

Product Variant	Demand
11.14.16	76
11.14.17	63
11.15.16	43
11.15.17	60
12.14.16	55
12.14.17	85
12.15.16	56
12.15.17	46
13.14.16	54
13.14.17	16
13.15.16	37
13.15.17	55

Consider a two-stage minicell configuration with two minicells in each stage for the above problem. The processing time for each product variant in each of the machines in all minicells was determined based on the option-machine matrix and the demand for product variants. For this analysis it is assumed that the setup times for processing the options is sequence independent and that they are included in the processing times shown in Figure 14. It is also assumed that all units of a particular product variant are processed together in one batch.

The product variants are then scheduled by applying the two strategies described above—CDS only and CDS & FCFS. For both strategies, each minicell is assumed to resemble a flow shop with multiple machine types. Several units of each machine type may be necessary in some minicells to provide the capacity required to process the demand. In such cases, all the machines belonging to one type are assumed to constitute a separate uniform scheduling problem where each product variant can be processed in any one of the machines of that type. All machines of the same type are compared to determine which machine becomes available first. Product variants are available for processing are then assigned to the machine that becomes available first—the machine with the lowest load.

If a particular product variant does not require processing in a certain minicell, it would be routed to the subsequent minicell in the process. However, if a product variant does not require processing in a particular machine within the minicell, it would have to wait—until all products that are ahead of it in the sequence are completed—to be

processed on the next machine. If there are multiple units of a machine type, this restriction is relaxed. In such situations product variants could be processed on an available machine of the type while previous product variants are being processed in parallel. Therefore, with FCFS, product variants that exit a minicell earlier are scheduled for processing in the subsequent minicell first, avoiding the need to stay in queues.

The completion time for each product variant in each of the minicells, for both scheduling methods, is summarized in Table 5. Minicells MC_{11}, MC_{12} are in the first stage and minicells MC_{21}, MC_{22} are in the second stage.

Table 5: Completion Time (CT) on Minicells

	CDS Only				CDS & FCFS							
	CT				MC_{11}		MC_{12}		MC_{21}		MC_{22}	
Seq.	MC_{11}	MC_{12}	MC_{21}	MC_{22}	Seq.	CT	Seq.	CT	Seq.	CT	Seq.	CT
11.14.17	0	184	473	538	11.14.17	0	11.14.17	184	11.14.17	473	13.15.17	429
11.15.17	0	233	344	436	11.15.17	0	11.15.17	233	13.14.17	253	13.14.17	308
13.14.17	0	210	427	482	13.14.17	0	13.14.17	210	13.15.17	221	12.15.17	379
13.15.17	0	315	315	642	13.15.17	0	13.15.17	315	11.15.17	344	11.15.17	436
12.15.17	45	250	445	543	12.15.17	45	12.15.17	250	12.15.17	309	11.14.17	558
12.14.17	85	398	670	785	12.14.17	85	12.14.17	398	12.14.17	652	12.14.17	768
11.14.16	397	653	1004	1143	11.14.16	397	11.14.16	653	11.14.16	957	12.15.16	788
12.15.16	470	618	693	1203	12.15.16	470	12.15.16	618	12.15.16	675	13.15.16	922
12.14.16	543	637	813	1254	12.14.16	543	12.14.16	637	12.14.16	813	12.14.16	925
13.14.16	587	719	889	1437	13.14.16	587	13.14.16	719	13.14.16	889	11.15.16	973
11.15.16	629	788	867	1390	11.15.16	629	11.15.16	788	13.15.16	765	13.14.16	1157
13.15.16	668	765	765	1508	13.15.16	668	13.15.16	765	11.15.16	867	11.14.16	1162

When CDS only strategy is applied, the processing sequence (denoted by Seq.) remains the same for all minicells in all stages, i.e.: sequence obtained by applying CDS heuristic to MC_{11}. Thus, the presence of a job that takes a longer time in one minicell—e.g. job 11.14.16 on minicell 3—delays the start of all subsequent jobs in the later minicell.

On the other hand, when CDS & FCFS is applied jointly, the job sequence is modified to reflect its completion time in the previous minicell. Thus, jobs with longer completion times are delayed until later, when they become available, reducing the impact on other jobs. With this method, product variant 11.14.16 enters minicell 4 last. This avoids other jobs being delayed, as was the case with the application of CDS only.

The makespan for completing the jobs using CDS only and CDS & FCFS strategy are 1508 and 1161 minutes, respectively. Thus, the use of ‘CDS only’ results in a significantly higher makespan (29.9%) than using CDS & FCFS. To evaluate the effectiveness of the strategy further, minicell configurations were developed for five more problems. These product variants were then scheduled for processing in the minicells by applying the two strategies to determine makespan. A comparison of the values obtained is shown in Table 6. The results for the problem illustrated above (# 3) are also shown in the table.

Table 6: Makespan for Processing Product Demand

Problem Number	Number of Product Variants	Makespan (mins)		Percent Differene {CDS only - (CDS & FCFS)}
		CDS & FCFS	CDS Only	
1	8	268	268	0.0%
2	8	199	210	5.2%
3	9	1162	1508	22.9%
4	18	362	381	5.0%
5	18	56	56	0.0%
6	27	1354	1362	0.6%

For four of the problems evaluated, the makespan with CDS & FCFS was lower than with CDS only. For the remaining two cases both strategies produced the same makespan. The results indicate that using CDS & FCFS is a better approach to minimize makespan in a minicell configuration and possibly also in multi-stage flow shops. Hence this strategy is used to schedule jobs in the minicell configuration.

4.5. Summary of Initial Experimentation

The objective of this research is to develop methods to design a minicell configuration for mass customization manufacturing. Specifically, this would involve determining the number of stages that must be used, selecting the cutoff point to create stages, developing guidelines to design the minicells within each stage, scheduling jobs in the minicells, and determining the optimal layout of these minicells to minimize the amount of handling required.

The initial experimentation, the results of which were described in this section, provided some important insights to help in the subsequent stages of the research. The number of machines required for the minicell configuration was seen to vary when the number of stages in the design was changed. Alternate cutoff points, with the same number of stages, was also found to have an impact on the machine requirements. The grouping of remainder minicells with other minicells is a possible strategy that can be used to reduce the total machine requirements. The scheduling strategy proposed—CDS & FCFS—provides better schedules to minimize makespan.

The example of customized bicycle manufacturing, with some modifications, was used in all the preliminary experimentation. The use of this example facilitated understanding many factors that must be considered in formulating a problem to design the minicell configuration, e.g.: back tracking to process in previously visited machines and modifying the option-machine matrix to avoid this situation. However, this example alone does not provide sufficient variety for the different analyses required to evaluate the minicell system design process. Therefore, different problems are generated for the later experiments.

5. MINICELL SYSTEM DESIGN

Two different methods were experimented for minicell system design: (1) genetic algorithms, and (2) a heuristic procedure. Detailed descriptions of these design tools, the approach used develop them, experimentation conducted, and the results are discussed in this section. A description of the information presented in each of the sub-sections is summarized in Table 7.

Table 7: Summary of Information Presented

Setion No.	Description
5.1	Outline of the minicell formation Genetic Algorithm
5.2	Experimentation conducted with the minicell formation Genetic Algorithm
5.3	Designing minicell configurations
5.4	Analysis of alternate minicell system designs
5.5	Evaluation of minicell configurations with fixed cutoff points
5.6	Outline of the Genetic Algorithm developed for minimizing machine capacity
5.7	Experimentation conducted with the minimum machine capacity Genetic Algorithm
5.8	Comparison of results for minicell formation Genetic Algorithm and minimum machine capacity Genetic Algorithm
5.9	Comparison of minicells and traditional cells
5.10	Heuristic procedure for minicell system design

5.1. Minicell Formation Genetic Algorithm

Genetic algorithms are a stochastic search algorithm that is based on the laws of natural genetics and selection. The technique has been widely used to find optimal solutions to

problems that are difficult to solve through other optimization techniques. In genetic algorithms, each solution to the problem is known as a chromosome and is made of a number of genes—depending on the nature of the problem. The set of solutions—known as a population—is made to evolve through a number of generations. The better chromosomes are carried forward to subsequent generations through natural selection. In this research, genetic algorithms are used to determine the best minicell configuration for the particular problem.

The objective of the minicell formation genetic algorithm (MMGA) is to determine a multi-stage minicell configuration that minimizes the makespan for processing a specific demand for a group of features and options using the machine capacity required to produce the expected demand. The MMGA determines the selection of cutoff points to assign machine types to stages as well as the formation of option families and minicells within each stage. The software to run the MMGA is developed using Microsoft Visual Basic for Applications (VBA).

The option-machine matrix, constructed from process planning data for the product variants as described previously, and the expected and predicted demand for product variants is the primary data used in the MMGA. This information is generated for each problem tested using the MMGA. The machines required to process each option is randomly determined; the processing time on each machine is then obtained using a uniform distribution. The expected daily demand for each product variant is generated using a uniform distribution. These expected demand values are then used to estimate the

predicted demand for each product variant using a normal distribution (mean = expected demand, standard deviation = x% of mean).

In designing the MMGA it is assumed that the number of stages required and the maximum number of minicells per stage is predefined. In practice, these may often be determined by management based on other criteria such as the number of skilled workers, supervisors available, or the number of units of a particular type of expensive equipment, etc. If these parameters are flexible the MMGA can be used to perform scenario-based planning to select the best configuration later. A general outline of the procedure followed in the MMGA is shown in Figure 15. The details are discussed in the sections that follow.

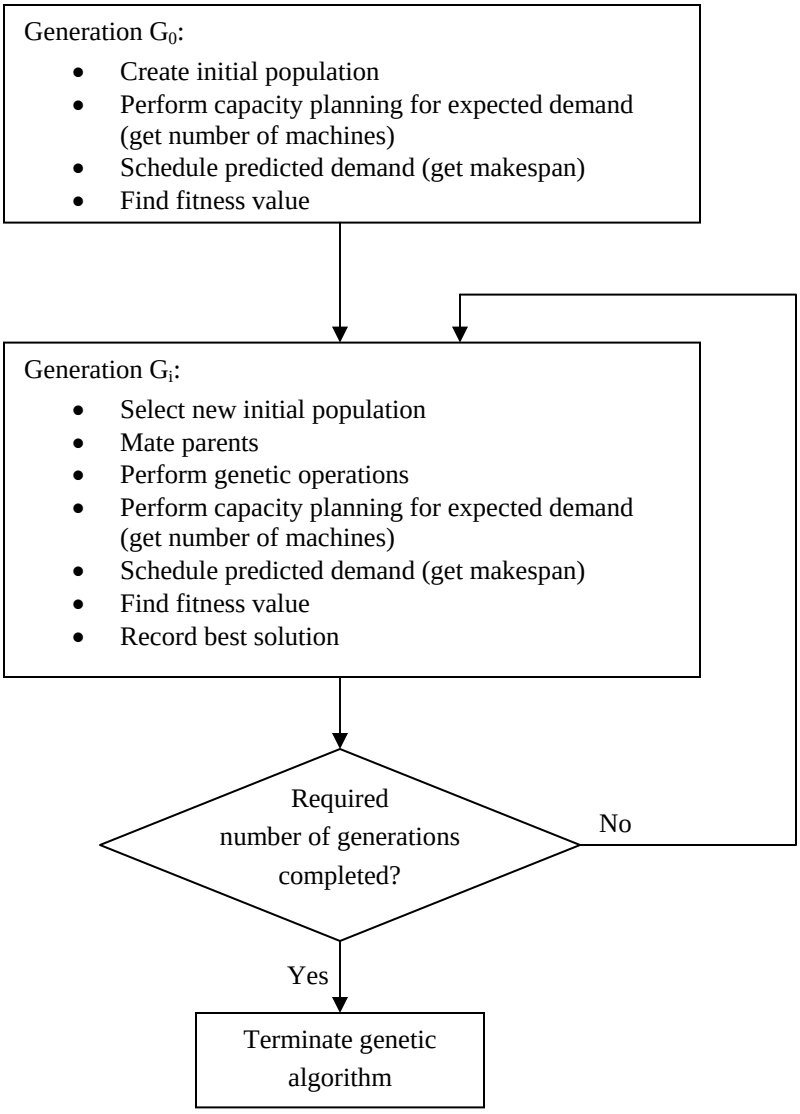


Figure 15: Outline of MMGA Procedure

5.1.1. Chromosome Representation

A multi-chromosome GA is used to represent cutoff point selection and minicell formation for the multi-stage minicell configuration problem. These chromosomes will

be referred to as C1 and C2, respectively. A solution to the problem is then denoted by the chromosome C (= C1 + C2).

C1 defines the number of different machine types in each stage and consists of *m* genes (*m* = number of stages). Thus the value of the first gene represents the number of machine types in stage 1, the value of the second gene the number of machine types in stage 2, and so on. Because the machine sequence is constant, knowing the number of machine types in each stage describes the separation of the matrix into stages.

For example, consider a three-stage configuration with 12 different types of machines in the option-machine matrix. Thus, C1 consists of three genes and an example is shown in Figure 16. Based on this chromosome, the option-machine matrix can be separated into three sub-matrices by cutting off after the 5^{th} and 8^{th} (= 5 + 3) machines respectively.

Stage	1	2	3
Chromosome	5	3	4

Figure 16: Chromosome (C1) Representation for Machine Types per Stage

C2 defines the assignment of options to minicells within each stage. These chromosomes are represented as *m* blocks of *n* genes each. Every block represents a separate stage in

the minicell configuration and has *n* genes to represent each of the options in the option-machine matrix. Thus the first *n* genes represent the assignment of options to minicells in the first stage, the next *n*+1 to 2*n* genes represent the assignment of options in stage 2, and so on.

For example, Figure 17 shows C2 for a three-stage minicell configuration with six options where the maximum number of minicells per stage is limited to three. Each gene in a block represents the minicell number to which the particular option is assigned to in that stage. In stage 1, option 1 is assigned to minicell 1; option 2 is assigned to minicell 3, and so on. The option families and minicells for the chromosome are shown in Table 8.

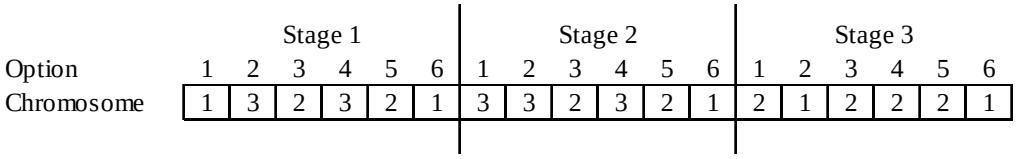


Figure 17: Chromosome (C2) Representation for Forming Minicells

Table 8: Minicells and Option Families

Stage	Minicell No.	Options
1	1	1,6
	2	3,5
	3	2,4
2	1	6
	2	3,5
	3	1,2,4
3	1	2,6
	2	1,3,4,5

5.1.2. Fitness Function

The objective of the minicell system design process is to divide the configuration into stages and determine option families and minicells that will reduce the time taken to produce a batch of customized products. Shortening the time taken between start and completion of a total batch of orders will contribute to achieving shorter delivery times. Therefore, the total time taken to complete processing the daily demand for all product variants, i.e.: the makespan, is taken as the fitness function. Lower makespan can be achieved with any configuration by adding extra machine capacity. In this case, the objective is to determine the minimum makespan design while restricting machine count to that required for producing the expected demand for product variants.

The machine capacities required to process an expected daily demand for the product variants in the configuration represented by each chromosome C is first calculated. The predicted demand for product variants is then scheduled for processing in each of the minicells on every stage, depending on the options required for the features and

processing needs for those options. The CDS & FCFS strategy, as described previously in Section 4, is used to schedule jobs in the multi-stage minicell configuration. The time at which the last product variant in the group leaves the system is taken as the makespan, and therefore the fitness function of the chromosome representing the configuration.

5.1.3. Reproduction

Every chromosome C is assigned a reproduction probability based on its fitness function value. Fitness function values for all chromosomes in a given generation are summed to determine the total fitness value (equation [2]). The adjusted fitness function value is computed for every chromosome by dividing the total fitness value by its own fitness value (equation [3]). Then a reproduction probability is calculated based on this adjusted fitness value as shown in equation [4].

$$TFF = \sum_{I=1}^{S} FF_i \qquad [2]$$

$$AF_i = \frac{TFF}{FF_i} \qquad [3]$$

$$p_i = \frac{AF_i}{\sum_{i=1}^{S} AF_i} \qquad [4]$$

Where,

FF_i = fitness function value for chromosome$_i$

TFF = total fitness function value

AF_i = adjusted fitness function value for chromosome$_i$

p_i = reproduction probability for chromosome$_i$

S = population size

5.1.4. Crossover Strategy

In order to increase the exploration of the solution space in the GA, different crossover strategies were employed for C1 and C2.

C1 denotes the assignment of machine types among the stages and is made of *m* genes. A single cut-point crossover strategy is applied for these chromosomes. C2 consists of *m* blocks of *n* genes each (i.e.: *m* x *n* genes) to represent the option assignment to minicells in each of the *m* stages in the configuration. Two different crossover strategies were applied to this part of the chromosome: (1) single cut-point crossover and, (2) swapping crossover.

For single cut-point crossover, a cutoff point is randomly chosen for each pair of parent chromosomes (P1 and P2). All genes to the right of this cutoff point from one parent are replaced with those of the other parent. This is illustrated for a pair of C1 in Figure 18 and C2 in Figure 19.

As evident from Figure 18, the application of crossover for C1 pairs could generate infeasible offspring. Here, O1 has 14 machines and O2 has 10 machines, which are both different from the actual available (12 machines).

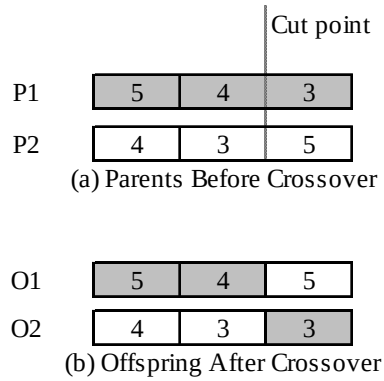


Figure 18: Single Cut-point Crossover Strategy for C1

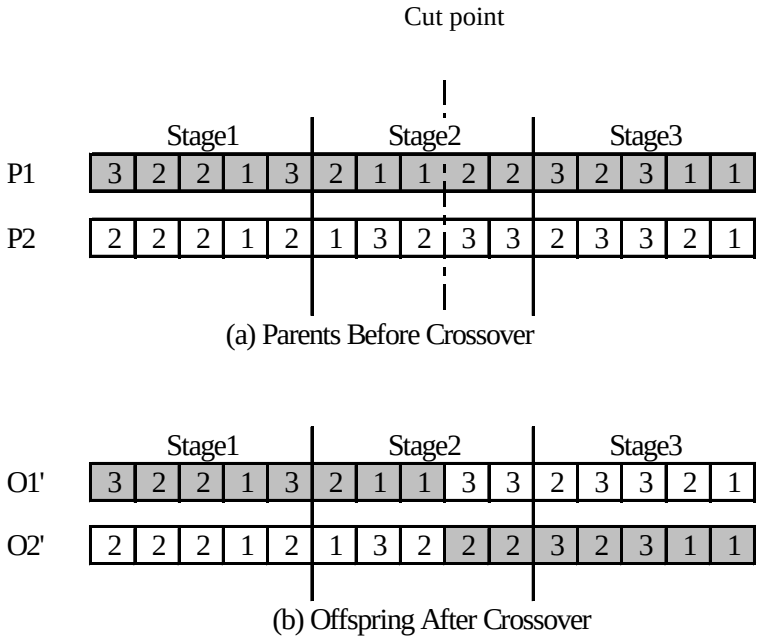


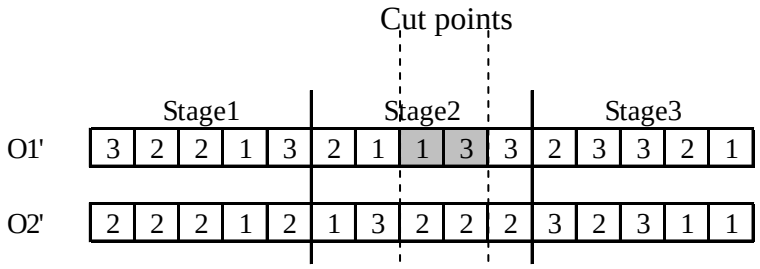
Figure 19: Single Cut-point Crossover Strategy for C2

In such situations, a repairing mechanism is applied to modify the chromosome to ensure it is a feasible representation of the solution. This is done by first determining the excess (or shortage) of machines represented in a chromosome relative to the total number of machine types in the option-machine matrix. A randomly chosen stage is adjusted by the amount of the excess (or shortage). In case of excess machines, the subtraction should not lead to zero machines in the randomly chosen stage. If this happens, one machine is reserved in that stage and the remainder is removed from a separate, randomly chosen stage. This process is repeated until a feasible chromosome is formed.

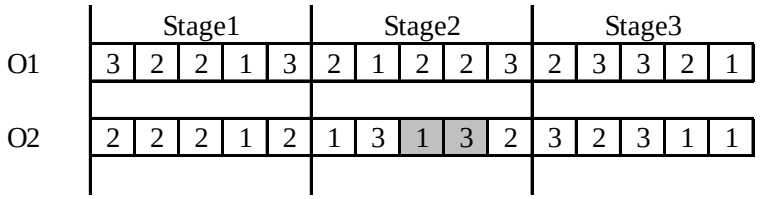
A single cut-point crossover strategy is insufficient when a multi-block chromosome is used; the amount of genetic change introduced is limited to the part of parents to the right of the cut point. In addition, the option families and minicells of parents in stages other than that with the cut point (stage 2 in Figure 19), are unaffected. The effect of this could be more pronounced for larger chromosomes, such as those used for option family formation in this problem (C2). Therefore, in this case, a swapping crossover strategy was also used to try and create offspring that are distinct from their parents for type C2.

The swapping crossover strategy was applied within every stage of parent chromosomes chosen for mating. Thus, for a chromosome with three stages, the swapping crossover is applied three times, once within each stage. Two cut points are randomly chosen within the part of the chromosome that represents a single stage. The genes within these two cut points of one parent are then interchanged with those within the same range of the other parent.

The application of the swapping crossover strategy is illustrated in Figure 20. This is applied to pairs of C2 chromosomes that are already genetically modified by single cut-point crossover. For example, the pair of chromosomes O1' and O2' shown in Figure 19 are subsequently modified by applying swapping crossover to create the final pair of offspring O1 and O2. This procedure is then repeated for all the stages in every pair of chromosomes.



(a) Parents Before Swapping Crossover



(b) Offspring After Swapping Crossover

Figure 20: Swapping Crossover Strategy to Generate Offspring

5.1.5. Mutation Strategy

The mutation operator is applied to each gene of the chromosome independently. Genes are chosen for mutation randomly based on the mutation probability. The value of the selected gene is replaced by randomly selecting a number from the eligible set.

The application of the mutation strategy to C1 is illustrated in Figure 21. The mutation strategy is applied to the shaded gene in chromosome P1 is generate O1. As can be observed, the resulting chromosome is infeasible if there are only 12 machine types in the option-machine matrix. Such situations require application of the repairing strategy described previously to make the chromosomes feasible.

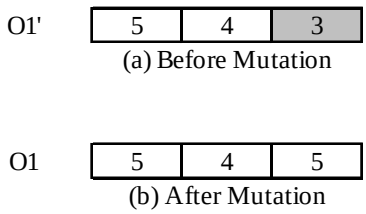


Figure 21: Mutation Strategy for C1

In the case of C2, the application of this operator to a particular gene results in the option being assigned to a different minicell within the stage as illustrated in Figure 22. As indicated by the shaded genes, option 3 in stage 1 and option 1 in stage 3 belong to

minicell 2 in their respective stages. After mutation they are assigned to minicell 3 and minicell 1, respectively.

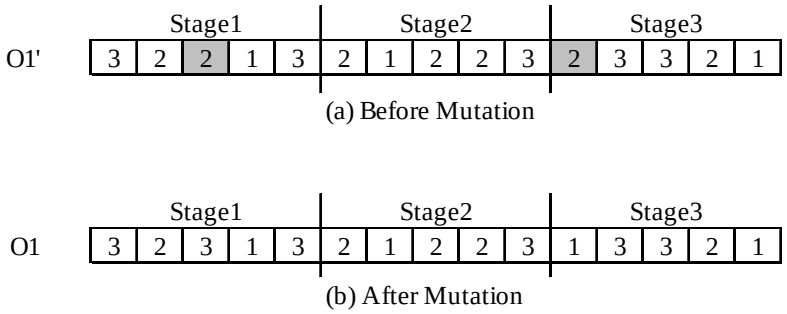


Figure 22: Mutation Operator

5.1.6. Experimentation with MMGA

Experimentation was then conducted using the MMGA model with crossover and mutation (C+M) to determine its effectiveness in finding good solutions to the minicell system design problem.

5.2. Analysis of MMGA Model

The experimentation conducted to evaluate the MMGA model is described in this section. The objective of the experimentation was to analyze the performance of the MMGA to evaluate how well it converges towards finding a good solution to the minicell system design problem.

The MMGA model with crossover and mutation strategies (C+M) was tested to determine the best solution—minimum makespan minicell configuration—by varying the population size and number of generations. The population size was tested at 10, 20, and 30. The number of generations experimented with each population size were 50, 100, and 200. The mutation probability was maintained at 0.1. Therefore, nine different population size/generations combinations were tested on each problem to evaluate the performance of the MMGA model. The software was used to execute six trials of five replications each—every replication is run for the number of generations required with the given population size—and the best solution was recorded. The results from the MMGA model are described in the following sections in detail for one problem.

The MMGA model was tested to find the best three-stage minicell design with a maximum of two minicells per stage for a situation where customized products are manufactured by varying the options available for three features. Each feature has three options (total options = 9) and, therefore, 27 different product variants can be derived by combining these options. Seven machine types are required to process the nine options. The option-machine matrix, in terms of processing time for options in the relevant machines, is given in Figure 23. The expected demand for each product variant as well as the actual demand is given in Table 9.

		Machines						
		A	B	C	D	E	F	G
Options	11	1.02		0.57	0.84		1.9	
	12		0.2		0.75			1.2
	13			0.19	0.02			
	14	0.18				1.18		0.84
	15				0.09		0.09	
	16	1.65	0.06	0.86	1.27		0.02	
	17	1.73	0.05	1.22	1	1.58		1.06
	18	1.65			0.33		0.43	0.14
	19		0.67	0.89		1.08		

Figure 23: Option-machine Matrix for MMGA Experimentation Problem

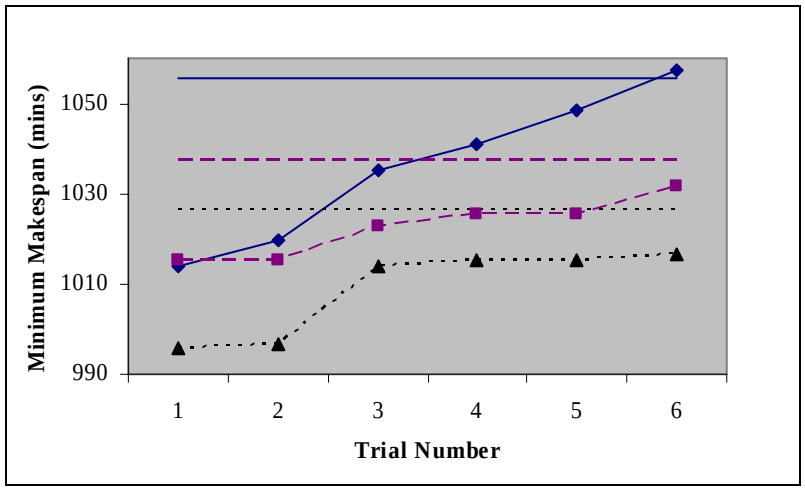
The options chosen for the features can be identified by the product variant number. For example, the variant 11.14.17 has options 11, 14, and 17 for the first, second, and third features, respectively.

Table 9: Product Variants and Demand

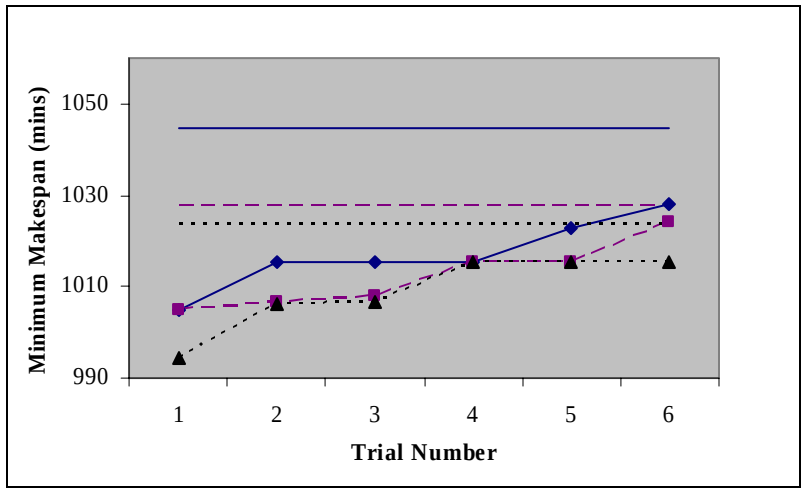
Product Variant	Expected Demand	Predicted Demand	Product Variant	Expected Demand	Predicted Demand
11.14.17	60	59	12.15.19	26	24
11.14.18	39	45	12.16.17	85	74
11.14.19	2	2	12.16.18	21	20
11.15.17	56	55	12.16.19	86	92
11.15.18	40	37	13.14.17	88	86
11.15.19	25	23	13.14.18	42	41
11.16.17	28	25	13.14.19	60	54
11.16.18	18	18	13.15.17	77	70
11.16.19	88	79	13.15.18	24	25
12.14.17	61	65	13.15.19	53	59
12.14.18	84	87	13.16.17	84	73
12.14.19	16	15	13.16.18	23	23
12.15.17	63	54	13.16.19	5	6
12.15.18	57	57			

The replications were grouped into six trials in the order they were conducted i.e. the first five replications constitute trial 1, the next five trial 2 and so on. The results for the individual replications were too varied for graphical comparison. Therefore, to improve presentation, the replications were grouped as described above. Subsequently the results for the six trials were sorted in increasing order of minimum makespan to ease the evaluation.

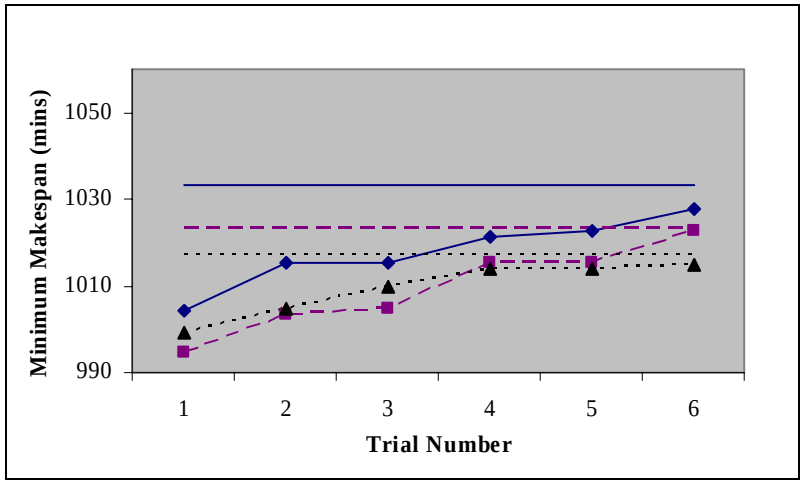
The comparison of results obtained using the MMGA model with the same population size for different numbers of generations is shown in Figure 24. These results compared at same numbers of generations but different population sizes are shown in Figure 25. The minimum makespan and the overall average makespan are presented in the figures. The minimum values for each trial are the lowest makespan value obtained from the five replications in that trial. The average makespan is the overall average makespan from all the thirty replications (six trials x five replications).



(a) Population size = 10



(b) Population size = 20



(c) Population size = 30

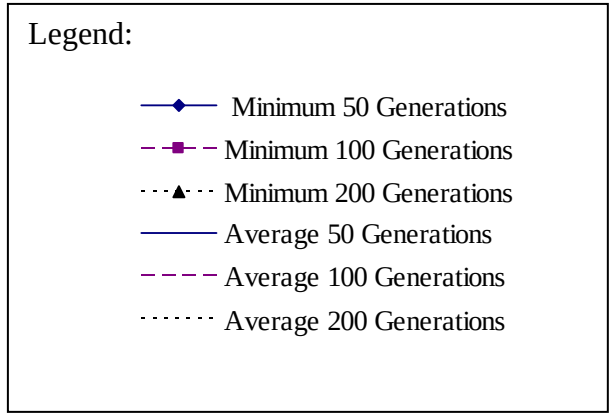
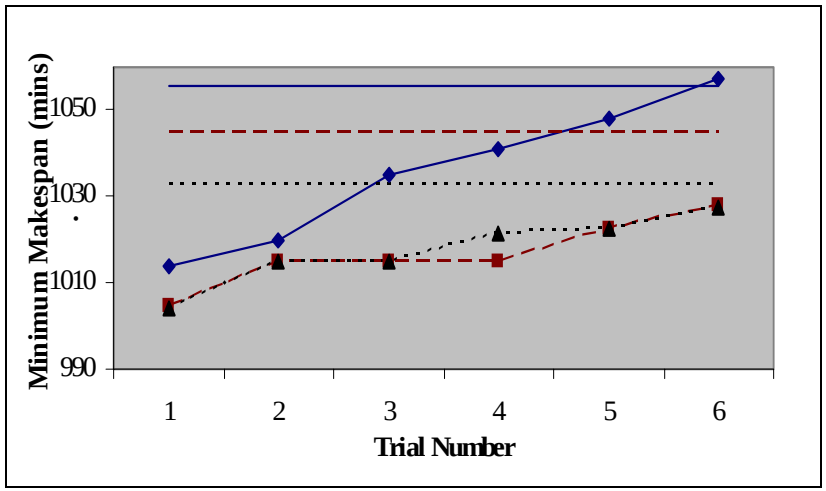
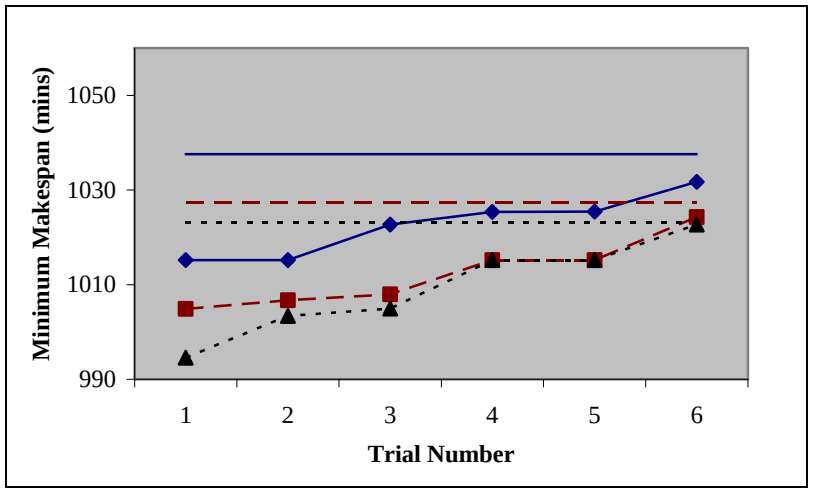


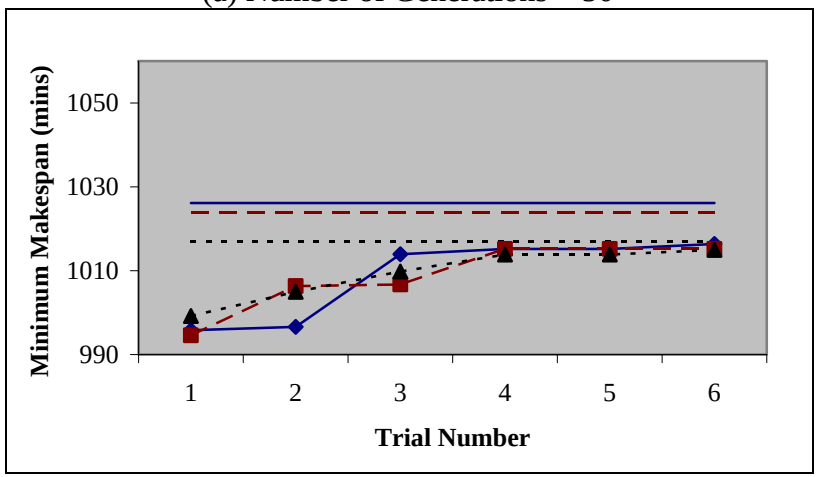
Figure 24: Comparison of MMGA Results at Different Population Sizes



(a) Number of Generations = 50



(b) Number of Generations = 100



(c) Number of Generations = 200

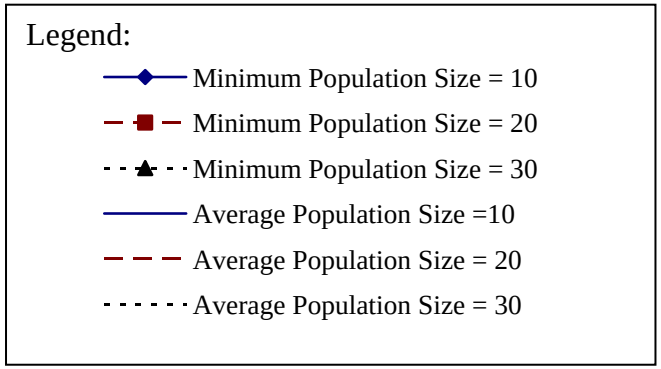


Figure 25: Comparison of MMGA Results at Different Number of Generations

As can be observed, better solutions are obtained at higher generations with the same population size. The improvement in solutions is more prominent when the population size is low. Thus, with a population size of 10, better solutions (lower minimum makespan) are found more consistently (lower average makespan) with 100 generations than with 50. Similar results can be observed as the number of generations is increased from 100 to 200.

At higher population sizes, better solutions are found as the number of generations is increased from 50 to 100. However, an increase to 200 generations does not appear to contribute as much to improving the final solutions. At population sizes of 20 and 30, the decrease in average makespan is higher when the number of generations is increased from 50 to 100 than when increased from 100 to 200. Doubling the population size or the number of generations had an almost proportional impact on the time taken to solve the MMGA.

In order to obtain better results, it appears that the MMGA model may have to be tested for a larger number of generations at a population size of 10. Increasing the number of generations—for example to 200—would take almost twice the time to run the MMGA. However, as seen from the results, the improvement in the solution obtained is much smaller in magnitude. Therefore, when using the MMGA, the importance of attaining better solutions by increasing population size and/or number of generations must be weighed against the additional time required to find the solution.

The minimum makespan minicell system design found using the MMGA model with C+M is graphically shown in Figure 26. The resulting configuration has two minicells in the first and third stages and one minicell in the second stage. The different machine types are designated different shapes and the number of units of each type in every minicell is indicated. The minicells are identified as MC_{11}, MC_{12} etc; the first subscript indicates the stage and the second the number of the minicell within that stage.

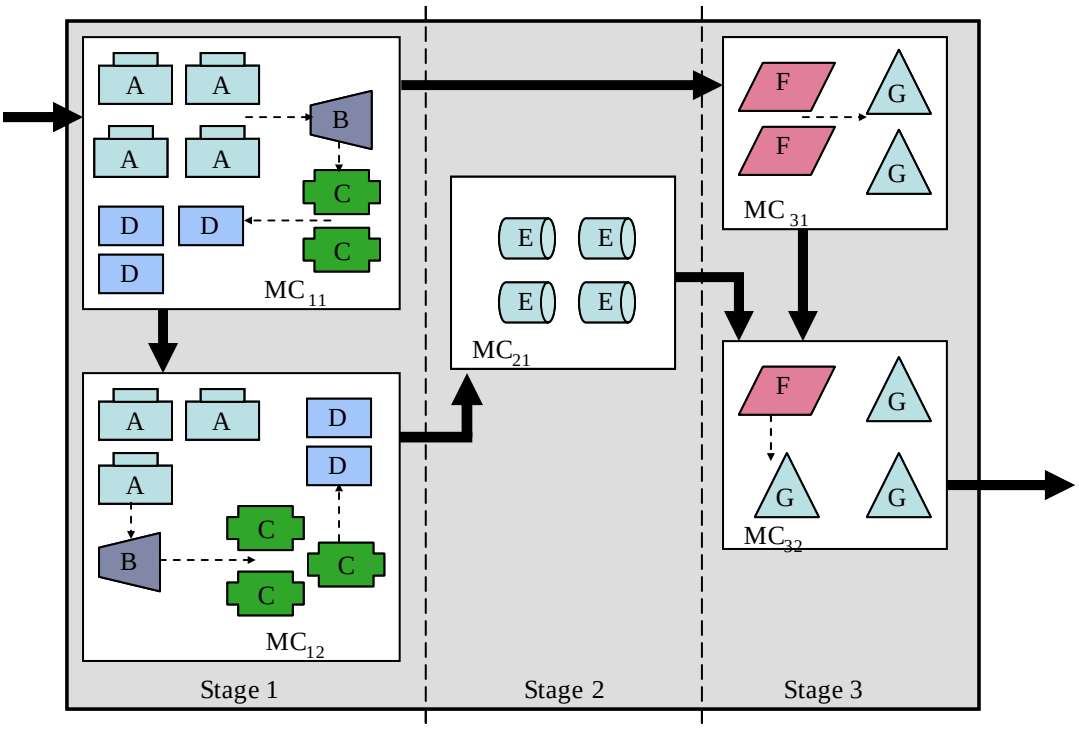


Figure 26: Minimum Makespan Three-stage Minicell System Design

The flow path for product variants between minicells is shown by the dark arrows. The general flow of product variants within a minicell is indicated by the dashed arrows. In

this problem all product variants enter the system through minicell M_{11} in stage 1. Some variants then bypass stage 2 and flow directly to minicell M_{31} in stage 3. The remainder are routed to M_{12} for processing and subsequently enter M_{21} prior to moving to stage 3. Part of the product variants that enter M_{21} are processed and routed to M_{31}. All products are finally sent to minicell M_{32} to complete the processing. When a particular product variant does not require processing in a machine type, that is bypassed and the product visits the next machine within the minicell based on the process plan.

5.3. Designing Minicell Configurations

The MMGA finds a minimum makespan minicell design to produce a specific demand for the set of product variants. The configuration designed will be the most favored for that particular demand scenario. However, with mass customization manufacturing, the product demand is highly dynamic in terms of the mix as well as quantity required. Therefore, using a configuration designed based on a single scenario is insufficient and could be sub-optimal in other demand scenarios. On the other hand, frequent system redesign to meet the specific requirements of each period, in this case one day, is infeasible because of the cost and time involved.

An alternative is to design the minicell system through a scenario-based approach. The method reduces the need for frequent reconfigurations but provides a suitably flexible design to accommodate changes in product demand within a certain range. The scenario analysis used to determine a flexible minicell configuration using the MMGA and simulation is described in this section.

Two decisions are pertinent when designing and operating a flexible minicell configuration for mass customization manufacturing. The first involves determining an optimal configuration that provides the flexibility to accommodate the dynamic demand experienced in the short term. The approach to determining such a design is described in Section 5.3.1. The minicell configuration must also have the capability to accommodate long-term changes in the expected demand. The second decision involves determining system reconfiguration requirements—if it is required and how frequently—over the longer term. The approach that can be followed to analyze minicell performance to evaluate the reconfiguration requirements is described in Section 5.3.2.

5.3.1. Flexible Minicell Configuration Design

Different minicell configurations can be derived through the MMGA for various predicted demand scenarios of the same problem. However, before any such configuration can be implemented, it must be validated to ensure desired performance can be delivered over a variety of predicted demand conditions. The flexibility of the designs is studied by simulating the performance of the configurations for different demand situations. The most robust design is then chosen as the best minicell configuration. The steps followed to find the robust design are listed below and described in detail in the following sections.

1. Generate predicted demand for each product variant based on expected demand
2. Solve the MMGA to determine best minicell configuration

3. Repeat 1 – 2 for *s* randomly generated predicted demand scenarios
4. Generate *z* additional predicted demand scenarios. Simulate the performance of the *s* configurations with each of the *z* predicted demand scenarios
5. Select the configuration that gives overall best performance based on the performance measure chosen for evaluation.

For each problem, the MMGA is used to determine a minicell configuration for several different (*s*) predicted demand scenarios. In all the *s* cases, the number of stages, the maximum minicells per stage, and expected product variant demand are maintained constant. However, the predicted demand is varied randomly based on the expected demand to reflect the dynamic conditions experienced in mass customization environments and is generated by assuming a normal distribution, with the mean and standard deviation equal to the expected demand and 0.1(expected demand), respectively.

The MMGA is then used to find the best minicell configuration for each of those *s* demand scenarios. The assignment of machine types in the option-machine matrix to stages and the formation of minicells and option families within each stage is found by the MMGA. The makespan for processing the predicted daily demand using the machine requirements to process the expected daily demand are determined for each configuration.

Simulation is then used to determine the makespan for a different, larger set of predicted demand scenarios (*z*) on each of the *s* configurations found by the MMGA. For any given

problem, only a few alternate minicell configurations are likely to be found; the MMGA has to be run several times to find a reliable solution and this is time consuming. To evaluate the performance of the designs found by MMGA, they must be tested using a larger set of predicted demand scenarios. Increasing the number of predicted demand scenarios used for the simulation will enable selecting a more robust design. Therefore, it is recommended that $z \geq s$.

The makespan to process each of the *z* demand scenarios will be dissimilar in the *s* configurations due to differences in cutoff points and family formation; a particular configuration could have the best makespan for one demand scenario while giving much worse outcomes with other scenarios. Therefore, performance measures must be established to select the overall best configuration. A few different performance measures that can be used to evaluate minicell configurations are presented below.

$$MS_{MinAvg} = Min\left[AMS_1, AMS_2, \ldots, AMS_s\right] \quad [5]$$

$$MS_{MinMax} = Min\left[MaxMS_1, MaxMS_2, \ldots, MaxMS_s\right] \quad [6]$$

$$MS_{MaxMin} = Max\left[MinMS_1, MinMS_2, \ldots, MinMS_s\right] \quad [7]$$

$$MS_{MinMed} = Min\left[MedMS_1, MedMS_2, \ldots, MedMS_s\right] \quad [8]$$

where,

MS_{MinAvg} = Minimum average makespan

MS_{MinMax} = Minimum of maximum makespan

MS_{MaxMin} = Maximum of minimum makespan

MS_{MinMed} = Minimum of median makespan

AMS_i = Average makespan on configuration i, i = 1, 2,…s

$MaxMS_i$ = Maximum makespan on configuration i, i = 1, 2,…s

$MinMS_i$ = Minimum makespan on configuration i, i = 1, 2,….s

$MedMS_i$ = Median makespan on configuration i, i = 1, 2,…s

s = Number of configurations tested

MS_{Avg}, MS_{MinMax}, and MS_{MaxMin} select the best configuration based on overall average makespan, best of worst makespan, and worst of best makespan, respectively. All these measures are sensitive to the extreme values for makespan obtained in each configuration. Given such alternate performance measures, the user can select the most appropriate based on what is desired. For example, a more cautious approach might be to use MS_{MaxMin}.

In this research MS_{Avg} —lowest average makespan—is used as the performance measure to evaluate alternate minicell designs. Therefore, after simulating performance for z predicted demand scenarios in all the configurations, one that generates the lowest average makespan is chosen as the most robust design for meeting the customized manufacturing needs.

To illustrate the flexible minicell design process, consider the product variants, expected demand, and the predicted demand for four different scenarios ($s = 4$) shown in Table 10 for a particular problem. The processing time for each option in the respective machines, ordered in sequence, is shown in Figure 27.

Table 10: Product Variants and Demand Information

Product Variant	Expected Demand	Predicted Demand			
		Scenario 1	Scenario 2	Scenario 3	Scenario 4
11.13.16	78	83	72	78	79
11.13.17	3	3	3	3	3
11.13.18	1	1	1	1	1
11.14.16	53	54	53	54	57
11.14.17	80	77	80	102	79
11.14.18	33	36	27	32	34
11.15.16	60	58	55	57	65
11.15.17	98	98	97	104	103
11.15.18	66	71	60	59	76
12.13.16	48	45	49	50	55
12.13.17	84	88	76	75	97
12.13.18	84	86	87	71	81
12.14.16	29	25	35	27	28
12.14.17	99	97	99	102	101
12.14.18	1	1	1	1	1
12.15.16	57	56	61	54	50
12.15.17	1	1	1	1	1
12.15.18	28	26	33	30	35

		Machines						
		A	B	C	D	E	F	G
Options	11		0.35	2	0.7	1.27	1.63	1.14
	12		0.33		0.25			
	13				1.54			1.65
	14	0.45		1.91		1.33	0.61	
	15	0.48	0.7		0.27	0.61		0.03
	16	0.56	1.27	0.71	0.58	0.48	1.63	
	17			0.82	0.51			
	18				0.03		0.19	1.57

Figure 27: Option-Machine Matrix

The MMGA is used to determine four, two-stage minicell configurations with two minicells per stage for each of the demand scenarios shown in Table 10. The population size for the tests was set at ten chromosomes and the MMGA was run for 100 generations to determine the minicell configurations shown in Table 11.

Table 11: Minicell Configurations for Different Demand Scenarios

Configuration Number	Machine Types		Chromosome															
	Stage1	Stage2	Stage 1								Stage 2							
1	5	2	1	2	1	1	1	2	2	1	1	1	1	1	2	2	2	1
2	6	1	1	2	1	2	1	2	1	1	1	1	2	2	1	1	1	1
3	6	1	2	1	2	2	1	2	1	1	1	2	1	1	1	1	2	2
4	3	4	1	2	2	2	1	2	1	2	1	1	2	2	1	2	2	2

The number of machine types assigned to each stage indicates how the option-machine matrix is divided into stages. The assignment of options to minicells within each stage is

shown by the chromosomes. As can be observed, the separation of the matrix into stages is identical in configurations 2 and 3. However, the minicell formation within the stages is varied to accommodate for the differences in product demand in the two situations. For the other two configurations the cutting points to create stages as well as minicell formation within are different.

The four minicell configurations in Table 11 are designed for different predicted demand scenarios derived from the same expected product variant demand. These configurations must then be analyzed to evaluate their performance under a variety of different predicted demand conditions. This is achieved by simulating the performance of these configurations for fifteen (z = 15) different sets of product variant demand derived from the expected demand as described previously. The makespan to complete processing the jobs in each predicted demand scenario on each of the four configurations was estimated. For each configuration, the makespan to complete processing the demand for which it was designed (shown in Table 10), the machine requirements for the configuration, and the average makespan to complete processing the new predicted demands are shown in Table 12.

Table 12: Simulation Results for Minicell Configurations

Configuration Number	Design Makespan (mins)	Machine Count	Average Simulation Makespan (mins)
1	1278	28	1332
2	1175	26	1311
3	1313	27	1418
4	1272	26	1244

All the above configurations are designed with sufficient capacity to produce a quantity equal to the expected demand. It must be noted that the capacity required for each configuration—in terms of number of machines—is different, though all are designed to accommodate the same expected demand. This is due to the variation in minicell formation to achieve the minimum makespan design. When the assignment of machine types to stages and to minicells, the number of units of each machine type required can vary depending on the option families formed. Therefore, for example, though configurations 2 and 3 have the same number of machine types in the two stages (6 and 1), the minicell formation for the two situations is different (see Table 11). This gives rise to different capacity requirements for the two configurations.

The second configuration has the lowest design makespan (1175 minutes) and corresponds to the product variant demand scenario specific to that configuration. Simulation of system performance using different (z = 15) demand scenarios reveals that configuration 4 generates the lowest average makespan (1244 minutes). Hence, though configuration 2 shows better results for the predicted demand it was designed for, it lacks

the flexibility to generate similar results under different demand scenarios. Configuration 4, on the other hand, has the lowest average makespan over the demand scenarios simulated. Therefore, this design has a greater flexibility to accommodate changes in predicted demand than the rest within the range of situations evaluated.

The scenario-based analysis described above can be used to determine a flexible minicell system design. However, the chosen configuration may turn out to be inefficient if the expected demand increases significantly. Capacity requirements for the minicell system design are based on expected product variant demand. Major increases in the expected demand will require additional capacity and using a previous minicell configuration, which was designed with lower capacity, may lead to longer makespan. Reconfiguring the system to accommodate the new circumstances may become a necessity at this point. On the other hand, a large decrease in expected demand will generate additional capacity in the system and could contribute to attaining lower makespan. Though the presence of unutilized capacity may not be economical, the system performance—makespan—is not undermined when expected product demand decreases.

5.3.2. Reconfiguration of Minicell System

Reconfiguration of the minicell system may become necessary if the expected demand for product variants changes significantly. On the other hand, though the change in expected demand may be large, the predicted demand in a period might not be significantly different from the expected demand for which the particular configuration

was initially designed. In such circumstances, the existing system may still perform satisfactorily even if expected demand changes.

Further, in some instances, though expected product demand rises, some part of this increase can be absorbed by the system without significantly affecting makespan due to changes in the product mix. For example, if the product mix changes such that more products with less processing are needed, the existing system would have the capacity to accommodate such a change. However, these adaptations are difficult to predict in advance due to the difficulty in forecasting demand for mass customized products. Therefore, increases in expected product demand may require system reconfiguration though the resources may remain under utilized in some periods.

Two different approaches to system reconfiguration are possible: (1) Strategy 1 – adding capacity to the existing system to accommodate increased demand, or (2) Strategy 2 – redesigning the minicell system by determining stages and minicells all over again to match increased demand. The latter is more involved in terms of time and cost required while the former may only be marginally better in delivering the desired results. However, the better approach is likely to depend on the actual circumstances governing a particular problem and both approaches must be analyzed.

To evaluate the reconfiguration requirements of minicell system designs, the performance of the configuration designed in the previous section was analyzed by increasing the expected demand. For each new expected demand model (7 different models—2%, 5%,

10%, 20%, 30%, 50%, and 100% increases), fifteen new predicted demand scenarios were generated. The following tests were then performed to determine the average makespan for processing the new predicted demand.

1. Simulation was used to determine the average makespan to process the fifteen different predicted demands, for each of the seven different models, using the configuration designed in Section 5.3.1 above with a design capacity of 26 machines.
2. Assuming reconfiguration involves merely adding capacity—Strategy 1—the additional machines required and the average makespan to process the new predicted demand, in all the seven models, with this increased capacity was determined.
3. A completely redesigned minicell configuration—Strategy 2—was found for each increased expected demand model using the MMGA and simulation as illustrated in Section 5.3.1. The average makespan to process the predicted demand and the machine requirements were then estimated for the seven models separately.

The results of these experiments are summarized in Table 13. The percentage increase in demand shown is for the expected demand. The machine capacity required to process the initial expected demand is 26 units. In addition to the makespan for completing the increased demand in the three different configurations, the total capacity required with Strategy 1 and Strategy 2 to process the increased demand is also shown. The variation in the makespan in the three types of minicell designs is shown graphically in Figure 28.

Table 13: Experimental Results with Increased Expected Demand

Increase in Demand (%)	Makespan			Machines		
	Original Config.	Strategy 1	Strategy 2	Original Config.	Strategy 1	Strategy 2
0	1244			26		
2	1321	1321	1293		26	26
5	1368	1368	1348		26	26
10	1472	1472	1456		26	29
20	1558	1548	1481		29	29
30	1770	1699	1677		34	32
50	2007	1934	1889		34	36
100	2676	2492	2467		47	43

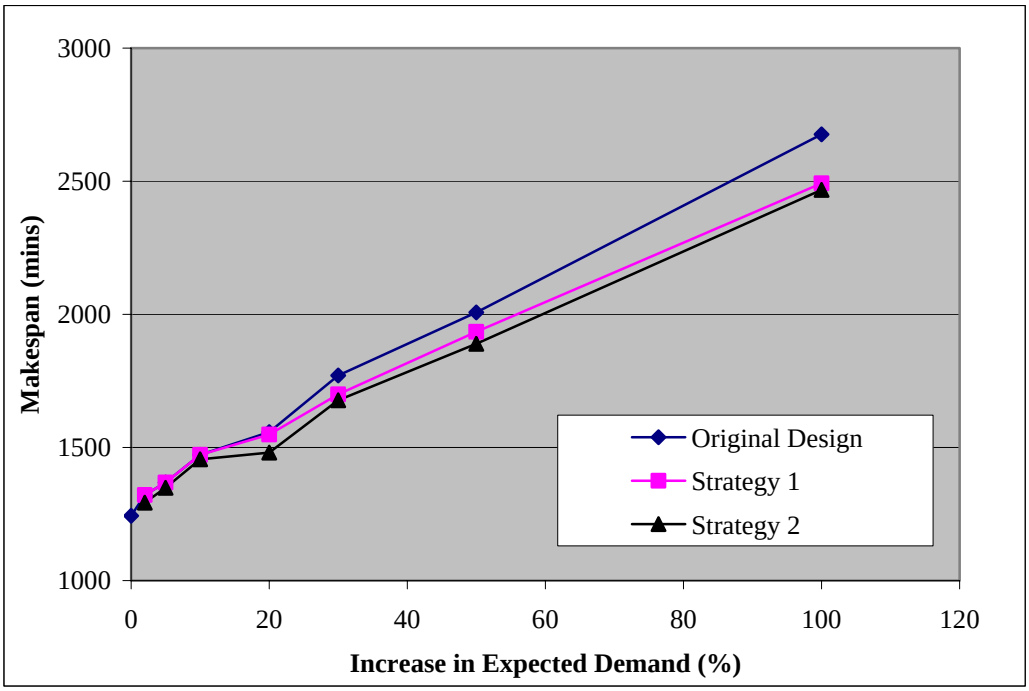


Figure 28: Makespan in Three Configurations

If the first approach to reconfiguration is used—Strategy 1—additional capacity is not required to process increases in expected demand up to 10%. However, if the increase is over 10%, more machines must be added to provide the capacity required for increased processing. Adding more capacity helps achieve a lower makespan than if the existing minicell system is used at original design capacity. The capacity required for the redesigned system—Strategy 2—is only very slightly different from the original design for up to a 20% increase in expected demand. The makespan that can be achieved with the new designs is slightly lower than with the other two cases. When demand increases further, better performance can be achieved by completely redesigning the system. Using an equivalent capacity—as in the reconfigured system—with the original minicell design, does not generate similar makespan.

This can be explained by studying the best designs for each increased expected demand scenario. The assignment of machine types to stages and the chromosome for minicell formation for Strategy 2 is shown in Table 14.

Table 14: Minicell Designs for Increased Expected Demand

Increase in Demand (%)	Machine Assignment to Stages		Chromosome for Minicell Formation
	Stage 1	Stage 2	
0	3	4	1222121211221222
2	3	4	1112121111121122
5	5	2	2122221112211212
10	5	2	2122211212212212
20	5	2	2121221211212222
30	6	1	1222122122221112
50	5	2	2121221212111112
100	5	2	2112221212111112

The capacities required for the newly designed systems are very similar to the requirements of Strategy 1. However, the assignment of machine types to stages as well as minicell formation is very different (Table 14). This is because the minicell system design process used in the MMGA considers the increase in expected demand (in determining capacity required) as well as the variations in product mix (to adjust minicell formation based on makespan) to determine the best configuration. Also, the best minicell design is chosen only after being evaluated for flexibility using simulation. Adding capacity to an existing minicell design, however, only accounts for the additional processing necessary for the increased expected demand. Therefore, the completely reconfigured system is better suited to process the demand in the new scenario than the original with increased capacity.

The reduction in makespan, when using the minicell systems redesigned according to Strategy 1 and Strategy 2, compared to the original design is shown Figure 29.

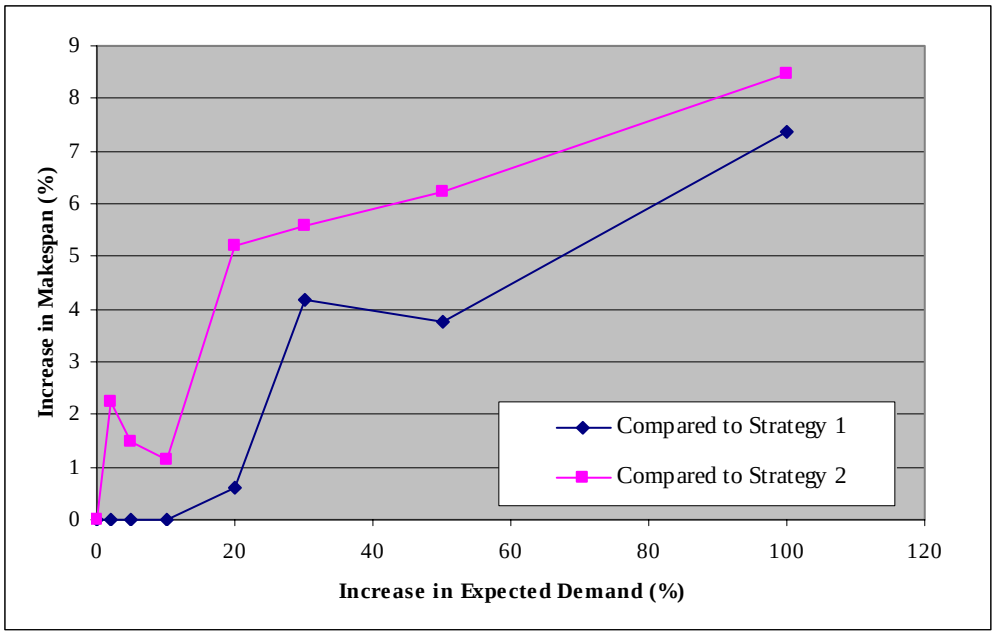


Figure 29: Increase in Makespan with Original Design

For instance, in this example, the makespan in the original design increases only by approximately 2% (compared to strategy 2) even if the demand increases up to 10%. Also, adding capacity to the existing system does not appear to contribute much. Therefore, the cost due to increased makespan might be lower than the reconfiguration cost or the cost of additional machines. Further, if achieving lower makespan is essential, using overtime with existing capacity is another alternative that can be evaluated and pursued. However, as demand increases above 10%, larger savings in makespan are possible by reconfiguration.

5.4. Alternate Minicell System Designs

The effectiveness of the MMGA model was analyzed previously in Section 5.2 using the minicell formation results for one problem. The model was used to determine the minimum makespan minicell design with three stages and a maximum of two minicells per stage.

The preliminary analysis (in Section 4) revealed that the number of stages and maximum number of minicells per stage are two parameters that can influence minicell system design: they may affect the total machine requirement as well as the time taken to process product variants. Therefore, prior to choosing a minicell design for implementation, alternate designs that can be generated by varying the number of stages and maximum minicells per stage need to be investigated. The impact of using different numbers of stages and maximum minicells per stage on minicell system behavior is analyzed in this section.

The design of minicell configurations for the customized manufacture of a product with three features (3, 5, and 4 options each, respectively – 60 product variants) is evaluated. The option-machine matrix (the 12 options require 9 machine types for processing) in terms of processing time in different machine types is shown in Figure 30.

		Machines								
		A	B	C	D	E	F	G	H	I
Options	11				1.48	1.10	0.94		1.99	
	12	0.75	0.64				0.87		1.37	1.10
	13			1.87	0.41		0.64	1.57	0.07	
	14	0.80	1.60	0.70	1.54		0.84			0.42
	15		0.71	0.53		0.03		0.56		
	16		0.70	1.52	0.08				1.21	
	17	0.87			0.25			0.77	0.36	
	18			1.75		0.41		1.78	1.93	
	19	0.93		1.25	1.20				0.71	
	20	0.95					0.49		0.19	
	21	0.34				1.87		0.87		
	22	0.87	1.22	0.31		1.08				

Figure 30: Option-Machine Matrix for Problem

Four two-stage and three-stage minicell models each were evaluated by varying the maximum number of minicells assigned to each stage from 1 to 3. For each model, a flexible minicell configuration was designed using the MMGA and simulation, as described previously.

The minicell configuration—number of stages, machine types per stage, and maximum number of minicells per stage—as well as the average makespan, machine count, and average flow time are summarized in Table 15. The results for two-stage and three-stage designs are shown graphically in Figure 31 and Figure 32, respectively. The average flow time (AFT) for each scenario is also shown in the figures.

Table 15: Comparison of Results for Alternate Minicell Designs

Configuration Number	Minicell Configuration					Makespan (mins)	Machine Count	Average Flow Time (mins)
	Stages	Machine Types in Stages			Minicells per stage (max)			
		Stage 1	Stage 2	Stage 3				
1	2	4	5	-	1	1690	75	1013
2	2	4	5	-	2	1566	82	863
3	2	2	7	-	3	1613	86	885
4	2	3	6	-	4	1566	88	898
5	3	5	2	2	1	1685	75	1005
6	3	5	1	3	2	1572	81	878
7	3	2	1	6	3	1591	85	951
8	3	4	4	1	4	1576	88	959

As can be expected, adding more minicells to a stage increases the total machine requirements because options are grouped into smaller families and machines may have to be duplicated in minicells. Thus configurations with a single minicell require the fewest machines whether with two or three stages. A significant improvement in the makespan is observed when the number of minicells is increased from 1 to 2. The savings in terms of makespan with more minicells may be due to the availability of multiple cells for processing thus avoiding long waiting times that are likely with only a single cell. In both two-stage and three-stage designs the average flow time also shows considerable improvement when the number of minicells is increased from 1 to 2.

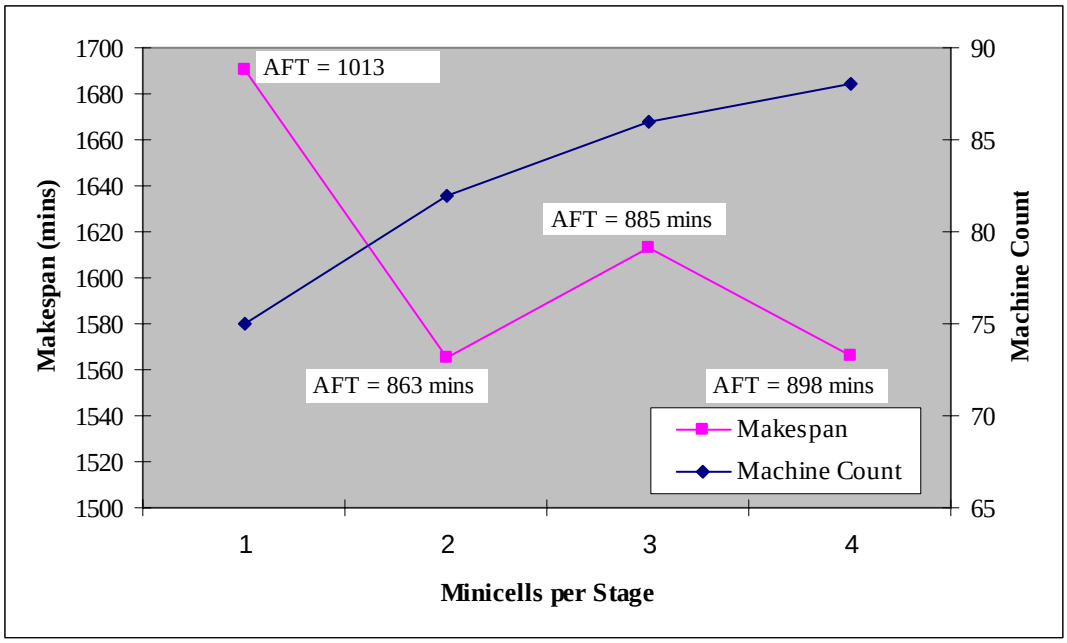


Figure 31: Comparison of Minicell Designs with Two Stages

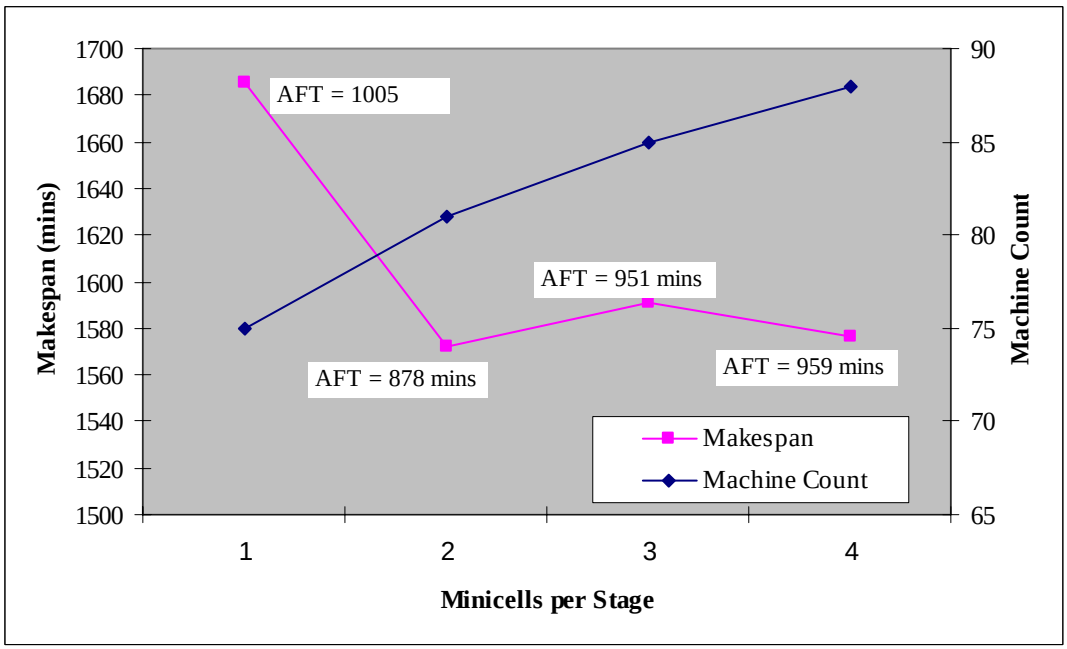


Figure 32: Comparison of Minicell Designs for Three Stages

An interesting variation in the performance is evident when the number of minicells is increased further. The average makespan with 3 minicells—for both two and three-stage designs—is higher than with two minicells. When the number of minicells is increased further, the configurations generate slightly better makespan to produce the same demand. However, in both two and three-stage scenarios, the lowest average flow time is obtained using a configuration with two minicells per stage. Any increase beyond this leads to an increase in the average flow time.

The pattern of variation observed for average flow time may be due to the benefit of separating processes within a stage into multiple minicells being lost as the number of minicells increase. Adding more minicells to a stage complicates scheduling; the relative interdependence of the processing of product variants increases if more minicells are present. Therefore, though the makespan for three and four minicell configurations are only slightly different from each other, individual product variants may have to wait longer to be processed in the additional minicells. This can lead to increased flow times for product variants.

An increase in makespan and flow time as the number of minicells increases is also likely if the scheduling technique used (CDS & FCFS) turns out to be ineffective as the system gets more complex. The CDS heuristic is most effective for use in a conventional flow shop such as a single minicell. The heuristic is used to find a schedule that minimizes the makespan considering the processing requirements in all machines. However, as the number of stages and/or the number of minicells increase, CDS is only applied to the first

minicell in the initial stage. Scheduling in subsequent minicells is based on when each product exits the previous minicell but not on how much processing is required in the machines within that minicell itself. This procedure could be failing to generate lower makespan schedules that may exist if the processing within minicells is considered. Thus, if the scheduling strategy used is not the best feasible method, its effect on makespan may be compounded as the number minicells increases. This may be the reason for increases in makespan as the number of minicells increases from 2 to 3.

The results are similar for two and three-stage configurations. The makespan, minimum machine requirements as well as the average flow times are comparable and show the same pattern of variation. Therefore, these findings imply the number of minicells per stage to have a greater effect on system performance than the number of stages. This was verified by evaluating alternate minicell system designs for different problems and evaluating performance.

Another important issue that is highlighted by the analysis in this section is that the MMGA may not be exploring the solution space sufficiently to find solutions. When the MMGA model is used to find the best minicell design for a particular problem, the number of stages required and the maximum number of minicells per stage allowed are provided as inputs. In most cases, the MMGA determines configurations that have different numbers of minicells—sometimes less than the maximum allowed—in the stages.

The analysis for alternate designs of the same problem here reveals that a configuration with two minicells per stage performs better than one with three minicells. In that case, when the MMGA is run by setting the maximum minicells per stage to three, it must converge to a solution with only two minicells per stage. However, this does not seem to occur. This is an indication that the MMGA may only be exploring a part of the solution space for the problem during the experimentation. Since the number of variables in the minicell formation problem is very large, running the MMGA for a larger number of generations may aid in the convergence.

5.5. MMGA with Fixed Cutting Points

The cutoff points to separate the option-machine matrix into multiple stages are determined randomly in the MMGA model. The resulting configuration is evaluated by analyzing the impact on makespan and thereby determining the optimal cutoff points to assign machine types among the stages.

Two of the most important decisions in designing an optimal minicell configuration are determining the cutoff points to form stages and creating the minicells within. Evaluating the sensitivity of the cutoff points to system performance could provide valuable insights for selecting them. This will also help evaluate the effectiveness of the MMGA in finding the best cutoff points. If the precise selection of cutoff points turns out to be insignificant, then, minicell formation must be the focus of the design process.

In order to evaluate the effect of cutoff points on system performance, several problems were studied in detail. Initially, the optimal minicell configurations were determined using MMGA and simulation as described previously. These minicell designs were then slightly modified by shifting the cutoff points about those found by the MMGA. The performance of the resulting minicell designs were analyzed to determine the average makespan to complete processing a set of different predicted demand scenarios.

For the purpose of this analysis, the chromosome representation in the MMGA was modified to represent only minicell formation (i.e. only C1). As the assignment of machine types to stages needs to be fixed as required, the use of chromosomes to represent cutoff points need not be explored through the GA.

The analysis for two different examples is described here in detail. The first is for the design of a two-stage minicell system previously used to illustrate system reconfiguration in Section 5.3. All possible configurations for this problem can be analyzed easily as the design requires only two stages. The second example evaluated is for a three-stage configuration. For both problems the modified MMGA, together with simulation, is used to create different configurations by shifting the cutoff points.

The assignment of machine types to stages, the minimum average makespan for a minicell design with that assignment, and the machine count required for those designs is shown in Table 16 and Figure 33 for the first problem. The best minicell design found by the (original) MMGA is indicated in bold in the table.

Table 16: Different Designs with Alternate Cutoff Points – Example 1

Machine Assignment		Makespan (mins)	Machine Count
Stage 1	Stage 2		
1	6	1422	26
2	5	1336	26
3	**4**	**1244**	**26**
4	3	1324	26
5	2	1305	25
6	1	1349	27
7		1328	26

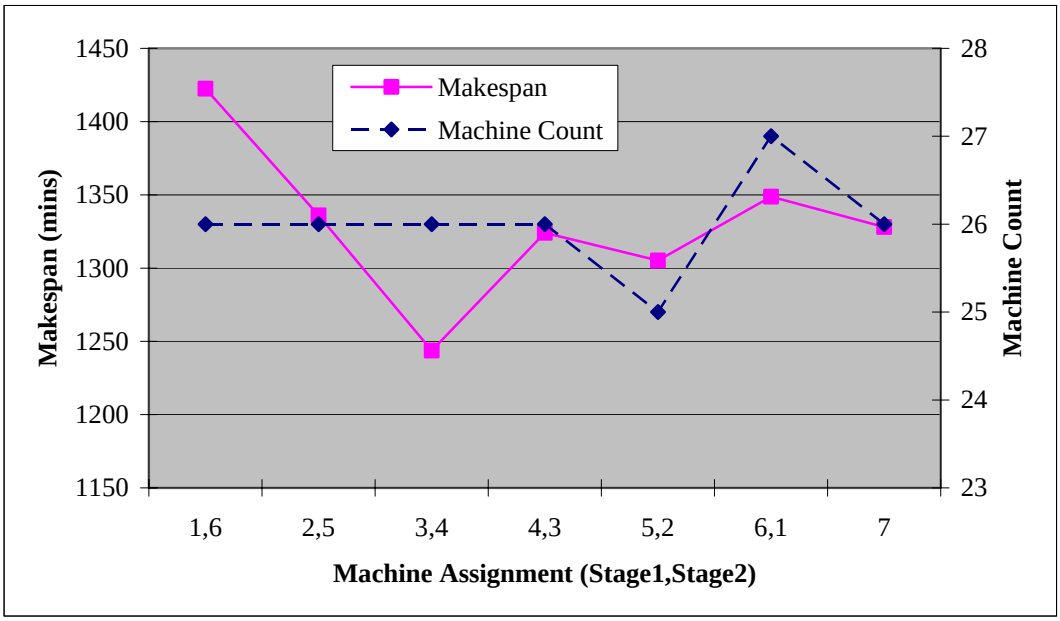


Figure 33: Variation of Makespan and Machine Count – Example 1

According to Figure 33, the MMGA is effective in finding the minimum makespan configuration; none of the other configurations perform as well with respect to makespan. Varying the cutoff point to any other location increases the makespan. It can also be seen

that considering the whole matrix as one—without separating into stages—results in a higher makespan than with the best design. However, the variation in machine requirements, between these different configurations, is very trivial. Determining the optimal cutoff points for designing the minicell configuration appears to have a greater impact on achieving minimum makespan than on reducing total machine requirement.

The alternate cutoff points evaluated for the second example—with three stages—and the results obtained are summarized in Table 17 and shown graphically in Figure 34. The lowest makespan minicell configuration found using the MMGA is shown in bold.

Table 17: Different Designs with Alternate Cutoff Points – Example 2

Configuration Number	Machine Assignment			Makespan (mins)	Machine Count
	Stage 1	Stage 2	Stage 3		
1	3	3	1	1369	52
2	2	4	1	1381	52
3	4	2	1	1359	53
4	**3**	**2**	**2**	**1345**	**51**
5	5	1	1	1394	52
6	3	1	3	1377	52

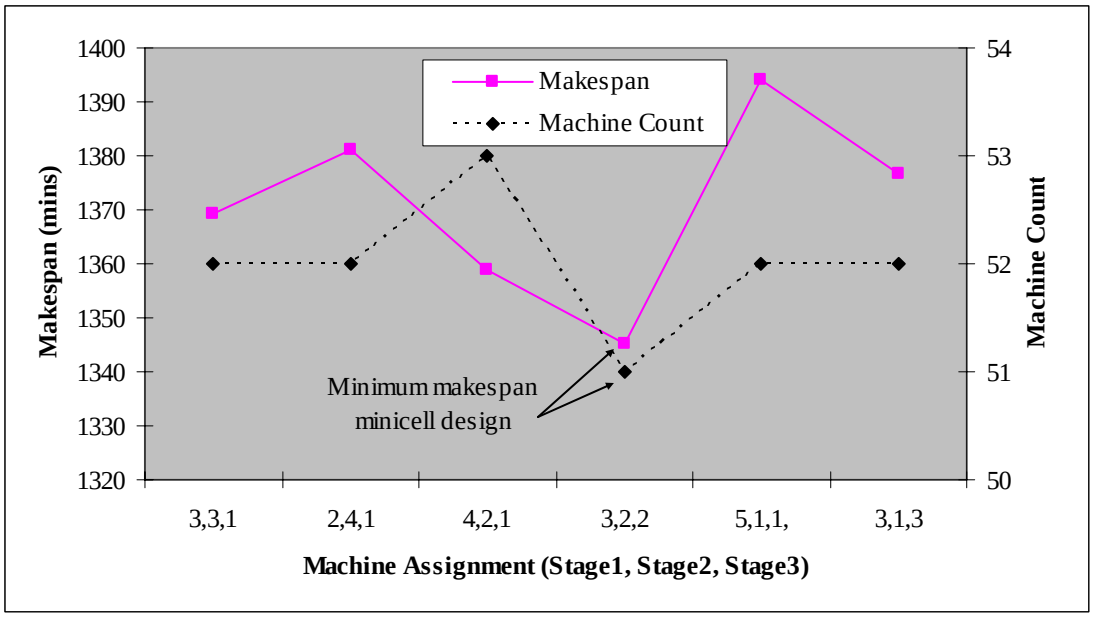


Figure 34: Variation of Makespan and Machine Count – Example 2

Minimizing makespan and machine capacity are conflicting objectives. However, in this problem, a dominant solution where the minimum makespan design is also the minimum capacity design is obtained. These results reinforce the findings from the previous example with respect to cutoff point selection. Thus, irrespective of the number of stages in the design, there appears to exist optimal cutoff points that are more effective in generating minimum makespan minicell designs.

5.6. GA for Minimum Machine Requirement

For every problem tested the MMGA determines the machine requirements for each chromosome based on capacity planning with the expected demand. Higher machine capacities would enable achieving a lower makespan. However, the decision to increase

machine capacity requires weighing the additional capital investment against possible savings from reduced makespan. Knowledge of minimum machine requirements to process a given demand—disregarding makespan objectives—would provide a benchmark to evaluate the quality of solutions generated by the MMGA. The information can also be used to perform incremental benefit/cost analyses to evaluate the shift from the minimum machine design to that found by the MMGA. Therefore, a new GA was developed to determine the minimum capacity (MCGA) minicell configuration for a given problem.

The chromosome representation for the MCGA is identical to that described previously for the MMGA. The capacity—total number of machines—required to process the expected demand for the product variants is taken as the fitness value of each chromosome. Genetic operations of crossover and mutation, as described in Section 5.1, are applied to parents selected based on their reproduction probabilities to generate new populations.

5.7. Minimum Capacity Configurations

The MCGA software was used to determine the minimum capacity minicell design for different problems. In each case the expected demand for product variants was used in determining this configuration. The average makespan for processing a set of different predicted demands—derived from the expected demand—on this configuration was also calculated after simulating performance. The results from the MMGA and MCGA for a set of different problems are summarized in Table 18. A comparison the machine

requirements and makespan found using the two models is shown in Figure 35 and Figure 36, respectively.

Table 18: Summary of Results from MMGA and MCGA

Problem Number	Problem Description			MMGA Results		MCGA Results	
	Options	Machines	Products	Makespan (mins)	Machines	Makespan (mins)	Machines
1	11	8	40	1529	65	1753	62
2	12	9	60	1591	85	1641	79
3	10	7	32	1616	50	1813	47
4	9	8	24	1637	43	1873	38
5	9	8	24	1594	43	1679	41
6	10	7	36	1369	52	1518	48
7	7	6	12	1227	17	1512	13
8	9	6	24	1313	36	1488	34

The MCGA finds minicell configurations that require fewer machines than with the MMGA. However, it is noteworthy that the optimal design found using the MMGA requires only a modest increase in the machine capacity—six machines at the most. Increasing the machine capacity above the minimum required should help achieve lower makespan values.

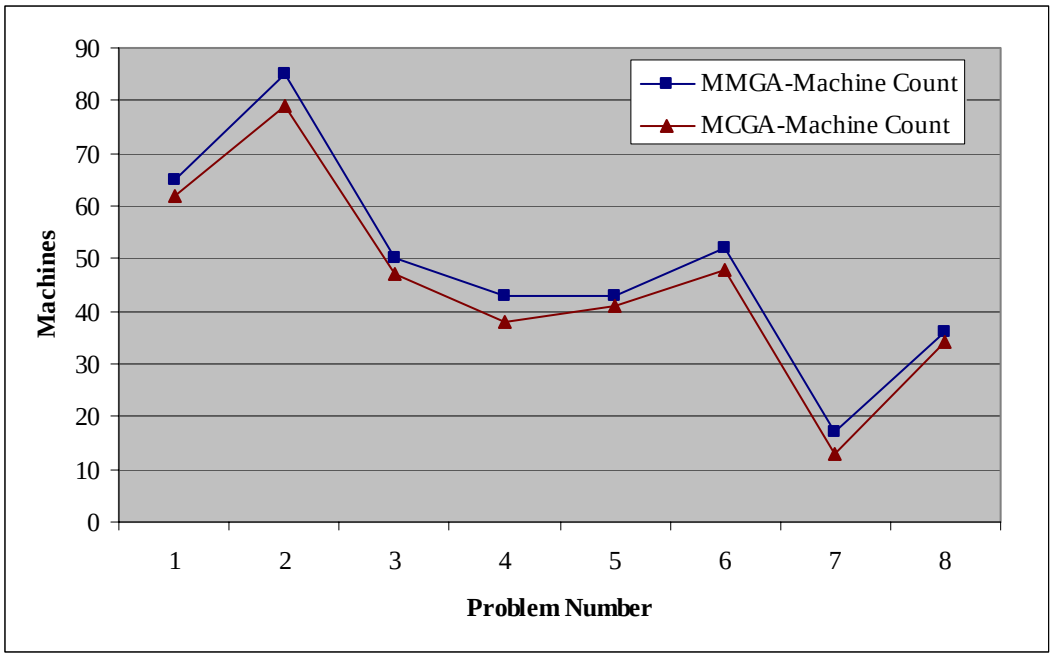


Figure 35: Machine Requirements for MMGA and MCGA Configurations

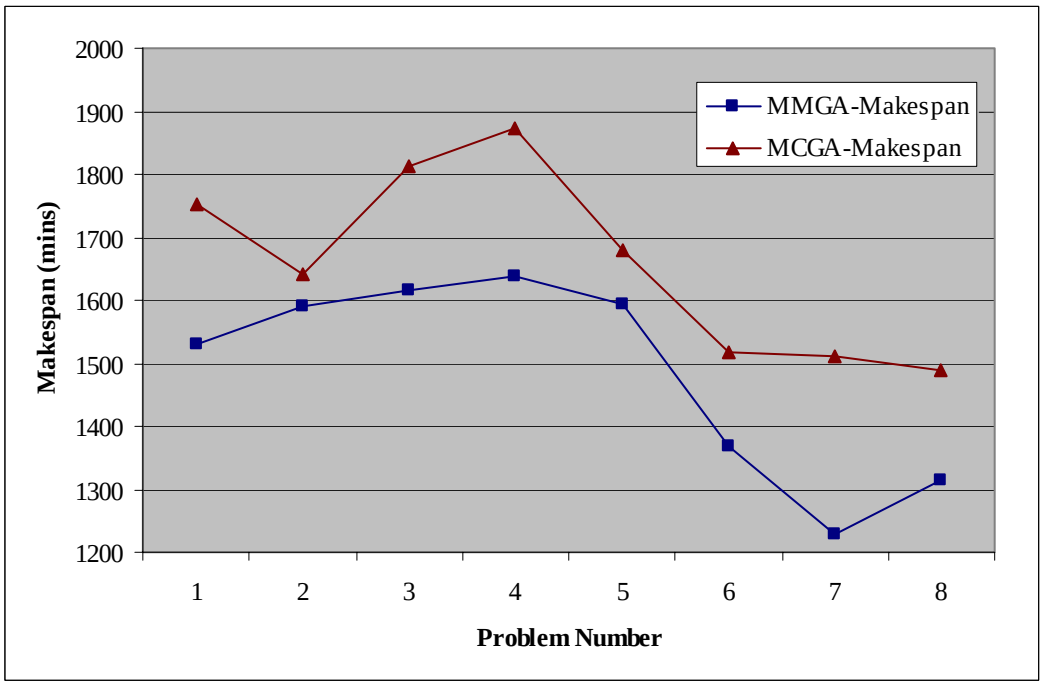


Figure 36: Makespan for MMGA and MCGA Configurations

As can be seen from Figure 36, the MMGA finds minicell configurations with lower makespan than by MCGA: this is achieved with only a slight increase in the machine count. Therefore, it can be concluded that the MMGA does not find minimum makespan minicell configurations by merely adding more machines into the system. The tradeoff to achieve a lower makespan configuration only involves the addition of a few more machines.

The cost of achieving lower makespan using the MMGA minicell configuration can be further analyzed by evaluating the type and cost of additional machines required in this design. For example, if the design requires a few more inexpensive machines—such as assembly units, work tables etc—the increase in cost will be minimal compared to the benefits that can be gained through reduced makespan. However, if the design requires costly equipment, a step-by-step analysis could be done to evaluate the incremental cost of adding machines and savings due to lower makespan. With this approach, the management will be presented with alternative designs that can be chosen based on budgetary constraints and operational requirements.

To illustrate differences in machine requirements, the MMGA and MCGA minicell designs for problem #6 (in Figure 35 and Figure 36) are shown in Figure 37. The problem involves designing a three-stage minicell configuration with a maximum of two minicells per stage. The product variants are generated by combining 8 options that require seven machine types for processing.

The minicell formations are shown by grouping and color-coding the options in the options-machine matrix to indicate their association to minicells in the different stages. The MMGA minicell design requires 52 machines whereas the MCGA model requires only 48 machines. The allocation of these machines to the minicells is also illustrated in Figure 37. The minimum makespan design (MMGA) requires four additional machines—one each of types B, C, D, and F. A benefit/cost analysis can be conducted to evaluate the performance in changing the minicell design from that given by MCGA to MMGA. Thus, by starting with the MMGA model but with MCGA generated machine counts, the reduction in makespan that can be achieved by adding machine types B, C, D, F, B &C, B& D, etc. can be analyzed. The benefit due to reduced makespan can be compared against the cost of adding machines in each of the different scenarios. The process enables evaluating which machines must be added first to increase the relative benefit.

MSGA Minicell Formation

Minicell Formation	A	B	C	D	E	F	G
11	0.22	0.77				0.63	1.56
12		1.98	0.37	1.2			1.73
14	0.57	1.91	1.2	0.04	0.47		0.77
15		1.75	1.63	0.46			0.43
16	1.18		0.77			1.78	1.48
19			1.44	0.08			
20	1.89	1.65				0.64	
13		1.57	1.63			1.79	
17		1.28	1.04	0.45			
18	1.25	0.06	1.06				
Machine Assignment	A	B	C	D	E	F	G
	5	10	7	3	1	4	7
	A	B	C	D		F	
	2	4	5	1		3	
Total Machines	7	14	12	4	1	7	7 = 52

(a)

MMGA Minicell Formation

Minicell Formation	A	B	C	D	E	F	G
11	0.22	0.77				0.63	
12		1.98	0.37			1.79	1.56
13		1.57	1.63	1.2			0.43
15		1.75	1.63	0.04		1.78	1.48
17		1.28	1.04		0.47	0.64	
18	1.25	0.06	1.06	0.08			1.73
19			1.44				0.77
20	1.89	1.65					
14	0.57	1.91	1.2	0.45			
16	1.18		0.77	0.46			
Machine Assignment	A	B	C	D	E	F	G
	5	11	9	2	1	6	4
	A	B	C	D			G
	2	2	2	1			3
Total Machines	7	13	11	3	1	6	7 = 48

(b)

Figure 37: Minicell Formation for Example Number 6

5.8. Analysis of MMGA and MCGA Minicell System Design Results

An examination of MMGA and MCGA results reveal the presence of multiple chromosomes (C1+C2) with same fitness function value. This implies the presence of *n-1* mapping from the coding space for the chromosomes to the solutions space [27], i.e.: multiple chromosome representations corresponding to a single solution. In order to evaluate the reasons and justification for the existence of such multiple chromosomes, the results of both GA's were analyzed further.

Several different chromosomes that represent alternate minicell configurations for the problem illustrated in section 5.2, MMGA analysis (page 128) are shown in Table 19 (C1 shown as machine types per stage and C2 shown separated into stages). The chromosomes represent three-stage minicell designs with a maximum of two minicells per stage. The minimum makespan chromosomes obtained through the analysis is shown in bold. The makespan and machine count for the designs represented by each chromosome are also given. All solutions—except the minimum makespan design—were obtained by running the MMGA model with a population of 10 chromosomes over 100 generations. A population size of 20 with 200 generations was used in obtaining the minimum makespan designs.

All except the minimum makespan solutions have identical machine type allocation between the stages. Further, all these chromosomes have identical option families in the first stage which has five machine types. However, the minicell formations in the second

and third stages appear to be completely different. Two of the chromosomes—*D* and *F*—require 29 machines while the others all require 31 machines.

Table 19: Alternate Chromosomes with Similar Makespan

Solution	Stage1	Stage2	Stage3	Machine Types per Stage			Machine Count	Makespan (mins)
A	1 1 1 2 1 1 2 1 2	2 1 2 2 2 2 1 1 1	1 1 1 1 1 2 2 2 1	5	1	1	31	1015
B	1 1 1 2 1 1 2 1 2	2 2 2 1 1 2 2 1 1	1 2 1 2 2 2 1 2 1	5	1	1	31	1015
C	1 1 1 2 1 1 2 1 2	2 2 1 2 2 1 1 2 1	1 2 2 2 1 1 1 2 2	5	1	1	31	1015
D	1 1 1 2 1 1 2 1 2	2 2 2 2 2 2 2 2 2	1 1 2 1 2 2 1 1 1	5	1	1	29	1015
E	1 1 1 2 1 1 2 1 2	1 2 1 2 1 1 2 2 2	1 1 1 1 1 1 1 2 2	5	1	1	31	1015
F	1 1 1 2 1 1 2 1 2	2 2 2 2 2 2 1 2 2	2 2 2 2 2 1 2 2 2	5	1	1	29	1015
J	1 1 1 2 1 1 2 1 2	2 2 2 2 1 2 2 1 2	1 2 1 1 2 1 1 2 2	4	2	1	31	995
K	1 1 1 2 1 1 2 1 2	2 2 1 2 1 1 2 1 2	2 2 2 1 1 1 1 2 1	4	1	2	31	995

To further illustrate the minicell designs represented by these chromosomes, the option-machine matrix for the problem is repeated in Figure 38.

		Machines						
		A	B	C	D	E	F	G
Options	11	1.02		0.57	0.84		1.9	
	12		0.2		0.75			1.2
	13			0.19	0.02			
	14	0.18				1.18		0.84
	15				0.09		0.09	
	16	1.65	0.06	0.86	1.27		0.02	
	17	1.73	0.05	1.22	1	1.58		1.06
	18	1.65			0.33		0.43	0.14
	19		0.67	0.89		1.08		

Figure 38: Option-machine Matrix for MMGA Experimentation Problem

Every gene in C2 indicates the assignment of an option to minicells within the corresponding stage in the configuration. However, the value of a gene is significant only if the option—corresponding to the gene—requires processing in that particular stage. For example, given the assignment of machine types between stages for chromosomes *A*-*F*, only options denoted by 11, 15, 16, and 18 require processing in stage 2; options 12, 14, 17, and 18 require processing in stage 3. Hence the genes corresponding to all the remaining options, in stages 2 and 3, are irrelevant; they have no effect on the configuration and therefore system performance. Therefore many alternate solutions can be derived by varying only these irrelevant genes. This is one reason for the presence of multiple chromosomes that give similar makespan. When only the significant genes are considered, chromosomes *B* and *E* result in the same minicell configuration; similarly, chromosomes *D* and *F* generate identical configurations.

However, even after disregarding the irrelevant genes, there still exist different chromosomes—and therefore minicell designs—that generate the same makespan (*A*, *B*, *C*, *D*, *J*, and *K*). These chromosomes demonstrate the n-1 mapping phenomena in the MMGA. Therefore, in the presence of multiple configurations that generate the same objective function values, additional criteria may have to be considered in evaluating them. Being able to achieve the same makespan with fewer machines reduces the cost. This is one criterion to eliminate duplicate solutions. However, there can still be alternate configurations with the same makespan and machine count. A third performance measure may be necessary to evaluate the design such situations.

As described previously in Section 3.2.6, the flow time to process product variants in each configuration were used as a third measure to evaluate the behavior of systems represented by similar chromosomes. The variation of flow time in the configurations given by chromosomes *A-D* is shown in Figure 39. The flow time for the minimum makespan designs (*J* & *K*) are shown separately in Figure 40.

The sequence of processing the product variants may not be identical in the different configurations shown by the chromosomes. Therefore the figures show the flow times for product variants in the sequence they exit the last minicell in the final stage of the configuration.

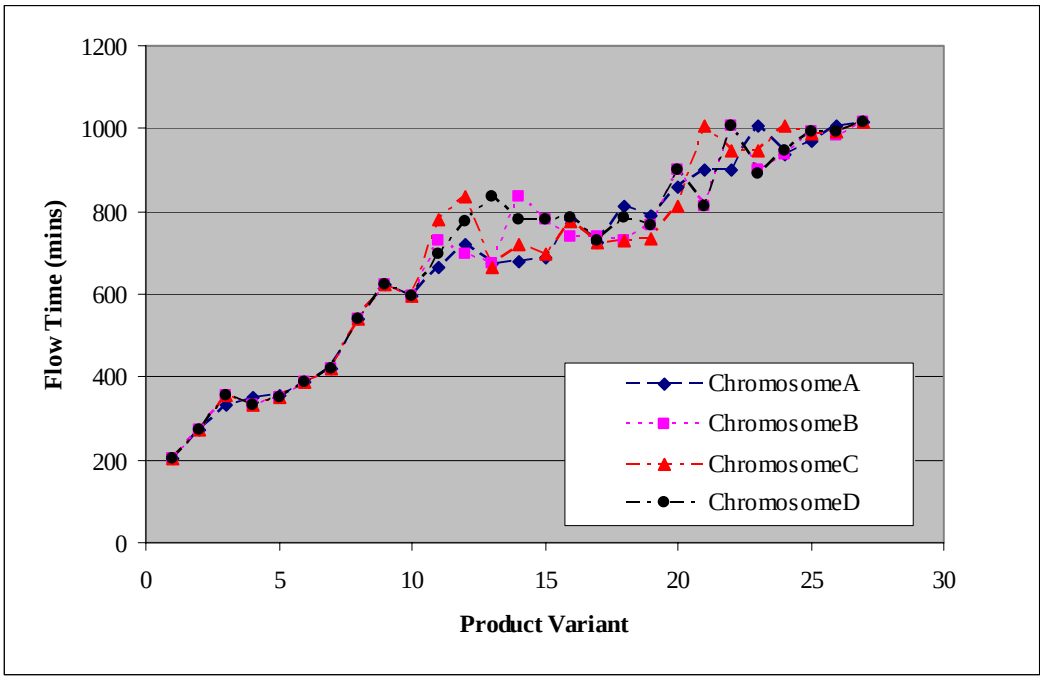


Figure 39: Flow Times for Chromosomes A-D

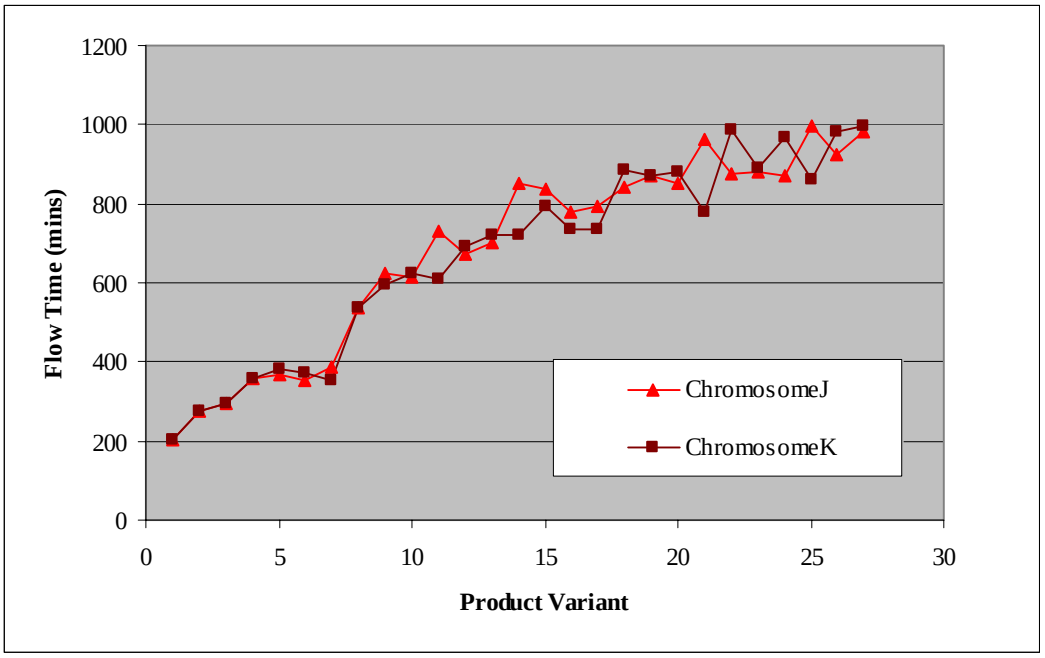


Figure 40: Flow Times for Minimum Makespan Chromosomes J & K

Figure 39 and Figure 40 reveal differences in flow time for product variants in configurations with same makespan. The variation in flow time is higher in some configurations than in others. The average flow time for the configurations represented by these chromosomes is shown in Table 20.

Table 20: Average Flow Time for Chromosomes

Solution	Makespan (mins)	Average Flow Time (mins)
A	1015	674
B	1015	678
C	1015	688
D	1015	684
J	995	612
K	995	598

Therefore, different minicell configurations can have the same makespan and machine count but dissimilar flow times to process the product variant demand. Therefore, a third performance measure—flow time—can be used to select the minicell system design that can give better overall performance. However, if the variation between these different configurations is less, selecting based on makespan and machine count will still be satisfactory.

A set of identical minimum machine capacity chromosomes (found using MCGA) for the same example are shown in Table 21. The makespan to process the predicted demand on the respective configurations is also shown. The results are presented graphically in Figure 41.

Table 21: Chromosomes with Equal Minimum Machine Requirements

Solution	Stage 1	Stage 2	Stage 3	Machine Types per stage			Machine Count	Makespan (mins)
P	222212222	112111211	222112211	2	4	1	26	2942
Q	212221112	111211121	212222122	1	3	3	26	2181
R	221111121	222222222	212212111	1	5	1	26	2164
S	221111212	111111111	121211222	1	5	1	26	2056
T	122212211	121222222	221222222	1	3	3	26	1798
U	111111111	212222122	111212121	4	2	1	26	2747

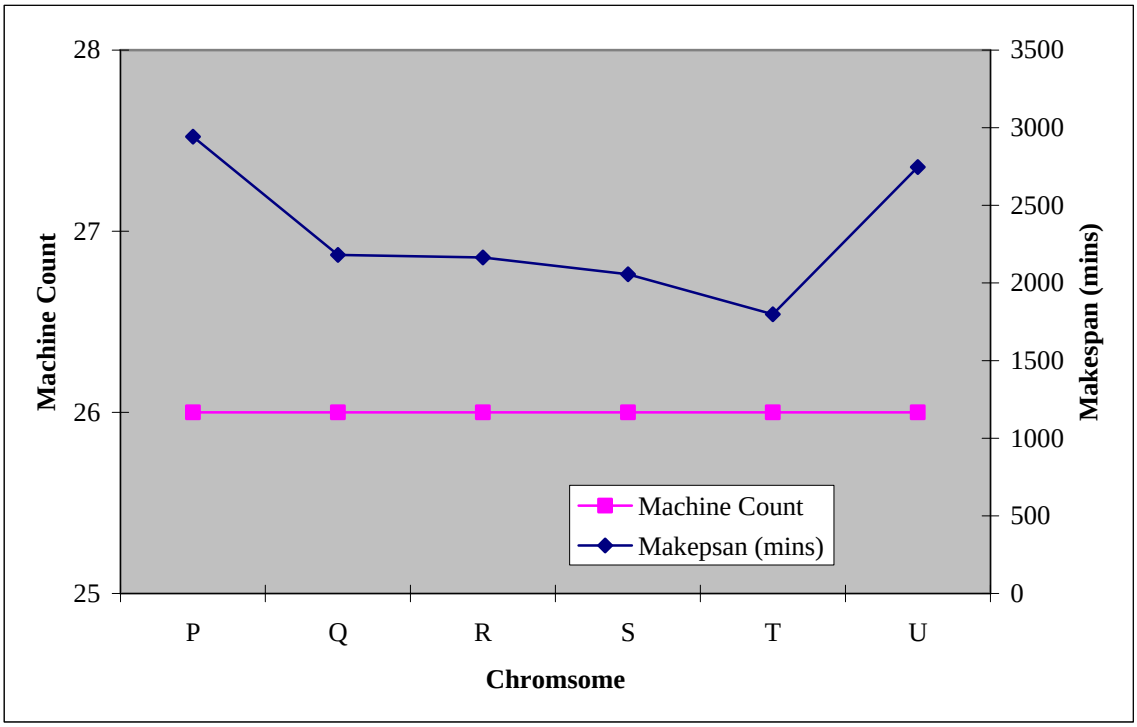


Figure 41: Variation of Machine Count and Makespan for MCGA Chromosomes

The MMGA finds alternate configurations with identical makespan and machine requirements as determined previously. However, alternate minimum machine

chromosomes found using the MCGA show very diverse values for makespan. Therefore, it appears that the MMGA is very effective in finding minimum makespan minicell designs without adversely effecting the total machine requirements significantly.

5.9. Comparison of Minicells and Traditional Cells

Traditional manufacturing cells are formed by creating product families and grouping the machines required to process it into a single cell. Minicells, on the other hand, are dedicated to option families. They are intended to provide greater flexibility to handle a dynamic product mix and changes in quantity demanded for product variants. The minicells were developed by extending and adapting the concepts of cellular manufacturing to meet the specific requirements of mass customization. Therefore, it is important that the performance of minicells be compared with traditional cells to evaluate its merits. The two types of cells are compared in this section and studied to analyze their performance under dynamic demand situations.

5.9.1. Traditional Cell Formation

To maintain consistency in the approach used to develop both types of cells, a separate GA was developed for traditional cell formation. The differences between the MMGA and the traditional cell formation GA (TCGA) are described below.

Chromosome Representation

The chromosomes in the TCGA indicate the assignment of product variants to the traditional cells. Therefore the chromosome is represented by *m* genes, one for each

product variant. The value of the gene indicates the traditional cell to which the product variant is assigned. A chromosome for a problem where two traditional cells are formed to process ten product variants is illustrated in Figure 42.

Product Variant	1	2	3	4	5	6	7	8	9	10
Chromosome	2	2	2	1	2	1	2	2	1	1

Figure 42: Chromosome Representation for TCGA

Accordingly, product variants 4, 6, 9, and 10 are assigned to the first traditional cell and the remainder is assigned to the second.

Crossover and Mutation Strategies

A single cut point crossover strategy, as illustrated in Figure 18 (page124) previously, is used with each pair of parent chromosomes selected for mating. The cut point is randomly selected and genes to the right of it are exchanged between the parents.

Mutation is applied independently to randomly selected genes depending on the mutation probability. The gene chosen for mutation is then replaced by changing its value to one of the remaining cells to which the product variant can be assigned (see Figure 21 in page 127 for illustration). The crossover and mutation operations do not generate infeasible

chromosomes except when no product variant is assigned to one traditional cell. In such situations a repairing strategy is applied to randomly select a gene—product variant—and to assign that to the vacant cell.

Fitness Function

The makespan to process the product variant demand in the traditional cells is taken as the fitness value of the chromosome. The TCGA uses the expected product variant demand to first estimate machine requirements for the cells. The predicted demand is then scheduled for processing by applying the CDS heuristic to determine makespan. Once the fitness values for all chromosomes have been calculated, reproduction probabilities are computed in a manner similar to that for other GAs described previously.

5.9.2. Developing Traditional Cell Configuration

The optimal traditional cell configuration for a problem is found by using an approach similar to that for minicells. Alternate predicted demand scenarios (s=4) are developed based on a given expected demand for product variants—assuming a normal distribution with mean equal to expected demand and a standard deviation of 10% of expected demand. First, traditional cells are formed for each of these demand scenarios using the TCGA (i.e.: four different configurations). Thereafter, a separate set of fifteen (z) predicted demand scenarios are generated and tested in these configurations through simulation to compute makespan. The average flow time is also calculated. The

configuration that generates the lowest average makespan—same as for minicells—is selected as the best traditional cell design.

5.9.3. Comparison of Traditional Cells and Minicells

A comparison of using traditional cells and minicells is described in detail for the example used to illustrate the MMGA analysis previously in Section 5.2 in page 128.

Four different predicted demand scenarios were created and the MMGA and TCGA were used to find the best configuration through each approach. Both GAs were run with a population size of 10 chromosomes for 100 generations. A mutation probability of 0.1 was maintained. A three-stage minicell configuration with 2 minicells per stage and traditional cellular design with two cells were found using the GAs. Simulation was then used to select the robust design after simulating performance for fifteen predicted demand scenarios. The machine requirements, average makespan, and average flow time on the best configuration for each type of cellular design is shown in Table 22.

Table 22: Performance Measures in Traditional Cells and Minicells

	Configuration	
	Traditional Cells	Minicells
Machine Count	32	31
Average Makespan (mins)	1209	1214
Average Flow Time (mins)	791	780

The traditional, two-cell configuration has a very slightly lower (0.4%) makespan compared to the minicell design. However, the average flow time is lower (2.4%) in the minicell configuration. It was expected that separating the machines into smaller cells to create minicells would increase the total machine requirements compared to traditional cells. To the contrary, as can be seen from the results here, the minicell configuration requires one less machine than the traditional cells.

To investigate the variation in makespan and average flow time with the two types of cellular designs, these values for the 15 predicted demand scenarios were compared. The variation is shown in Figure 43. The makespan and average flow time appear to be more consistent for traditional cells than with the minicell-based design. The makespan turns out to be higher with minicells than with traditional cells more often than the average flow time, thus explaining the cause for values shown in Table 22. Also, the average flow time, though more dynamic than in traditional cells, is lower in the minicells for most demand scenarios.

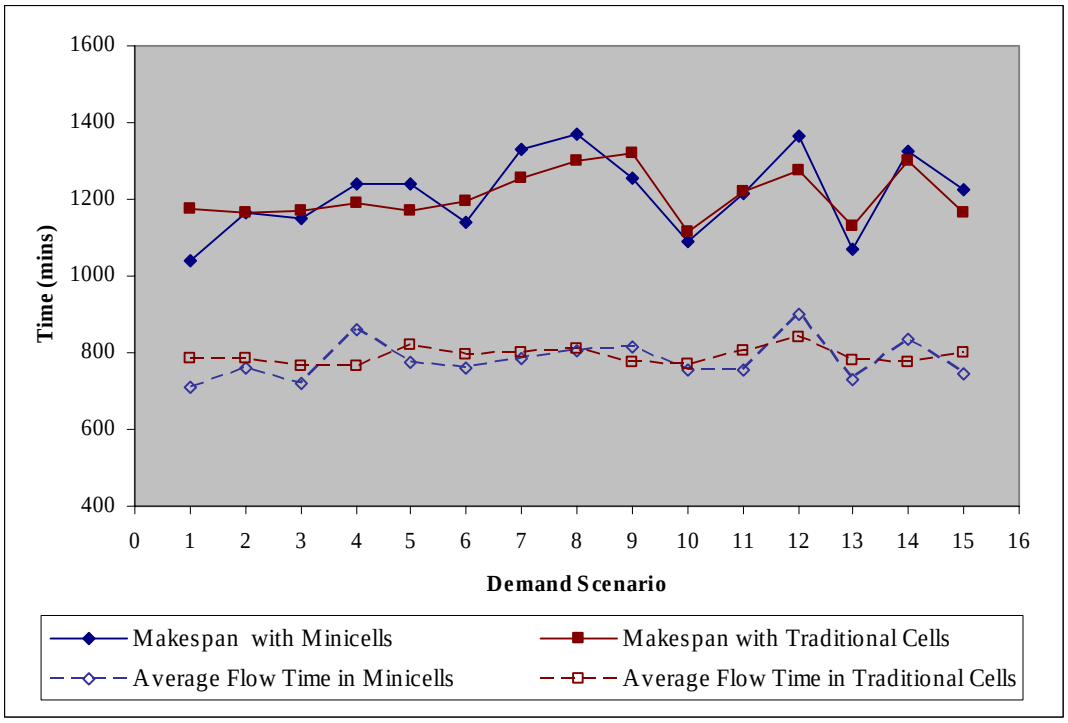


Figure 43: Comparison of Makespan and Average Flow Time

These results indicate that minicells perform slightly better in achieving lower average flow time and show comparable performance with respect to makespan with a lower machine requirement.

The cells in traditional cellular manufacturing are equivalent to a single-stage flow shop and therefore the CDS heuristic can be used to find satisfactory schedules for minimizing makespan. However, the minicell configuration is more complex—several minicells are organized into multiple stages. The use of CDS & FCFS was an effort to extend the strategy developed for a single-stage flow shop to the minicell design. Therefore, the

results for makespan obtained by using this procedure may not be optimal; better scheduling procedures—if developed and used—could generate even better results with the minicell configuration.

The schedules in each configuration were further analyzed to investigate the time each product variant spends in the system, compared to the actual processing time. The composition of the completion time for each product variant in the traditional cells and minicells is shown in Figure 44 and Figure 45, respectively.

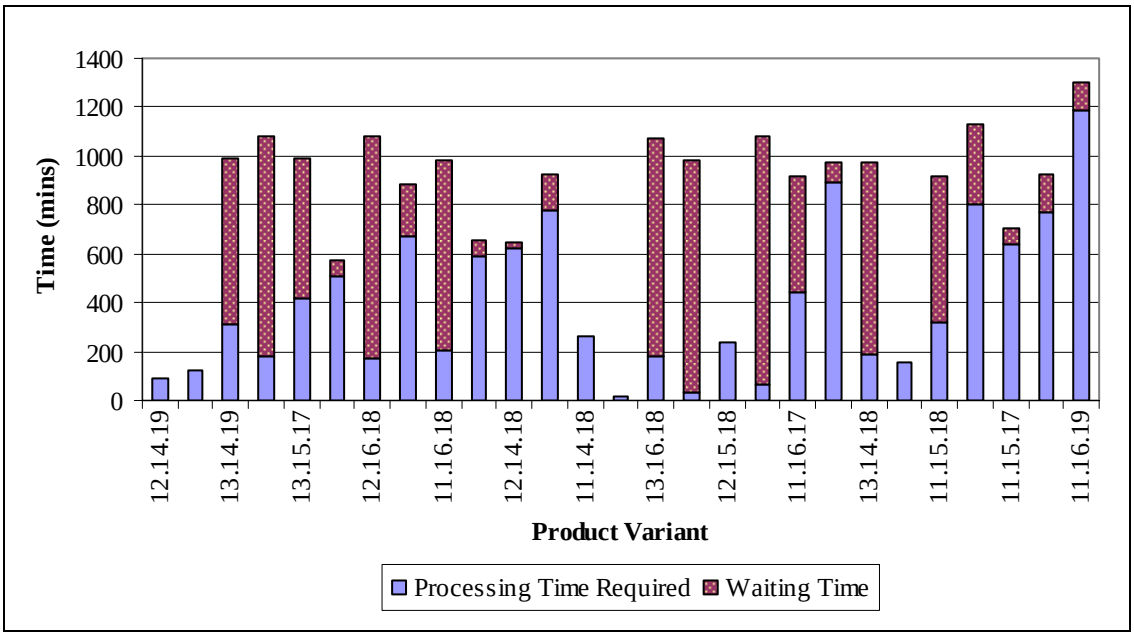


Figure 44: Composition of Completion Time in Traditional Cells

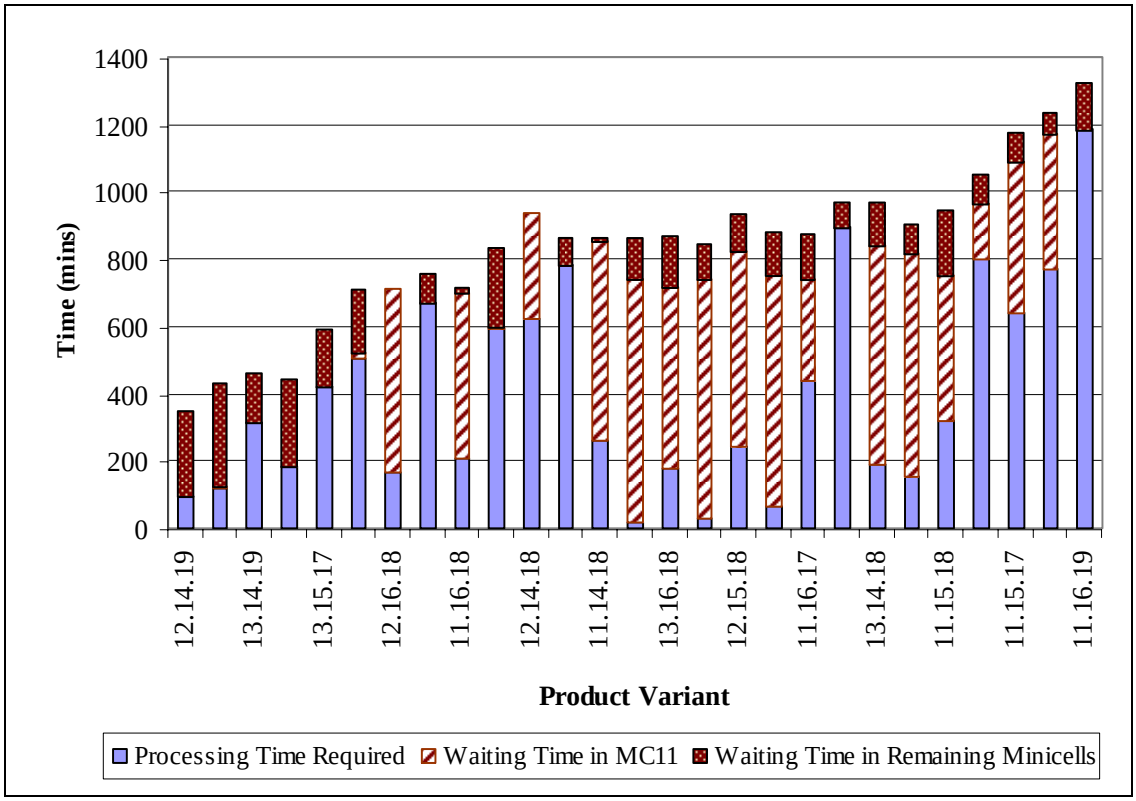


Figure 45: Composition of Completion Time in Minicell Configuration

With the traditional cell configuration, several product variants are completely processed without any waiting. Because the makespan from applying CDS is driven by the product variant with largest processing requirements, several other product variants which require less processing have to remain in the system for longer.

For the minicell configuration Figure 45 shows the waiting separated into waiting time in the first minicell (MC_{11}) and waiting time in the remaining minicells. Here, all product variants have to wait for some amount of time before leaving the system. Some product

variants do not require waiting in MC_{11}, for the same reason described previously for traditional cells. However, for most of the product variants a large percentage of the completion time is spent waiting in the first minicell. For more than 60% of the product variants (12 out of 19) that have to wait in MC_{11}, the total time required for processing is less than 50% of the time spent within the system. For three product variants (11.14.19, 13.16.19, and 13.15.18) total processing time is less than 10% of their completion times.

These values reflect the potential for improving the scheduling method used in minicells to generate better performance. Though achieving a better makespan may be difficult, there appear to exist opportunities to reduce the flow time for individual product variants, while trying to not adversely affect the makespan.

Therefore, based on the results presented, minicells appear to generate similar—if not better with respect to flow time—performance compared to traditional cells. Also, the performance of minicells could possibly be further improved by devising a scheduling strategy that can accommodate the characteristics of the minicell design better.

5.9.4. Robustness of Traditional Cells and Minicells

High variability in quantity demanded as well as product mix are characteristic of mass customization manufacturing. The use of the option-machine matrix to create smaller minicells—in several stages—dedicated to option families is intended to provide more flexibility to accommodate such variations in demand. To evaluate the sensitivity of the

traditional cells and minicells to changes in predicted product variant demand, the following analysis was conducted.

In the analyses described thus far, the predicted demand scenarios were created by assuming a normal distribution about the expected demand with a standard deviation equal to 10% of expected demand. To evaluate system performance with more dynamic demand, new configurations were developed by increasing the standard deviation to 25% of the demand. The respective GAs and simulation were used to find these configurations. The results for machine requirements, average makespan, and average flow time on the two types of systems are shown in Table 23. The variation of makespan and average flow time from the simulation is shown in Figure 46.

Table 23: Summary of Results with Higher Demand Variance

	Configuration	
	Traditional Cells	Minicells
Machine Count	31	31
Average Makespan (mins)	1300	1302
Average Flow Time (mins)	876	764

The makespan obtained with the traditional cells is similar to that with minicells. Also, both configurations require the same amount of machines to process the expected product variant demand. However, the minicells are able to process the demand with lower flow time than traditional cells.

Observation of the results across the demand scenarios reveals that the makespan with minicells is higher than with traditional cells only in six instances. On the other hand, the average flow time in the minicell configuration is consistently lower than in traditional cells.

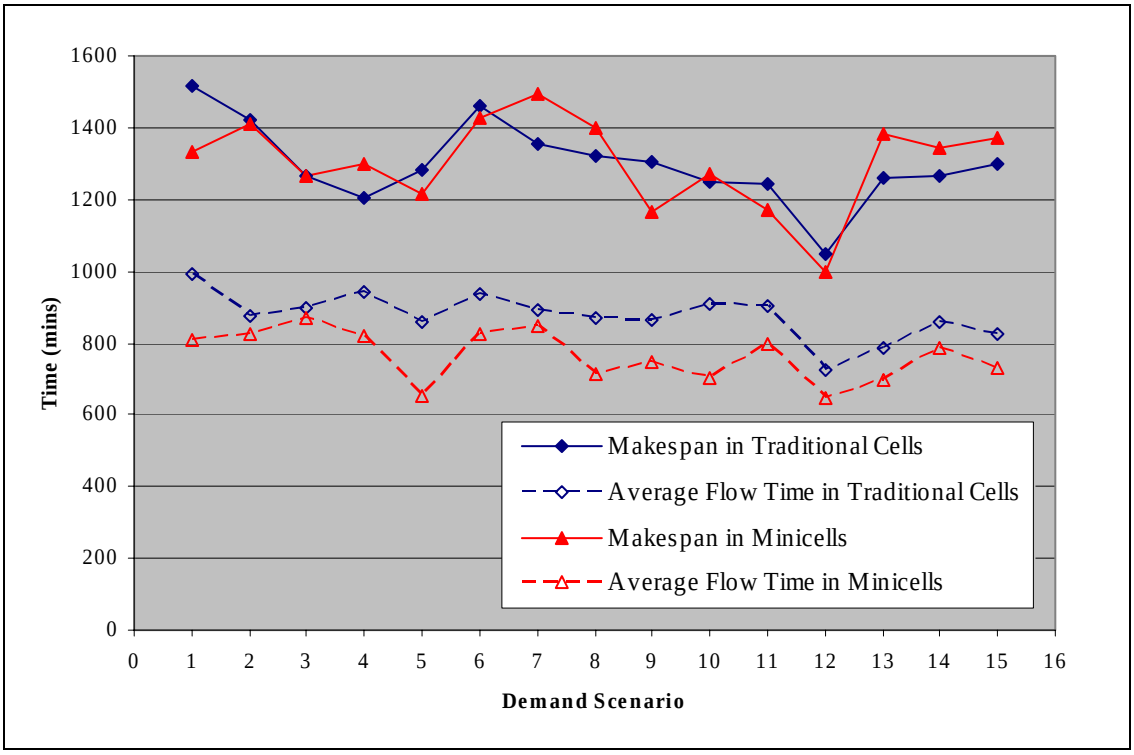


Figure 46: Makespan and Average Flow Time with Higher Demand Variance

These analyses reveal that the minicell configuration performs better particularly when changes in predicted demand are more dramatic. The traditional cells, on the other hand, appear to perform as well in situations where the variation in predicted demand is less.

Based on these analyses it can be concluded that the minicell-based configuration is better for mass customization manufacturing environments where product demand is very dynamic.

5.9.5. Improving the Minicell Performance

Analyzing the completion times in the minicell configuration revealed that many product variants spend a large amount of time waiting to be processed in the first minicell. If the amount of time spent waiting in the first minicell could be reduced, that may contribute to achieving even better performance with minicells. One approach to accomplish this is to develop a better strategy for scheduling in the minicell configuration. A second approach would be to increase the capacity in the first minicell so that product variants do not have to wait as long to be processed in that minicell. Further analysis was conducted to evaluate minicell system performance if the latter approach is adopted. The experimentation conducted and the results obtained are discussed below.

The MMGA estimates the capacity required to process the expected product variant demand on a configuration represented by each chromosome. This capacity is then used to schedule the predicted demand. The MMGA was modified to evaluate the effect of adding more capacity to the first minicell as follows. The initial capacity planning is conducted as done previously. Thereafter the capacity of each machine type in the first minicell is increased by one unit. For example, if there are two machine types with 2 and 3 machines each in the first minicell, one more is added to each type to increase the capacity to 3 and 4 units, respectively. The capacity in the remaining minicells is kept

unchanged. The new machine capacities are then used to schedule the predicted demand and calculate the makespan.

The same example used previously to compare the performance of minicells and traditional cells were tested with the modified MMGA. Four different designs were found by running the GA for 100 generations with a population size of ten chromosomes. Simulation was then used to select the most robust design considering the fifteen predicted demand scenarios. The predicted demand for this analysis were the same values used previously (assuming a standard deviation equal to 10% of expected demand). The results obtained are summarized in Table 24.

Table 24: Results with Higher Minicell Capacity

	Configuration		
	Traditional Cells	Minicells	Minicells with more Capacity
Machine count	32	31	35
Average Makespan (mins)	1210	1214	1208
Average Flow Time (mins)	792	780	661

Increasing the capacity in the first minicell requires four more machines for the minicell configuration. Adding the machines helps achieve a makespan that is better than with the traditional configuration. The improvement in average flow time achieved by increasing the capacity is very significant. The total benefit—in terms of reduced makespan and

average flow time—that can be gained by adding capacity would far outweigh the cost of adding a few more machines to the configuration. These results are very encouraging and demonstrate the potential to achieve much better performance by using a minicell configuration for mass customization.

5.10. Heuristic Procedure for Minicell System Design

One other objective in this research was developing heuristic procedures to design the minicell configuration. The heuristics are intended to enable (a) selecting optimal cutoff points for creating stages, and (b) forming option families and minicells within each stage. The approach followed to investigate heuristic development and the findings are discussed in this section.

Data mining is the process of analyzing data to identify patterns and relationships. Different tools such as data visualization, case-based reasoning, and neural networks are used to identify hidden patterns in data. Identifying relationships between the inputs used for the design and the final minicell configuration developed is useful for heuristic development. Such relationships will provide insights to extract case-based rules to develop the minicell system for a given situation. Therefore, data mining through visualization was used initially to analyze minicell formation data.

The first step in heuristic development is forming rules to identify cutoff points that would separate the option-machine matrix into sub-matrices depending on the number of stages required. To attempt this, best performing minicell configurations were first

developed for a set of examples using the MMGA and simulation as described previously. The number of machines and options in these examples varied between 5 to 14 and 6 to 12, respectively. The number of stages required in the final configurations varied from two to four.

Information about the option-machine matrix, its density (number of '1' s in the matrix divided by number of 0's and 1's in the matrix) as well as the assignment of machine types to stages in the final configuration, the total number of machines per stage, percentage of processing in each stage, and the densities of the sub-matrices were then analyzed using data visualization tools. A comparison of machine types assigned to each stage, the densities of sub-matrices, and the percent of processing carried out in each stage for the examples is shown in Figure 47, Figure 48, and Figure 49, respectively. These results, separated based on the number of stages considered in each example, are shown in APPENDIX I: Comparison of Matrix Densities.

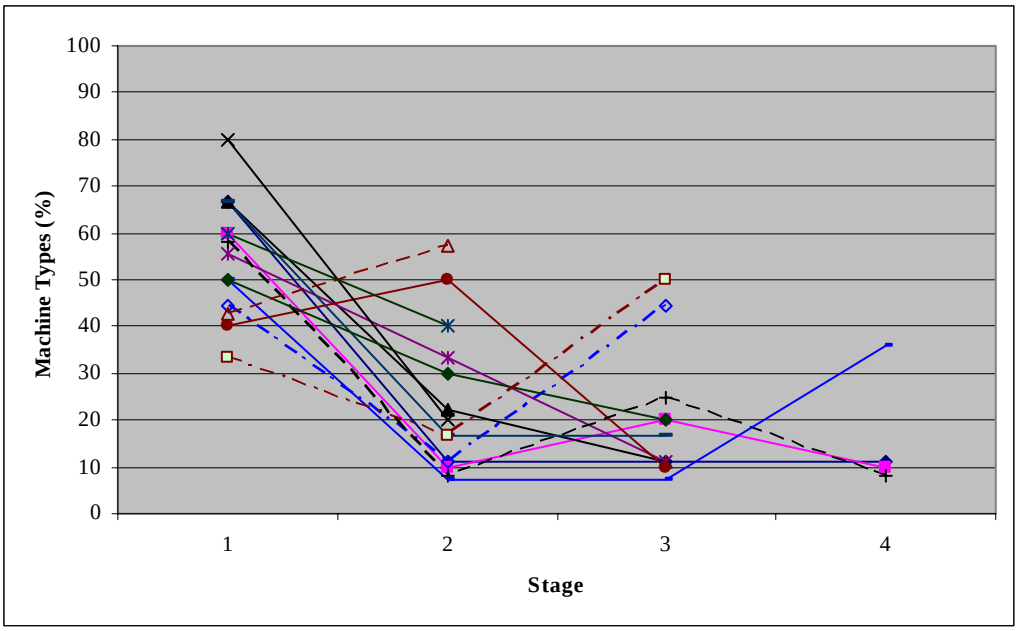


Figure 47: Percentage of Machine Types Assigned to Each Stage

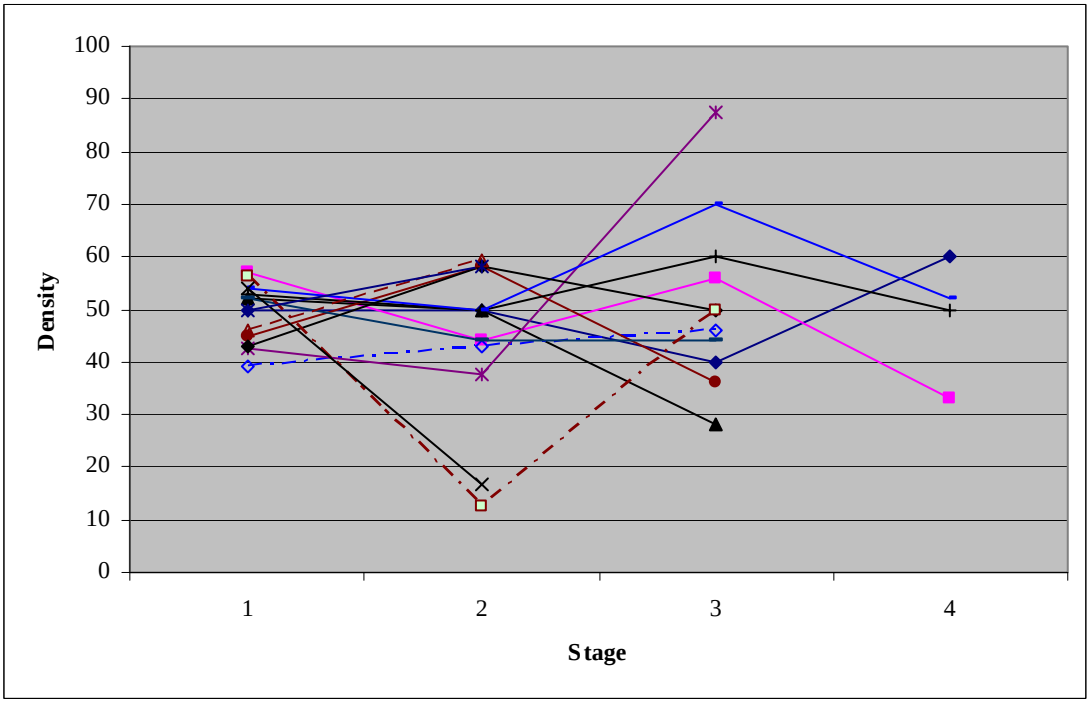


Figure 48: Densities of Sub-matrices in Each Stage

As can be seen from Figure 47 and Figure 48 the number of machine types assigned to each stage do not appear to have any relationship to the density of the sub-matrix in each stage. Both parameters appear to vary independently and do not provide any indication for identifying why the specific cutoff points were chosen. The option-machine matrices for the examples were also visually analyzed to identify possible patterns around cutoff points chosen; for example, if the matrix is separated adjacent to machine types used very frequently, less frequently, and so on. However, no identifiable relationships were found for the examples evaluated. The density of the sub-matrices varies significantly even between examples having the same number of stages (APPENDIX I: Comparison of Matrix Densities). Therefore, it appears that the density of sub-matrices do not provide any significant information to aid in determining cutoff points.

The percentage of machine types and the amount of processing in each stage show a fairly comparable variation—greater the machine types assigned to a stage, the percentage of processing done within is also likely to be larger. However, since they both follow the same pattern, the machine types assigned to a stage or the processing done within do not provide any insights on how the option-machine matrix can be separated into the stages.

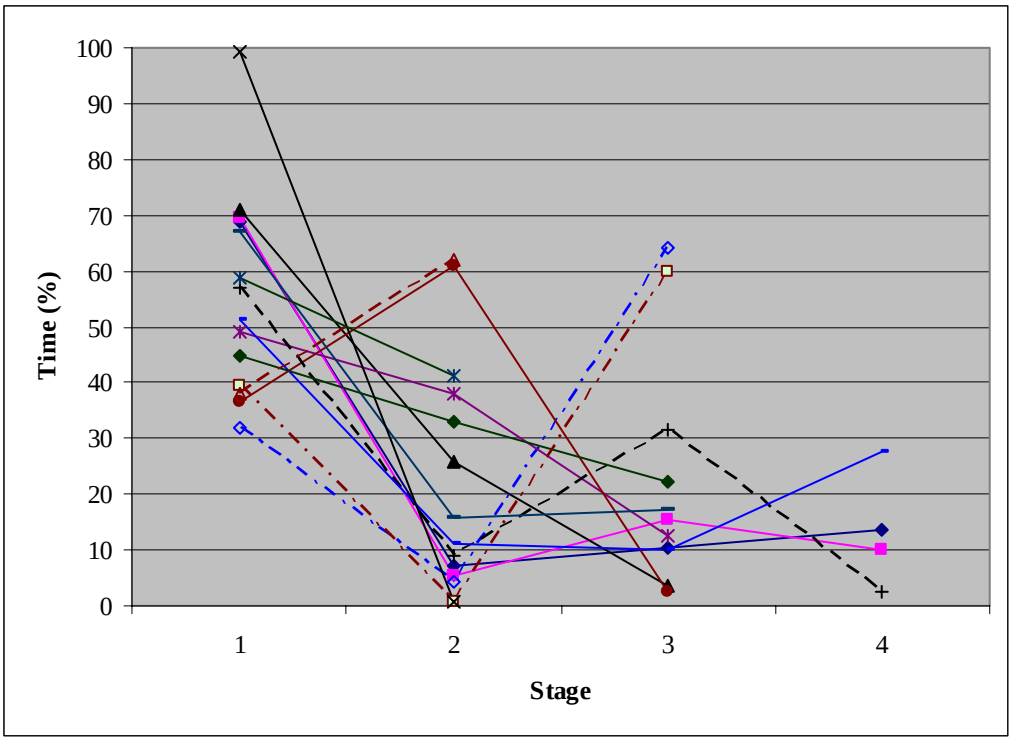


Figure 49: Percentage of Total Processing Assigned to Each Stage

Most of the examples evaluated above have different numbers of options and machine types. This complicates the information elicitation to identify patterns for developing heuristic procedures. Therefore, in order to simplify the search process and reduce the number of variables to be considered, data mining was again performed for another set of examples. This time, the dimensions of the option-machine matrix as well as the number of stages in the minicell configuration designed were held constant for all examples. However, the process plans for options and the demand for product variants were allowed to vary. A comparison of machine types assigned to each stage and the density of the sub-matrices for four such examples is shown in Figure 50 and Figure 51, respectively.

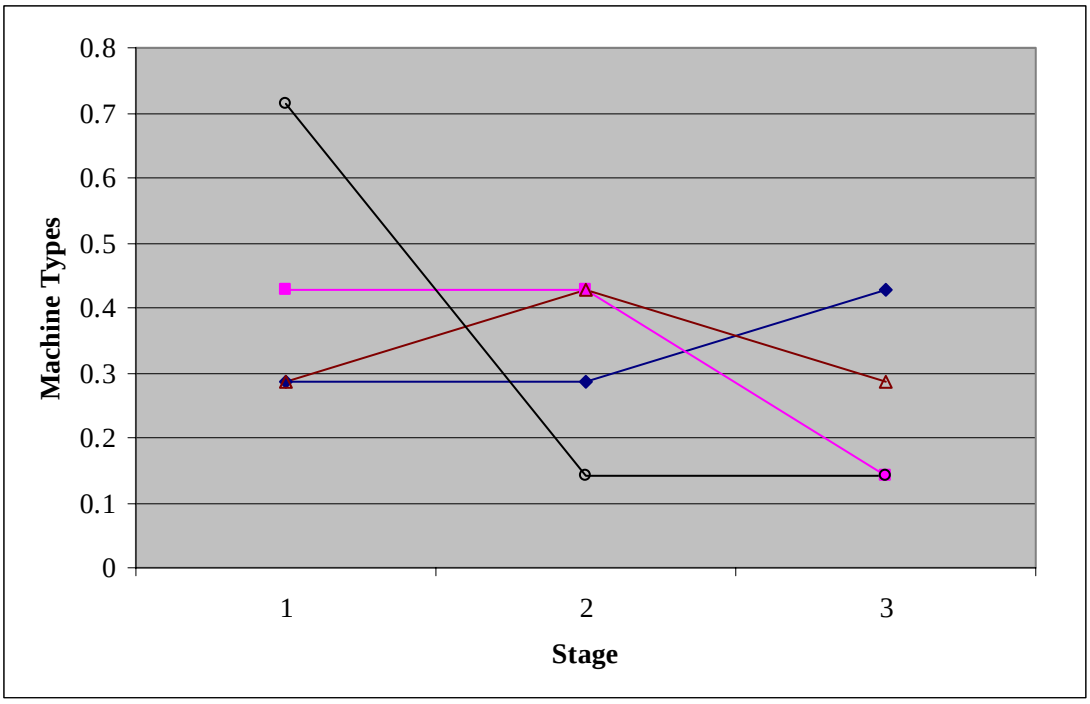


Figure 50: Comparison of Machine Types in Stages

As can be seen from these figures, no relationship about machine type assignment to stages is evident from the sub-matrix density. The percentage processing time in each stage showed a pattern similar to that for machine types. The results indicate a very high variation between the different parameters making it difficult to identify any patterns for use in developing heuristics.

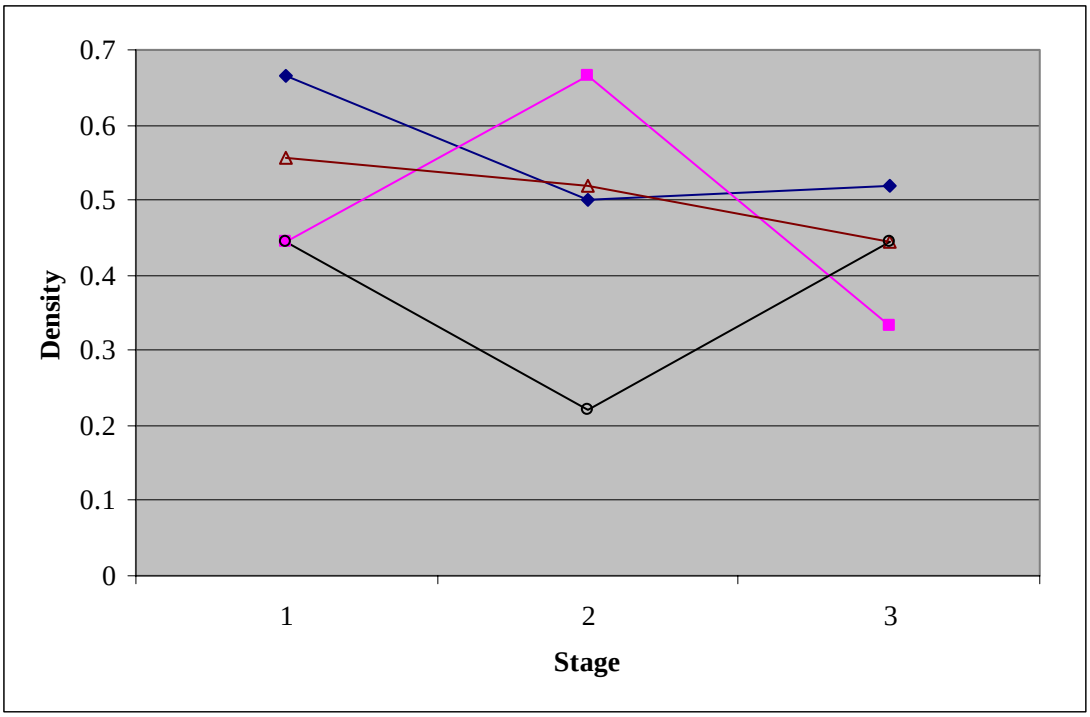


Figure 51: Density of Sub-matrices

Gandhi [26] explored the prospect of extracting rules for job-shop scheduling through inductive logic programming. He concluded that the schedules developed for different problems were too varied to successfully identify patterns through data mining. With minicell formation, the task is made even more complex due to the multi-stage configuration and the large number of variables involved in the design—number of options, their processing requirements (machines, times, and sequence) etc. The difficulty of deriving rules for minicell development is imminent from the preliminary analysis conducted in this study. Therefore, further analysis must be conducted to evaluate the possibility of forming heuristic procedures for minicell system design by identifying the

parameters that have the greatest impact on determining the cutoff points, and minicell formation.

6. FURTHER EXPERIMENTATION WITH GA

All the experiments conducted thus far were done using the MMGA model with crossover and mutation (C+M) strategies. Crossover was applied to all pairs of parents selected for mating whereas mutation was applied independently to randomly chosen genes. The mutation probability applied was 0.1. Additional experimentation was conducted to evaluate the performance of the MMGA with different crossover and mutation strategies. A separate multi-objective genetic algorithm—combining the two objectives of minimizing makespan and machine count—was also tested for minicell formation. The results of these analyses are described in this section.

6.1. MMGA Model with Different Genetic Operators

Further testing was conducted to evaluate the performance of the MMGA when using crossover only (CO) or mutation only (MO) strategies. With the CO model, the parent pairs selected for mating were only subject to crossover. In the MO model, parent chromosomes do not go through crossover. Instead in every chromosome, independently selected genes are subject to mutation based on the mutation probability (p_m).

The MMGA model with CO and MO strategies were run for six trials of five replications each with a population size of 10 chromosomes at 100 generations. The mutation probability used in the MO model was 0.1. Figure 52 shows the minimum makespan obtained for each trial and the overall average makespan with C+M, CO, and MO strategies.

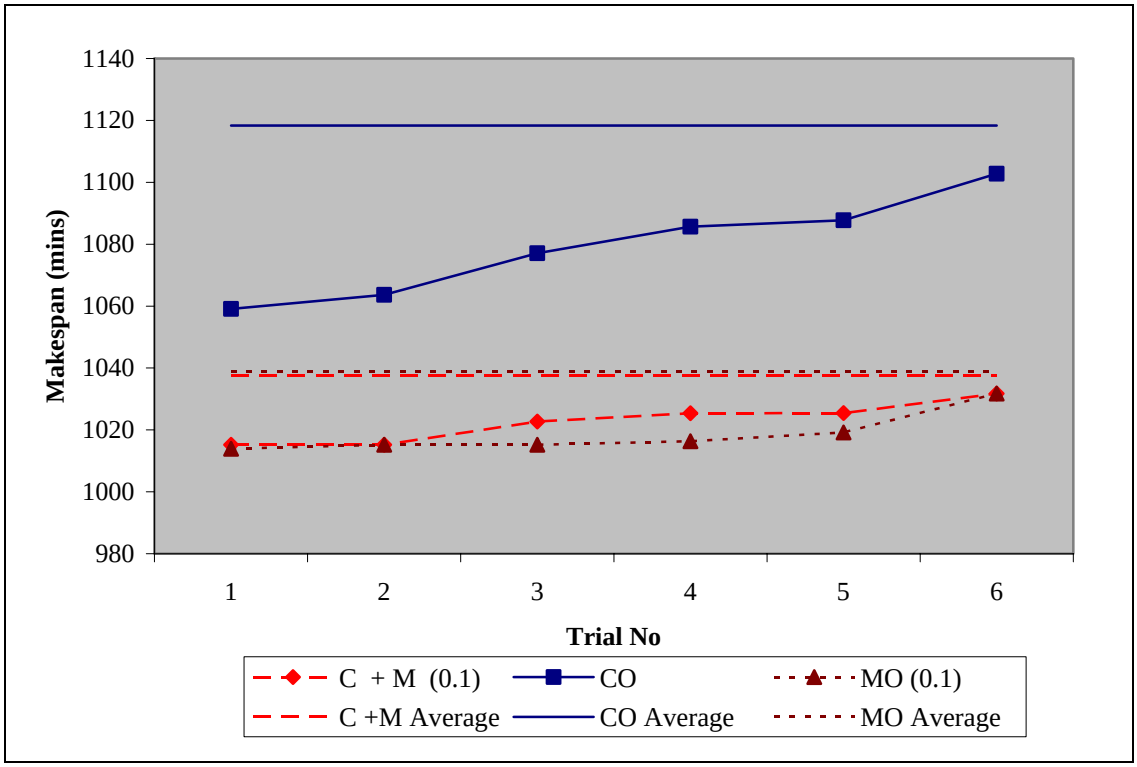


Figure 52: Comparison of Results for Different Strategies

The results reveal that the MMGA models with C+M or MO strategies consistently produce better solutions than with CO. The results of the two former strategies are very similar; using MO generates minicell configurations with lower minimum makespan than with C+M in three trials. However, using C+M produces solutions that on average have lower makespan than with MO. Therefore, based on this experimentation, it can be concluded that using the MMGA model with CO will not be effective in finding solutions to the minicell system design problem.

To further evaluate the effectiveness of using the C+M and MO strategies the models were tested with a mutation probability (p_m) of 0.3. A comparison of results at p_m= 0.1 and p_m = 0.3 are shown in Figure 53.

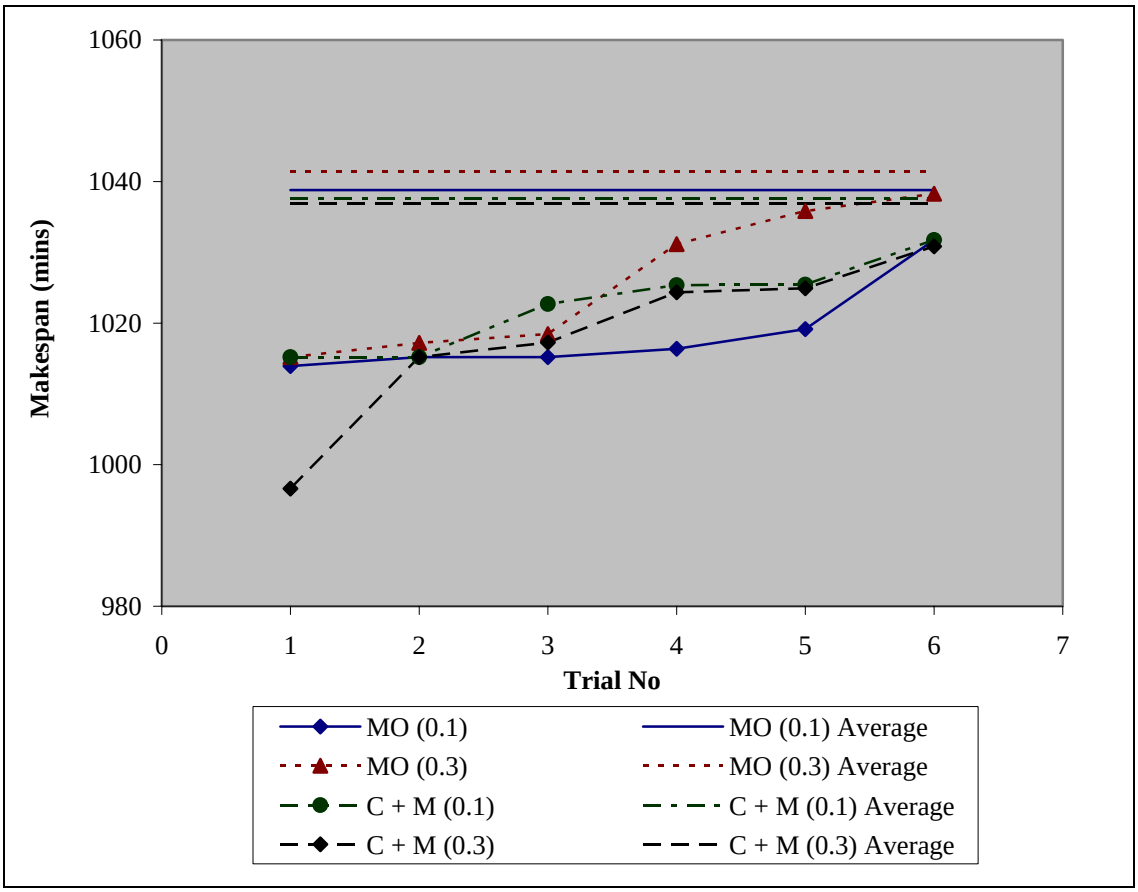


Figure 53: Comparison of Results for C+M and MO Strategies (p_m = 0.1 and 0.3)

Using the MMGA model with MO at a higher mutation probability (p_m=0.3) generates designs with higher makespan than with p_m=0.1. However, an interesting variation is

apparent when the MMGA model with C+M is used with p_m=0.3. This model generates minicell designs that are better—or at least as good—than those found using C+M with p_m=0.1 in all trials. However, the overall average from all trials with p_m=0.1 and p_m=0.3 are almost identical for C+M.

The results of these experiments are too varied to conclude which strategy—MO or C+M—must be used with the MMGA. Though using higher probabilities of mutation with the C+M strategy appears to generate better results, similar results are not found when MO is used with the same probabilities. Therefore, it is difficult to conclude whether using mutation only has a greater impact on finding better solutions. Previous analyses in this section revealed that using CO is not effective. Hence, further experimentation is necessary to evaluate if both crossover and mutation (C+M) or mutation only (MO) must be used in the MMGA.

6.2. Multi-Objective Optimization for Minicell Formation

In the MMGA used for all the analyses in this research, the makespan to manufacture the predicted product variant demand, with the machine capacity for the expected demand, was taken to be the objective function. Therefore, the MMGA determines the machine count that is required to achieve the makespan as part of the solution to any problem solved using the model. The solutions obtained from the MMGA model for the example illustrated in Section 5.2 are presented in Figure 54 to show the relationship between the machine count and makespan for each case.

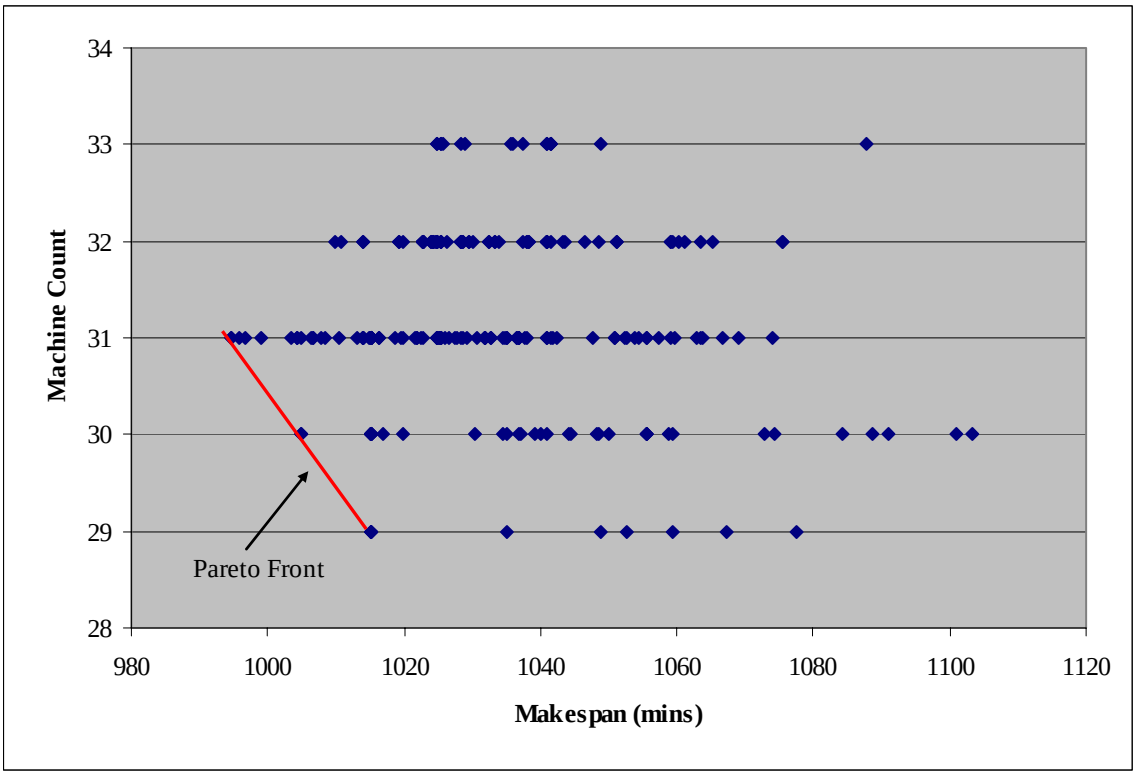


Figure 54: Non-Dominated Solutions for Example

The results reveal the presence of a set of compromised solutions, instead of a single unique solution. The non-dominated solutions are those lying along the Pareto Front, as indicated. Thus, with the two conflicting objectives of achieving minimum makespan and low machine count, a single optimal solution is not feasible.

The MMGA places emphasis on minimizing makespan and the MCGA is designed to find the minicell configuration that minimizes the machine count. Given that the two objectives are conflicting, one could argue that the MMGA does not place sufficient emphasis on keeping the machine count low in finding minimum makespan solutions.

However, it must be noted that the MMGA minimizes makespan while constraining the machine count to that required for producing the expected demand. Nevertheless, if both objectives must be considered in solving the minicell design problem, it is possible to combine them by determining the relative importance of each.

A multi-objective genetic algorithm (MOGA) to minimize makespan and machine count was designed and experimented with to evaluate the effectiveness of the original MMGA (minimizing makespan subject to machine constraint). The MOGA model development, experimentation, and comparison with original MMGA results are discussed in this section.

6.2.1. Fitness Function for MOGA

For the MOGA weights were assigned to each objective—makespan (MS) and machine count (MC)—to convert them to a single objective for optimization. Given the need to determine the optimal minicell design that minimizes both MS and MC, they can be combined to a scalar form (F) such that:

$$F = MS.w_1 + MS.w_2 \qquad [9]$$

$$w_1, w_2 > 0 \; and \; w_1 + w_2 = 1$$

The values of MS and MC corresponding to each chromosome can not be used directly in equation [9] to find the weighted fitness function. This is because they are very different in magnitude and the significance of the MC—smaller of the two values—will not be

reflected in the weighted fitness function *F*. Therefore, separate upper and lower bounds are established for each objective and these values are then used to compute the weighted fitness function as shown in equation [10].

$$F = \frac{MS_i - MS_L}{MS_U - MS_L} w_1 + \frac{MC_i - MC_L}{MC_U - MC_L} w_2 \qquad [10]$$

MS_i, MC_i = Makespan and machine count for chromosome *i*

MS_L, MS_U = Lower and upper bound for makespan for the problem

MC_L, MC_U = Lower and upper bound for machine count for the problem

For any given problem, the values for $MS_L, MS_U, MC_L,$ *and* MC_U must be established prior to running the MOGA. In this research, the existing GA models—MMGA and MCGA—were used to establish these limits. Thus MS_L *and* MC_U were determined using the MMGA and MC_L *and* MS_U were found using the MCGA. For both variables a margin of safety was added (or subtracted in case of lower bounds) when determining the limits to account for the possibility of MOGA finding solutions that fall outside the bounds.

6.2.2. Experimentation with the MOGA

The MOGA was used to find the best minicell configuration for the same example previously evaluated with the MMGA in Section 5.2. Different weights for MS and MC were used in the MOGA to find the best solution in each case. For every MS/MC

combination the MOGA was run for 30 trials of 100 generations each, with a population size of 10 chromosomes. The mutation probability was set at 0.1.

The results obtained using the MOGA are shown in Figure 55. For comparison, the results obtained using the MMGA ($w_1 = 1$ and $w_2 = 0$) as well as the MCGA ($w_1 = 0$ and $w_2 = 1$) are also shown.

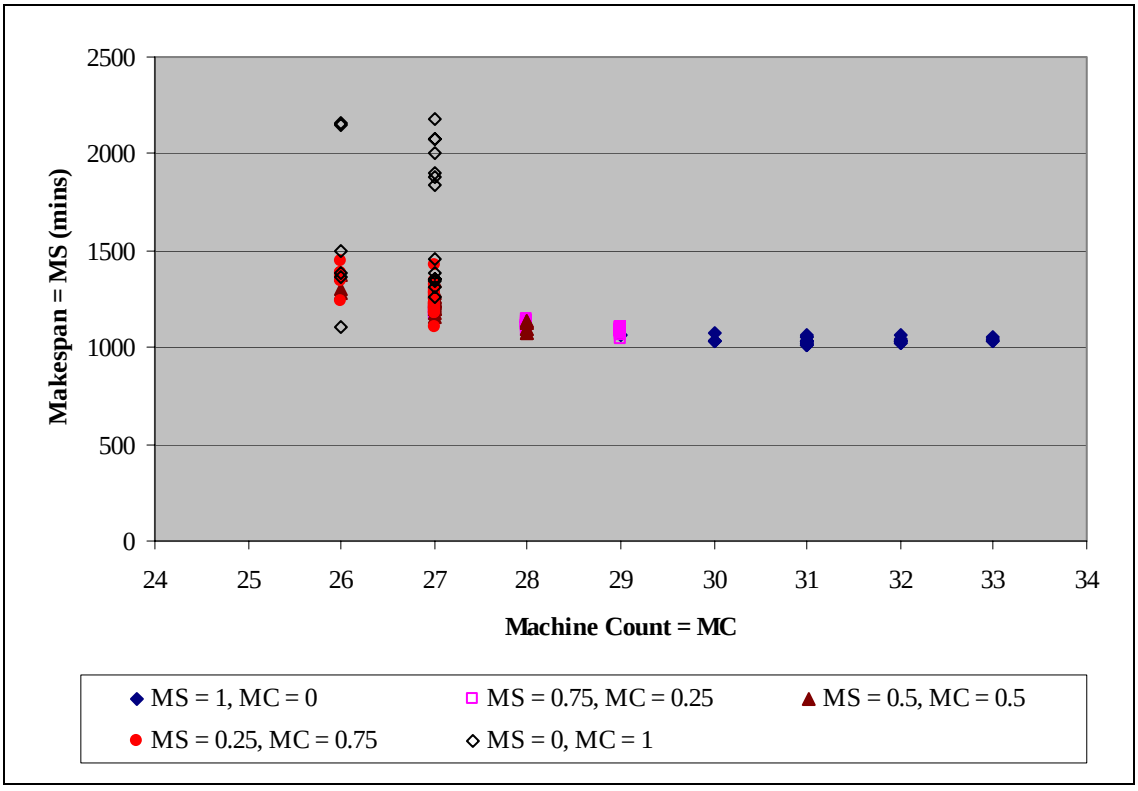


Figure 55: Results with Different Weights for MS and MC

The convex Pareto Front of non-dominated solutions is clearly evident from the figure—except for an outlier found using the MCGA. The makespan for the best minicell design found using the MMGA is 1015 minutes and the minimum machine count obtained using the MCGA is 26. The MOGA finds alternate solutions depending on the relative importance of each objective. The best solutions found using the MOGA—to optimize both objectives—always have higher MS and MC than the best minicell designs found using MMGA and MCGA, respectively. These results help validate the performance of the GA's developed to optimize the objectives separately. They also show that the MMGA is able to find minimum makespan minicell designs without significantly increasing the machine count. However, if both objectives must be minimized the MOGA can be used to find the most suitable design by assigning weights to the objectives.

Determining the relative importance of weights that must be used for MS and MC is one of the main difficulties in using the MOGA. The importance of minimizing makespan and/or machine count to achieve the goals of mass customization must be first evaluated. Minimizing makespan becomes important to be able to offer customized products with short delivery times. However, these products must also be offered at competitive prices and adding more machines will increase capital investment as well as operational costs. Given the two conflicting objectives, the relative importance of each could be difficult to estimate objectively.

7. SCHEDULING IN MINICELL CONFIGURATION

Previous analyses in this research exemplify the importance of using an effective scheduling strategy to improve the performance of minicell systems. Further testing conducted to evaluate the scheduling approach used in this research and experimentation to develop better strategies for minicell scheduling are discussed in this section.

7.1. Scheduling Analysis to Study Time Between Batches

The makespan determined in all the different problems discussed is the time taken to complete processing one set of product variants. The expected and predicted product variant demand was that corresponding to a single day and therefore the makespan reflects the time to complete processing the daily demand.

An examination of the makespan values obtained reveal that they are much longer than the daily processing capacity available—480 minutes, assuming an eight-hour day. The makespan determined is the time from start to completion for the first batch of product variants. Initial capacity planning was carried out assuming machine availability for 8 hours each day and it was done so for each machine separately. However, with the minicell configuration, the product variants require processing in numerous machines in the different minicells it must visit. Therefore, though any single machine would have sufficient capacity to process the assigned jobs within an 8-hour period, the total time taken to complete processing in all machines in the respective minicells and stages that must be visited will be much longer. The idle time spent waiting to be processed on

machines contributes to increasing the makespan as well. Therefore, the large makespan does not indicate a deficiency in the design.

Analyzing the time between completion of successive batches of product demand is useful to evaluate the accuracy of capacity planning. The capacity required to process the daily demand was estimated and used in minicell system design. Therefore, the capacity estimated should enable processing successive batches, on average, within the time available per day, i.e.: 8 hours. To evaluate the performance of minicell systems designed, different daily predicted demands were scheduled successively and the time to complete processing was estimated. The results are illustrated below for the minicell system designed for a problem with the option-machine shown in Figure 56. Products have three features and two options per feature, enabling eight different product variants to be formed.

		Machines						
		A	B	C	D	E	F	G
Options	11	1.51	1.25	1.7	0.97		0.57	
	12	1.1		1.16				
	13							0.72
	14				1.7	1.54		
	15	0.41				1.31		
	16		0.38	0.96		1.6	0.94	0.09

Figure 56: Option-machine Matrix for Example

A three stage minicell configuration to process a specific expected demand for product variants was determined for this example using the MMGA. The best configuration has machine types A-E assigned to the first stage, and types F and G in the remaining two stages in that order. There are three, two, and one minicell in the first, second, and third stages, respectively.

In order to evaluate the time between completing batches, ten different predicted demand scenarios were derived from the expected demand assuming a normal distribution. These product variant batches were then scheduled for processing in the minicell design described above. The expected demand and predicted product variant demand for the ten scenarios are shown in Table 25.

Table 25: Product Variant Demand for Scheduling Analysis

Product Variant	Expected Demand	Predicted Demand									
		Batch1	Batch2	Batch3	Batch4	Batch5	Batch6	Batch7	Batch8	Batch9	Batch10
11.13.15	88	89	87	85	88	80	96	90	102	83	95
11.13.16	86	69	96	72	58	75	80	106	93	58	82
11.14.15	54	51	42	51	48	55	59	37	64	41	50
11.14.16	84	76	75	91	77	83	93	80	103	68	89
12.13.15	79	81	84	86	99	77	79	90	76	100	97
12.13.16	79	73	97	70	81	80	81	103	79	78	84
12.14.15	26	25	31	25	21	25	31	31	28	21	26
12.14.16	19	20	21	19	22	19	22	20	22	21	18

For each batch of product variants, the time required on the different machine types was calculated and the jobs were then scheduled using the CDS & FCFS, as described earlier. The start (assuming processing a new batch begins every morning) times, the total time taken to completely process all items in the batch, and the time between completing successive batches is shown in Table 26. The results are illustrated graphically in Figure 57.

Table 26: Batch Processing Times

Batch Number	Start Time (mins)	End Time (mins)	BatchProcessing Time (mins)	Time between batches Completing Batches (mins)
1	0	1133	1133	1133
2	480	1588	1108	455
3	960	2128	1168	540
4	1440	2700	1260	572
5	1920	3139	1219	439
6	2400	3638	1238	500
7	2880	4177	1297	539
8	3360	4812	1452	635
9	3840	5357	1517	545
10	4320	5728	1408	371
Average Time between Completing Batches				510

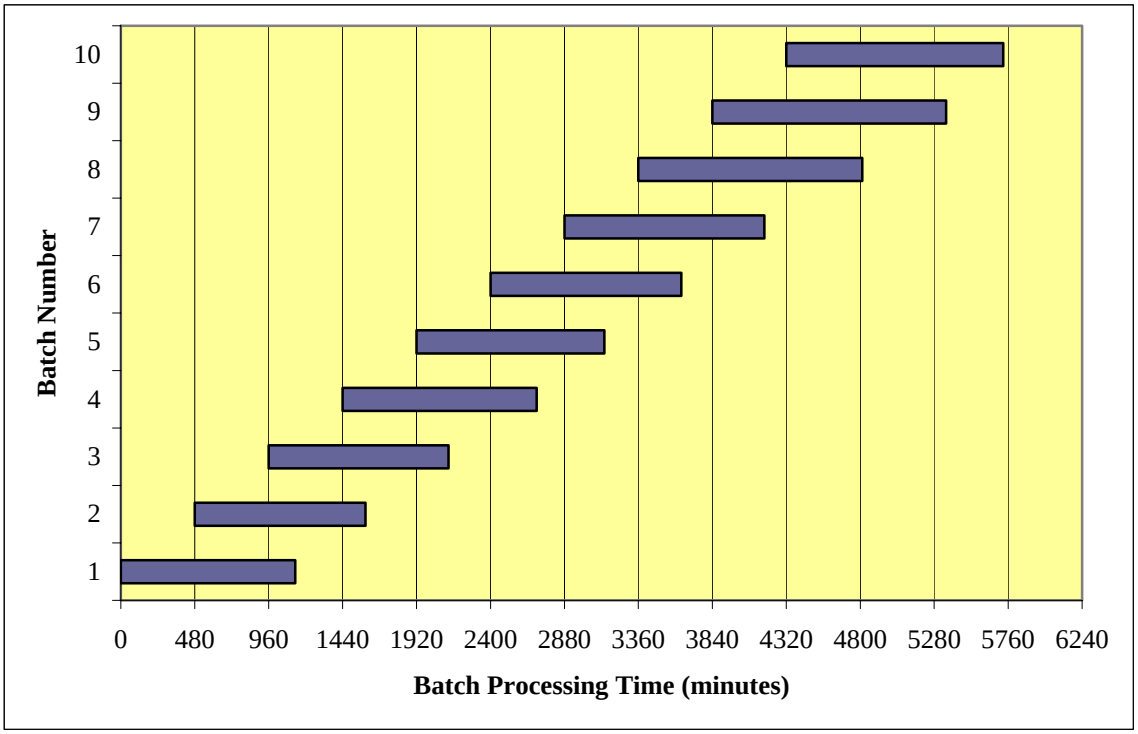


Figure 57: Batch Processing Times

The time taken to complete each batch depends on the quantity required as well as the product mix. Successive batches enter the system every 480 minutes (8 hours) and are completely processed—on average—at similar time intervals. The average outgoing time between successive batches is 510 minutes (8.5 hours, excluding the first batch). Therefore, given an 8-hour working day, the processing needs for batches can be met with the capacity available and a few hours of overtime if demand is large.

Similar analyses were conducted with other problems—different option-machine matrices, number of product variants, as well as demand—to evaluate the accuracy of

capacity planning in minicell system design. In all cases, the average time between completing successive batches was around 8 hours. These analyses validate the initial capacity planning performed in designing the minicell configuration.

7.2. New Methods for Scheduling in Minicell Configuration

The evaluation of completion times for jobs in minicells reveals the presence of large waiting time. Most of the delay can be attributed to the processing sequence in the first minicell. When jobs that are delayed in the first minicell also have to wait to be processed in the subsequent minicells, the total waiting time is further increased. Improving the scheduling strategy may provide opportunities to reduce the time spent waiting to be processed in minicells. Different strategies evaluated for scheduling in minicells and the results obtained are summarized in this section.

7.2.1. CDS & Ranking

The makespan to complete processing a batch of orders depends on the processing required for the longest order. Increased waiting for large jobs will increase the makespan even more. Therefore, one strategy to reduce makespan is prioritizing jobs that need more processing when being scheduled in minicells. However, unless such jobs are available for processing in the minicell, prioritizing will only delay processing of other jobs that could be completed earlier. Hence, scheduling jobs that become available earlier for processing and also require more processing—in that and subsequent minicells—could be more effective. This strategy, together with CDS, was used to schedule jobs in a minicell

configuration to reduce makespan and is referred to as ‘CDS & R’ in the subsequent discussions.

With CDS & R, all jobs in the first minicell in the initial stage are scheduled by applying the CDS heuristic. In each of the remaining minicells, all jobs are sorted in ascending order of completion time in the previous minicell and each job is assigned a rank based on its availability for processing: the job completed first is assigned a rank of 1, the next 2, and so on. The total processing time remaining—in the present and subsequent minicells—is determined: jobs are assigned a second rank based on the descending order of processing time remaining. The job with largest amount of processing remaining is assigned a rank of 1, the next 2, and so on. The total rank for a job is the sum of rank based on completion time and processing time remaining. The processing sequence for jobs in the minicell is obtained by sorting the jobs in the ascending order of total rank. A comparison of results obtained by applying CDS & FCFS and CDS & R are shown in Table 27 and Figure 58.

Table 27: Comparison of Results for CDS & R and CDS & FCFS

Strategy	Makespan (mins)	Average Flow Time (mins)
CDS & FCFS	1326	837
CDS & R	1388	1033

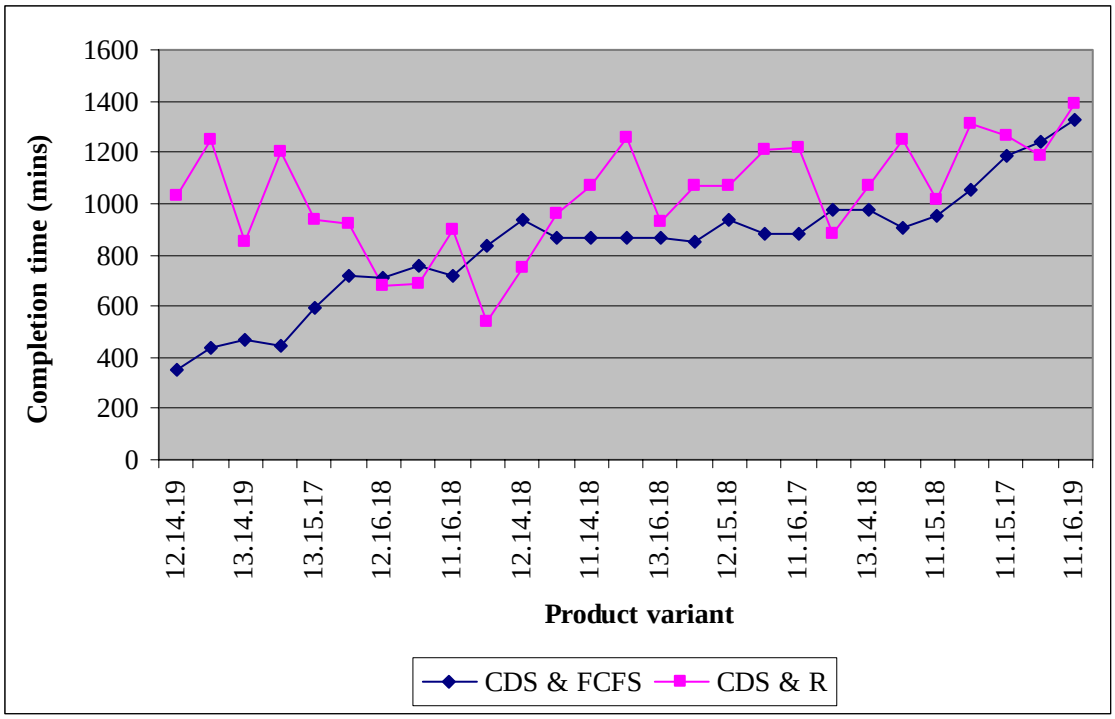


Figure 58: Completion Time for Jobs with CDS & R and CDS & FCFS

The application of CDS & R generates a makespan that is slightly higher than with CDS & FCFS. However, the average flow time for the processing the jobs is much higher with the former. A comparison of the completion times for jobs with the two strategies is shown in Figure 58. Though the two approaches generate similar makespans, the completion time for jobs with CDS & R is much higher than when using CDS & FCFS. Except for a few jobs, the CDS & FCFS strategy generates in lower completion times. Therefore, it appears that using the CDS & R strategy is not as effective as CDS & FCFS for scheduling in minicells.

7.2.2. Extended CDS

The CDS heuristic [16] is an extension of Johnson's [41] algorithm (to schedule jobs in a two-machine flow shop) to a multiple (*m*) machine flow shop to minimize makespan. With CDS, the best schedule is found by determining the sequence for *m*-1 two-machine flow shops and selecting the one that gives the minimum makespan. Given a multi-stage flow shop—with many machines—such as a minicell configuration, a logical extension of CDS would be to:

1. Determine alternate sequences by applying CDS to each minicell
2. Schedule jobs in all minicells based on these sequences
3. Select the sequence that gives minimum makespan to schedule jobs

This approach will be referred to as ExtCDS (for Extended CDS) hereafter. The strategy was applied to schedule jobs in a minicell configuration with five minicells and ExtCDS generates five different sequences. The makespan and average flow time with each of these and CDS & FCFS are tabulated in Table 28. As described previously CDS & FCFS involves applying the sequence obtained by applying CDS to MC11 followed by FCFS in subsequent minicells. The results are presented graphically in Figure 59.

Table 28: Comparison of Results for ExtCDS and CDS & FCFS

Scheduling Strategy	Makespan (mins)	Average Flow Time (mins)
CDS for MC11	1161	814
CDS for MC12	1688	984
CDS for MC21	1618	719
CDS for MC31	1129	806
CDS for MC32	1879	1347
CDS & FCFS	995	670

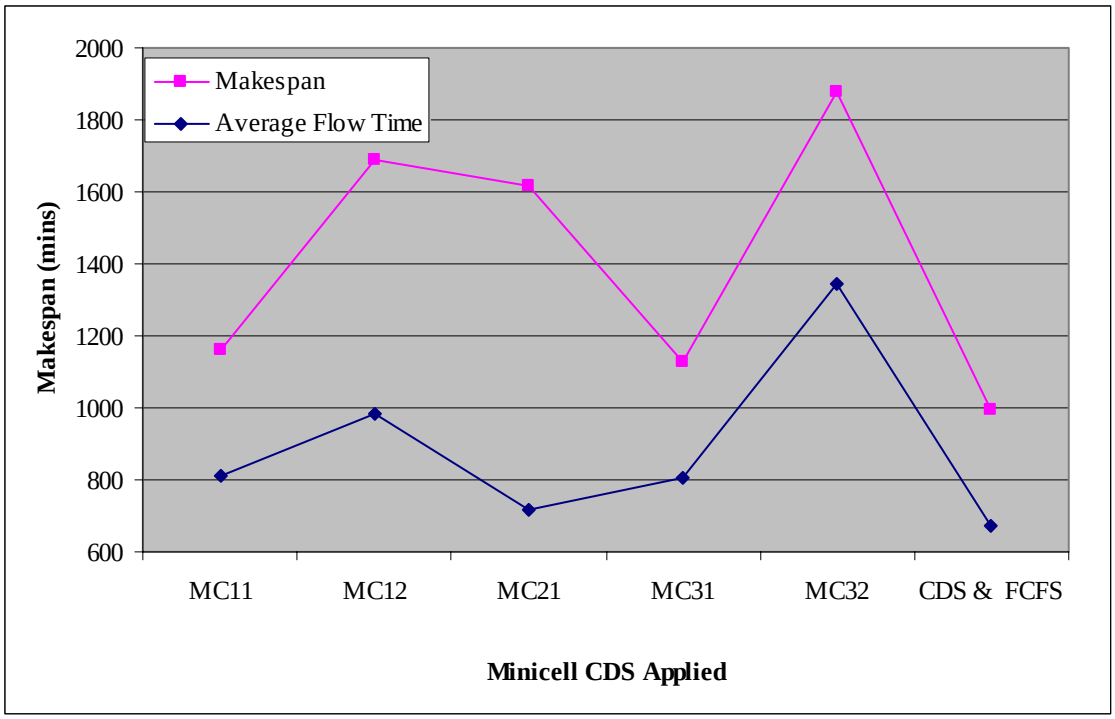


Figure 59: Performance with ExtCDS and CDS & FCFS

As can be observed, the use of CDS & FCFS provides much better results for makespan than ExtCDS. Some schedules generated using ExtCDS—for example, in MC21—

provide average flow times that are only slightly higher than with CDS & FCFS. However, the makespan and average flow time from the CDS & FCFS strategy is much better than with those obtained by ExtCDS.

Based on these preliminary analyses, CDS & FCFS is a better strategy for scheduling jobs in the minicell configuration compared to CDS & R or ExtCDS. However, further experimentation is necessary, with different examples, and possibly modifying these approaches, to evaluate their effectiveness for scheduling in minicell configurations. A strategy that can provide better schedules to minimize makespan in a minicell configuration can also be used in multi-stage flow shop to achieve better results.

8. MINICELL LAYOUT

Once a suitable minicell configuration has been determined for a particular situation, the next step in the design process involves finding the optimal layout for the minicells within the stages to minimize total cost of material handling.

Two different approaches were used to find the optimal solution to the minicell layout problem: (1) mathematical modeling, and (2) genetic algorithms. These two approaches are described in detail in the following sections.

Several assumptions were made in determining the optimal layout for the minicells. The objective in minicell layout is to determine the optimal locations for the minicells, within their respective stages, to minimize total material handling cost. It is assumed that the material handling cost is proportional to the distance traveled. Therefore, the total distance traveled between the minicells, to produce the total expected demand for product variants during the planning horizon, must be minimized. Inter-machine travel distances within minicells is unaffected by the location of the minicells and is not considered in this analysis.

The machine types as well as the number of units of each type assigned to a minicell may differ and therefore the space required for different minicells could vary. In the minicell layout analysis it is assumed that all available locations are designated to provide

sufficient space to accommodate any minicell in the design. It is also assumed that travel between minicells is along a rectilinear path.

8.1. Mathematical Model for Minicell Layout

Koopmans and Beckmann [47] developed a quadratic assignment model for the multi-row layout of traditional cells. The multi-stage minicell configuration can be compared with a multi-row traditional cell layout problem by considering each stage a separate row. The approach used in the Koopmans and Beckmann model is modified to solve the minicell layout problem by including additional constraints to accommodate the presence of multiple stages in the configuration and the need to lay minicells within their designated stages.

The variables used in the formulation are:

n = *number of minicells and, therefore, number of locations*

f_{ik} = *number of material handling trips between minicell i and k*

d_{jl} = *distance between locations j and l*

$$X_{ij} = \begin{cases} 1 & \text{if minicell } i \text{ is assigned to location } j \\ 0 & \text{otherwise} \end{cases}$$

$\{C_s\}$ = *set of minicells in stage s*

$\{L_s\}$ = *set of locations in stage s*

The objective is to locate the minicells, within their respective stages, such that the total distance traveled is minimized and this can be expressed as shown in equation [11]. Constraints [12] and [13] ensure that each minicell is assigned to one location and that each location has only one minicell, respectively. For each stage *s* in the configuration, constraint [14] ensures that minicells not belonging to set $\{C_s\}$ are not assigned to locations $\{L_s\}$. $\{C_s\}$ and $\{L_s\}$ denote the set of minicells and locations in stage *s*, respectively. Constraint [15] ensures that all x_{ij} values are integers.

Objective function:

Minimize: $$F = \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} \sum_{l=1}^{n} f_{ik} d_{jl} X_{ij} X_{kl} \qquad [11]$$

Subject to:

$$\sum_{i=1}^{n} X_{ij} = 1 \qquad for\ all\ \ j = 1, \ldots, n \qquad [12]$$

$$\sum_{j=1}^{n} X_{ij} = 1 \qquad for\ all\ i = 1, \ldots, n \qquad [13]$$

For each stage s,

$$X_{ij} = 0 \qquad for\ all\ i, j\ that\ do\ not\ belong\ to\ \{C_s\}\ and\ \{L_s\}\ respectively \qquad [14]$$

$$X_{ij} = 0\ or\ 1 \qquad for\ all\ i, j = 1, \ldots, n \qquad [15]$$

8.2. Genetic Algorithm for Minicell Layout

A GA was developed to determine the optimal layout of the minicells (MLGA) in the minicell configuration. The details of the MLGA are described in the sections below. The objective of the MLGA is to determine the optimal assignment of minicells to different locations within each stage to minimize total distance traveled.

8.2.1. Chromosome Representation

Each chromosome consists of *m* genes (*m* = number of minicells in the configuration and, therefore, number of possible locations for these minicells) divided between *n* blocks (for stages). The position of a gene in the chromosome indicates the minicell number. The value of the gene represents the location to which the minicell is assigned to.

For example, suppose the optimal minicell configuration to a particular problem has three stages with 3, 4, and 3 minicells in the first, second, and third stage respectively. Therefore, locations numbered 1-3 are in the first stage, those numbered 4-7 in the second stage, and 8-10 in the last stage. A solution to this problem is shown in the chromosome in Figure 60.

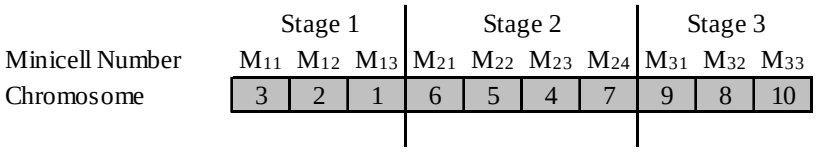


Figure 60: Chromosome Representation for MLGA

In the chromosome represented minicells M_{11}, M_{12}, and M_{13} are assigned to locations 3, 2, and 1 respectively that are in the first stage and so on.

8.2.2. Fitness Function

The objective of minicell layout is minimizing total distance traveled. Therefore the total distance traveled between the minicells is taken as the fitness value of each chromosome. This is obtained by multiplying the expected number of trips between the two minicells—during the period under consideration—by the distance between them. The total distance traveled is the sum of the distances traveled between all pairs of minicells in the configuration.

8.2.3. Reproduction

The minicell layout problem involves an objective function that must be minimized. Therefore, the fitness value of each chromosome must be adjusted to assign higher probabilities to those with lower fitness function values. Reproduction probabilities for the MLGA chromosomes are calculated by following a procedure similar to that described previously for the MMGA in section 5.1.3.

8.2.4. Crossover Strategy

A single cut-point crossover strategy is applied to all pairs of chromosomes selected for mating in the MLGA. For each pair of chromosomes, a cut point is chosen randomly. The genes to the right of one parent are then exchanged with that of the other to create offspring. The procedure is illustrated for a pair of chromosomes in Figure 61.

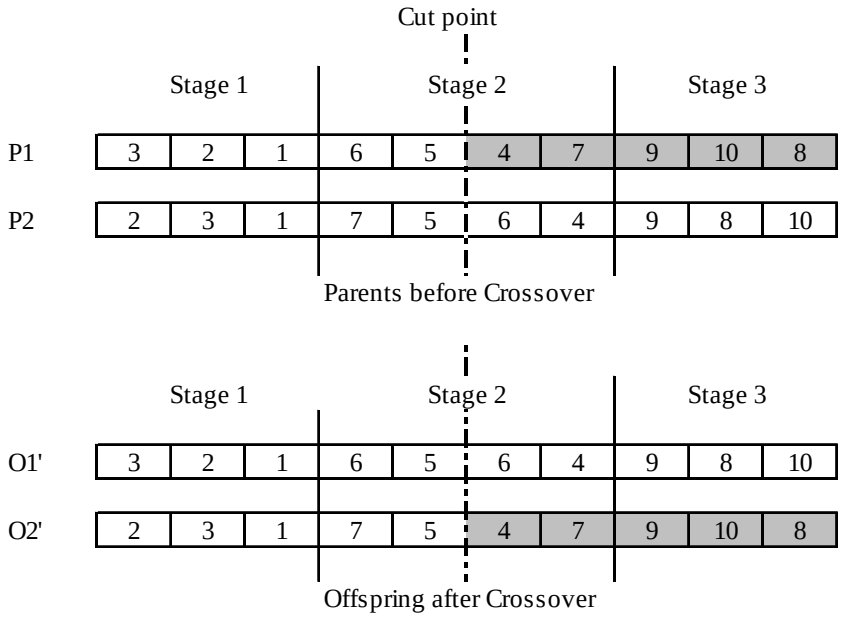


Figure 61: Crossover Strategy for MLGA Chromosomes

As illustrated, genes to the right of the cut off point from parent P1 are exchanged with those of P2 to create offspring O1' and O2'. Application of the crossover strategy may generate infeasible chromosomes in which multiple minicells are assigned one location. A repairing mechanism is necessary to correct such chromosomes. Consider the offspring O1' created after applying crossover. In the layout represented by this chromosome, two minicells—M_{21}, M_{23}—are assigned to location 6 while none are assigned to location 7. Repairing is done by examining which genes are duplicated and replacing one of them—selected randomly—by the gene that has been omitted. The repaired chromosomes O1 and O2 are shown in Figure 62.

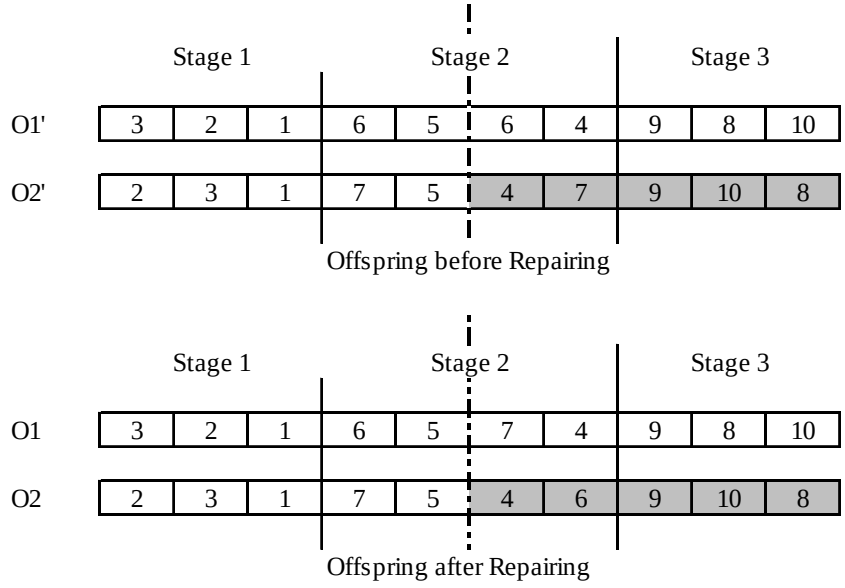


Figure 62: Corrected Chromosomes after Repairing

8.2.5. Mutation Strategy

Genes are selected for mutation independently based on the mutation probability. Each gene selected for mutation is replaced by a number—chosen randomly—that represents a different location within the same stage. Then, the gene in the second location is replaced by the value of the gene initially selected for mutation. The process is illustrated for one chromosome in Figure 63.

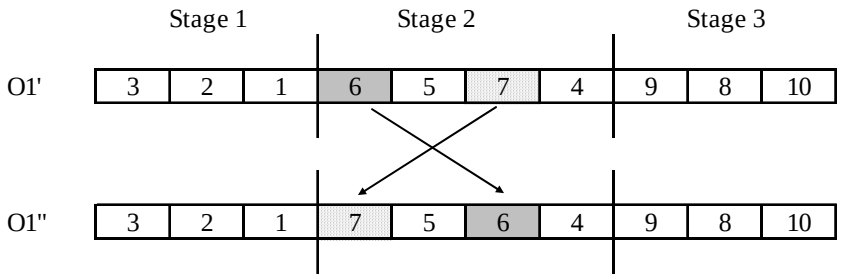


Figure 63: Mutation for MLGA Chromosomes

Assume that the 4th gene in the chromosome is randomly chosen for mutation. This gene corresponds to location 6 which is in stage 2 of the configuration. Locations 4, 5, and 7 qualify for mutation with this gene and have an equal of probability of being chosen. If location 7 is selected randomly, the mutated chromosome O1" is formed by exchanging the positions of 6 and 7 as shown above. Application of the mutation strategy does not generate infeasible chromosomes and therefore, repairing is not required after mutation.

The MLGA is terminated after a specific number of generations to find the optimal solution to the minicell layout problem.

8.3. Experimentation with Minicell Layout Models

The performance of the mathematical model and the MLGA are illustrated for an example where a three-stage minicell configuration designed with three minicells per stage. The information required for solving these models are:

- Expected number of trips between every pair of minicells in the configuration
- Distance between all pairs of locations within which the minicells can be laid out.

Once the total number of minicells (and therefore, the locations) in a minicell configuration is known the above data can be represented in a matrix form. The matrix for number of trips between minicells—calculated based on the processing needs for the expected demand over the planning horizon—is shown in Figure 64. It is assumed that the locations available are organized in the form of a grid such that the linear distance between two adjacent locations is 2 units. A distance matrix, as shown in Figure 65, can be derived based on the inter-minicell distances. In the figure L_1, L_2, etc. denote the locations 1, 2, and so on.

From \ To	M_{11}	M_{12}	M_{13}	M_{21}	M_{22}	M_{23}	M_{31}	M_{32}	M_{33}
M_{11}	-	12		36	30	30	12		
M_{12}		-		14	14	16			
M_{13}		12	-		28	32		8	
M_{21}				-	2		10	20	18
M_{22}					-		11	37	26
M_{23}						-	8	42	28
M_{31}							-		
M_{32}							25	-	
M_{33}									-

Figure 64: Number of Trips between Minicells

	L_1	L_2	L_3	L_4	L_5	L_6	L_7	L_8	L_9
L_1	0	2	4	2	4	6	4	6	8
L_2	2	0	2	4	2	4	6	4	6
L_3	4	2	0	6	4	2	8	6	4
L_4	2	4	6	0	2	4	2	4	6
L_5	4	2	4	2	0	2	4	2	4
L_6	6	4	2	4	2	0	6	4	2
L_7	4	6	8	2	4	6	0	2	4
L_8	6	4	6	4	2	4	2	0	2
L_9	8	6	4	6	4	2	4	2	0

Figure 65: Distance Matrix for Layout Example

8.3.1. Evaluation of Mathematical Model

The mathematical model described in section 8.1 was developed for this example and tested using Microsoft Excel Solver to find the optimal solution to the minicell layout problem. The optimal solution found using the model is summarized in Table 29. The total distance traveled, with the minicells assigned to the locations shown, is 1596 units.

Table 29: Assignment of Minicells to Locations

Minicell Number	Location Assigned
M_{11}	3
M_{12}	2
M_{13}	1
M_{21}	6
M_{22}	5
M_{23}	4
M_{31}	9
M_{32}	8
M_{33}	7

The mathematical model for a different problem and the solution found using the optimization software LINGO is shown in APPENDIX II: Mathematical Model & solution in LINGO.

8.3.2. Testing with MLGA

The MLGA was tested to find the optimal layout of minicells for this example by varying the population size and number of generations. The population sizes used were 10, 20 and 30. The numbers of generations tested were 20, 50, and 100. The mutation probability was set at 0.1. For each population size/number of generations combination, the MLGA was run for six trials of five replications each. For each trial the best solution and the average total distance traveled was recorded.

The results obtained from the testing are summarized in Figure 66 and Figure 67. Figure 66 shows the variation at different numbers of generations with a population size of 10 chromosomes. The results for different population sizes with 100 generations are shown in Figure 67.

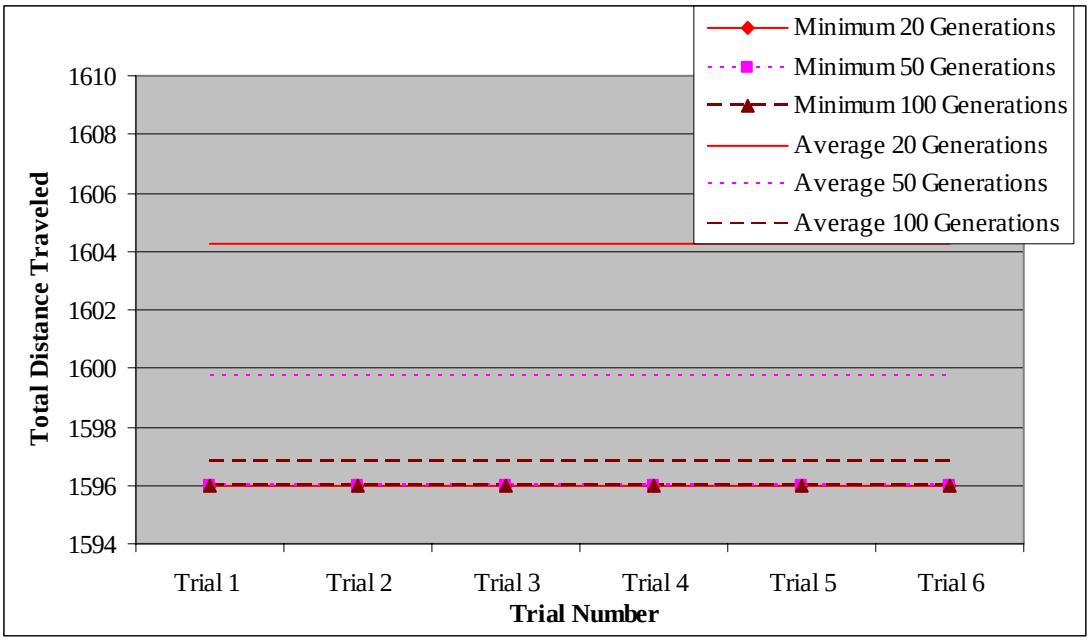


Figure 66: Comparison of Results of at Different Numbers of Generations

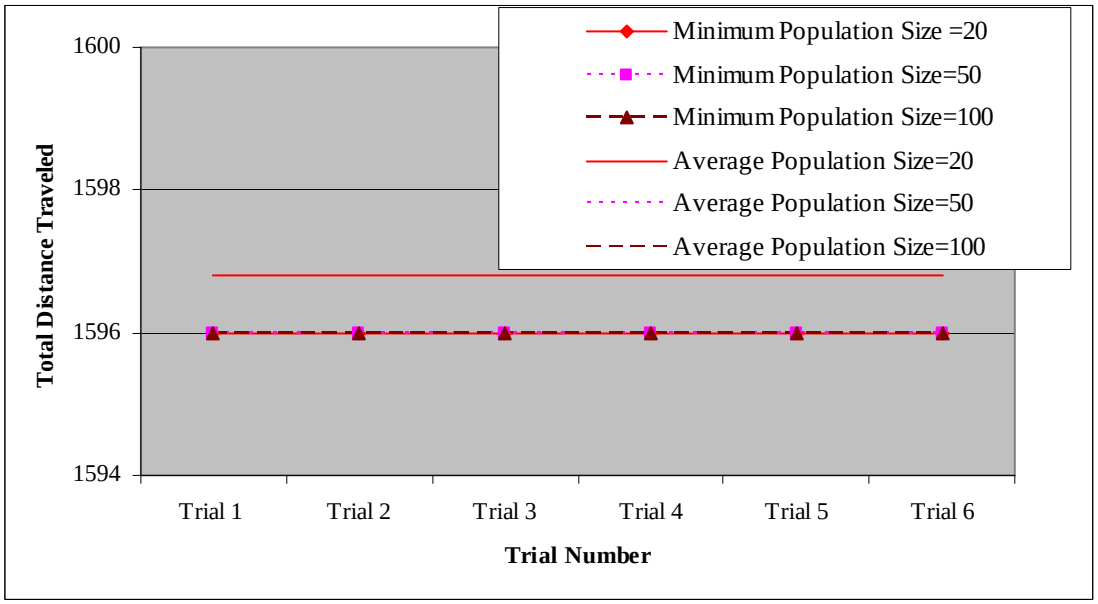


Figure 67: Comparison of Results at Different Population Sizes

As evident from the figures above, the MLGA finds the optimal layout for minicells in all the trials at all population sizes and numbers of generations. According to Figure 66, at lower numbers of generations the MLGA does not find the optimal solution as frequently as at higher generations. However, when the population size is increased (see Figure 67) the optimal solutions are found at almost all the replications in all trials, except with the lowest population size.

The results reveal the effectiveness of the MLGA in determining the optimal solution to the minicell layout problem. Also the MLGA takes a very short time (less than 5 seconds) to find the optimal solution. The relative simplicity of the layout problem, compared to minicell formation, assures the finding of solutions using the GA even with a small population size and low number of generations. Writing out the mathematical model becomes complicated as the dimensions of the problem—number of stages and minicells per stage—increase. The MLGA takes very little time for formulation—once it has been developed—and can be used to find the optimal minicell layout even for large problems without difficulty.

9. CONCLUSIONS

The objective of this research was to develop methods to design a manufacturing system for mass customization where customized products are offered by allowing customers to choose between different options for the products' features.

9.1. Minicell Configuration for Mass Customization

A new approach to design a cell-based system for mass customization, by extending the concepts of cellular manufacturing, was presented. The platform-based approach to product design—different product variants derived from a single platform by changing the options available for features—which is widely used in mass customization environments, provided the basis for choosing the approach to design the new system.

With the new approach, options offered for the customized products' features and their process plans are used to design the proposed configuration. This information is formed into an option-machine matrix and then used for cell formation. A new type of cells called minicells—small manufacturing cells dedicated to process a part of the operations required for an option family—are the building blocks in the new system. The processing operations for the options are divided into multiple stages—by dividing the option-machine matrix—and option families and minicells are formed within them to create a multi-stage minicell configuration. Here, each option visits no more than one minicell in every stage whereas a product variant could require processing in multiple minicells depending on the options chosen for the features.

A modular production system is achieved as a result of creating a multi-stage structure and forming small minicells within them. A larger variety of product variants can be manufactured by selecting the minicells required to process the particular options and routing them accordingly.

9.2. Methods to Design Minicell Configuration

A multi-chromosome genetic algorithm was developed to design a minicell configuration for a given product variant demand. The genetic algorithm determines the minimum makespan configuration while limiting machine capacity to that required for producing the expected product variant demand. The MMGA converged to find better solutions as the population size and number of generations was increased. However, the relative improvement in the solution was less compared to the additional time spent to find those solutions. The MMGA also exhibits *n*-1 mapping, where multiple chromosomes in the coding space correspond to the same outcome in the solution space.

The genetic algorithm finds the best minicell system design considering a single predicted demand scenario. However, the chosen design must have the capability to handle the dynamic demand situations encountered in mass customization. An approach to find a flexible minicell configuration to handle variations in product mix and volume, using the genetic algorithm and simulation, was presented.

In the combined approach, the genetic algorithm was used to determine alternate minicell configurations for different product variant demands. The performance of these configurations was then simulated for a set of larger predicted demand scenarios. The most flexible configuration can be chosen based on the desired performance measure e.g. minimum average makespan, minimum worst makespan etc.

The results from the genetic algorithm and simulations were used to evaluate the formation of heuristic procedures for minicell system design; determining cutoff points to create stages and forming option families and minicells. No pattern could be identified between the variables in the problems to provide any guidelines for heuristic development. This may be due to the complexity of the minicell formation problem—given an option-machine matrix and number of stages and minicells required, the options can be combined in a variety of different forms to generate a configuration.

9.3. Performance of Minicell Configuration

Changes in the expected product variant demand is likely to affect minicell system performance. The behavior of the minicell configurations was evaluated to determine their robustness to deal with increases in expected demand and to evaluate the need for reconfiguration—form and frequency. The minicell designs were found to have the flexibility to handle up to 10% increases in expected demand without a significant adverse effect on makespan. As the demand increases further, it becomes necessary to reconfigure the system, either by adding more machines to the existing design or

completely redesigning. The benefits gained by completely redesigning turns out to be greater when the increase in expected demand is large. However, the cost and time taken for reconfiguration must be weighed against the potential benefits.

Alternate minicell designs and the performance of the system with such designs were evaluated to investigate the approach to selecting the most appropriate minicell configuration. The effect of pre-selecting different cutoff points to separate the option-machine matrix was analyzed to evaluate the performance of the MMGA in choosing these locations. Cutoff points found by the MMGA generated configurations better than those found by using the pre-selected ones attesting to the effectiveness of the MMGA.

The effect of varying the number of minicells when the number of stages in the configuration is fixed was also analyzed. Irrespective of the number of stages in the design, increasing the number of minicells from 1 to 2 helped lower the makespan as well as average flow time for the products. The reduction in the size of minicells and the amount of time spent waiting to be process could be attributed to the improved performance. However, as the number of minicells increased further, it was found to have an adverse impact on the makespan.

Comparison of the performance of minicells with traditional cells revealed that the new configuration can deliver better results, particularly in dynamic demand—volume and mix—situations encountered in mass customization. The minicell configuration designed to achieve minimum makespan has greater flexibility to also produce lower flow times.

Given the two conflicting objectives minimizing makespan and flow time, the ability to achieve better performance for both with the minicell configuration—compared to traditional cells—is very promising. All this is achieved without an increase in the total machine requirements.

The scheduling strategy used for minicells—CDS & FCFS—appeared to introduce considerable waiting times in minicells. Comparative analyses of scheduling results in traditional and minicells revealed the potential for improving the performance in the latter by using better scheduling techniques. Increasing the machine capacity of each type by one unit in the first minicell—to avoid long waiting times in that cell—helps to achieve lower makespan and significantly better average flow times compared to traditional cells.

9.4. Layout of Minicell Configuration

A mathematical model and genetic algorithm to lay out the minicells within the stages were presented. Both approaches determine the optimal layout to minimize the total distance traveled. The mathematical model must be formulated for each problem to be tested and is time consuming when the problem size gets bigger. The MLGA, once designed, can be used to find the optimal solution to the minicell layout problem without difficulty.

9.5. Further Experimentation with Genetic Algorithms

For successful mass customization, a manufacturing system that has the capability to produce a dynamic demand with short response times is required. Therefore, a minicell-based configuration to minimize makespan was developed in this research. However, in some instances, manufacturers may also desire a system that reduces capital investment by minimizing machine requirements. A separate multi-objective GA was developed to minimize both makespan and machine count. The MOGA found minicell designs to achieve both objectives when the relative importance of each is known. The results also revealed the effectiveness of the original MMGA in finding good minicell designs to minimize makespan without adding a lot more machines to the system.

9.6. Summary

The minicell configuration is an attempt to combine the benefits of cellular manufacturing and job shops to meet the requirements of mass customization. The proposed design is more flexible than traditional cellular manufacturing systems particularly in dynamic demand—volume and mix—environments seen in mass customization. Forming options families and minicells helps benefit from group technology concepts while still retaining some of the flexibility offered in job shops. With the minicell configuration, the desired performance—makespan and flow time—can be achieved without significantly influencing machine requirements.

9.7. Future Work

The analysis of minicell formation results to investigate developing heuristic procedures did not produce any promising outcomes. This needs to be explored further using more results and different methods to evaluate if any patterns can be identified from the data.

The CDS & FCFS strategy was used for scheduling in the minicell configuration. The performance of a system as the number of minicells increase and when comparing to traditional cells revealed the need to reconsider the scheduling strategy. Further research is necessary to develop a better approach to schedule jobs in the minicell configuration.

A multi-objective GA was experimented to determine solutions to the minicell formation problem. Multi-objective optimization is always more complex than finding solutions to optimize a single parameter. The strategy used to compute the combined objective function can affect the quality of the solutions found. The effectiveness of the weighted objective function in exploring the solution space for genetic algorithms needs further attention. The population of chromosomes generated in each generation and how these affect the convergence of the MOGA is another issue that must be studied further. Therefore, more experimentation needs to be conducted with the MOGA before it can be used to find solutions for the minicell design problem.

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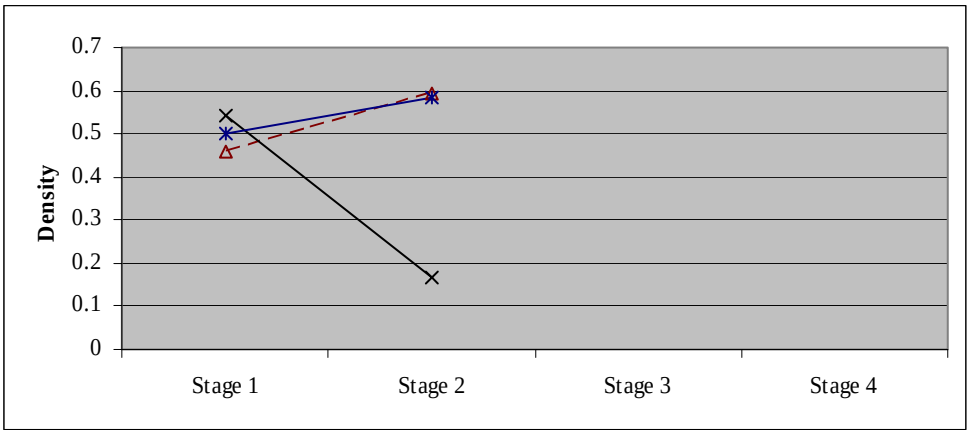
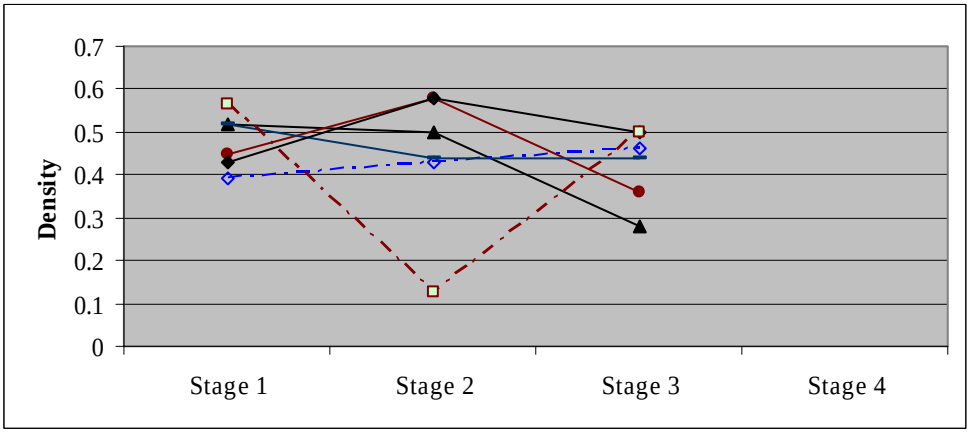
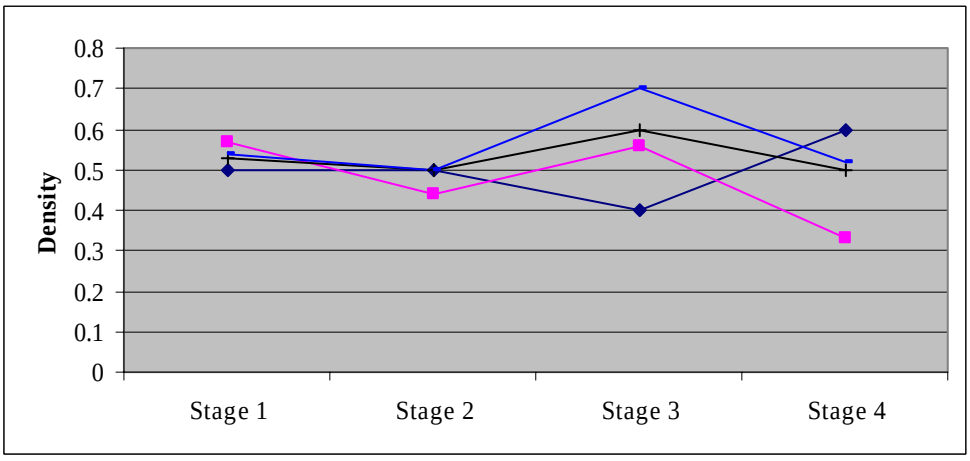
11. APPENDIX I: COMPARISON OF MATRIX DENSITIES



(a) Two stages



(b) Three stages



(c) Four stages

Figure 68: Comparison of Sub-Matrix Density for Examples

12. APPENDIX II: MATHEMATICAL MODEL & SOLUTION IN LINGO

Mathematical Model in LINGO

```
[OBJECTIVE]
min=f11*d11*x11*x11+f11*d12*x11*x12+f11*d13*x11*x13+f12*d11*x11*x21+f12*d
12*x11*x22+f12*d13*x11*x23+f13*d11*x11*x31+f13*d12*x11*x32+f13*d13*x11*x
33+f11*d21*x12*x11+f11*d22*x12*x12+f11*d23*x12*x13++f12*d21*x12*x21+f12*
d22*x12*x22+f12*d23*x12*x23+f13*d21*x12*x31+f13*d22*x12*x32+f13*d23*x12*
x33+f11*d31*x13*x11+f11*d32*x13*x12+f11*d33*x13*x13+f12*d31*x13*x21+f12*d
32*x13*x22+f12*d33*x13*x23+f13*d31*x13*x31+f13*d32*x13*x32+f13*d33*x13*x
33+f21*d11*x21*x11+f21*d12*x21*x12+f21*d13*x21*x13+f22*d11*x21*x21+f22*d1
2*x21*x22+f22*d13*x21*x23+f23*d11*x21*x31+f23*d12*x21*x32+f23*d13*x21*x3
3+f21*d21*x22*x11+f21*d22*x22*x12+f21*d23*x22*x13+f22*d21*x22*x21+f22*d22
*x22*x22+f22*d23*x22*x23+f23*d21*x22*x31+f23*d22*x22*x32+f23*d23*x22*x33
+f21*d31*x23*x11+f21*d32*x23*x12+f21*d33*x23*x13+f22*d31*x23*x21+f22*d32*
x23*x22+f22*d33*x23*x23+f23*d31*x23*x31+f23*d32*x23*x32+f23*d33*x23*x33+f
31*d11*x31*x11+f31*d12*x31*x12+f31*d13*x31*x13+f32*d11*x31*x21+f32*d12*x
31*x22+f32*d13*x31*x23+f33*d11*x31*x31+f33*d12*x31*x32+f33*d13*x31*x33+f3
1*d21*x32*x11+f31*d22*x32*x12+f31*d23*x32*x13+f32*d21*x32*x21+f32*d22*x3
2*x22+f32*d23*x32*x23+f33*d21*x32*x31+f33*d22*x32*x32+f33*d23*x32*x33+f31
*d31*x33*x11+f31*d32*x33*x12+f31*d33*x33*x13+f32*d31*x33*x21+f32*d32*x33
*x22+f32*d33*x33*x23+f33*d31*x33*x31+f33*d32*x33*x32+f33*d33*x33*x33;


! Define the variable used in the model;
@BIN(x11);
@BIN(x12);
@BIN(x13);
@BIN(x21);
@BIN(x22);
@BIN(x23);
@BIN(x31);
@BIN(x32);
@BIN(x33);
@BIN(x11);
@BIN(x21);
@BIN(x31);
@BIN(x12);
@BIN(x22);
@BIN(x32);
@BIN(x13);
```

```
@BIN(x23);
@BIN(x33);

!Constraints to ensure that only one minicell is in each location;
x11+x12+x13=1;
x21+x22+x23=1;
x31+x32+x33=1;
x11+x21+x31=1;
x12+x22+x32=1;
x13+x23+x33=1;

!Distances between the locations;
d11=0;
d12=2;
d13=2;
d21=2;
d22=0;
d23=4;
d31=2;
d32=4;
d33=0;

!Number of material handling trips between minicells;
f11=0;
f12=2;
f13=8;
f21=1;
f22=0;
f23=9;
f31=0;
f32=0;
f33=0;

! Constraints to ensure that the minicells are not assigned to stages they do not belong to;

x13=0;
x14=0;
x23=0;
x24=0;
x31=0;
x41=0;
x32=0;
x42=0;
```

Solution to Mathematical Model from LINGO

```
  Linearization components added:
     Constraints:          64
     Variables:            16
     Integers:             16

   Global optimal solution found.
   Objective value:                              56.00000
   Extended solver steps:                               0
   Total solver iterations:                             0


                        Variable           Value        Reduced Cost
                             F11        0.000000            0.000000
                             D11        0.000000            0.000000
                             X11        0.000000            16.00000
                             D12        2.000000            0.000000
                             X12        1.000000            32.00000
                             D13        2.000000            0.000000
                             X13        0.000000            0.000000
                             F12        2.000000            0.000000
                             X21        1.000000            18.00000
                             X22        0.000000            36.00000
                             X23        0.000000            0.000000
                             F13        8.000000            0.000000
                             X31        0.000000            0.000000
                             X32        0.000000            0.000000
                             X33        1.000000            0.000000
                             D21        2.000000            0.000000
                             D22        0.000000            0.000000
                             D23        4.000000            0.000000
                             D31        2.000000            0.000000
                             D32        4.000000            0.000000
                             D33        0.000000            0.000000
                             F21        1.000000            0.000000
                             F22        0.000000            0.000000
                             F23        9.000000            0.000000
                             F31        0.000000            0.000000
                             F32        0.000000            0.000000
                             F33        0.000000            0.000000
                             X14        0.000000            0.000000
                             X24        0.000000            0.000000
                             X41        0.000000            0.000000
                             X42        0.000000            0.000000

                             Row    Slack or Surplus      Dual Price
                       OBJECTIVE        56.00000           -1.000000
                               2        0.000000            0.000000
                               3        0.000000            0.000000
                               4        0.000000           -50.00000
                               5        0.000000            0.000000
                               6        0.000000            0.000000
                               7       -100000.0            0.000000
```

8	-100000.0	0.000000
9	0.000000	-1.000000
10	0.000000	-9.000000
11	-100001.0	0.4882764E-08
12	-99999.00	0.000000
13	0.000000	-8.000000
14	0.000000	0.000000
15	-100001.0	0.000000
16	-99999.00	0.000000
17	0.000000	0.000000
18	0.000000	-2.000000
19	-100000.0	0.9765625E-08
20	-100000.0	-0.4882812E-08
21	0.000000	0.000000
22	0.000000	-2.000000
23	0.000000	-4.000000
24	0.000000	-2.000000
25	-100000.0	0.000000
26	-100000.0	-0.1464844E-07
27	0.000000	0.000000
28	0.000000	-12.00000
29	-99999.00	0.000000
30	-100001.0	0.8300698E-07
31	0.000000	0.000000
32	0.000000	32.00000
33	-99999.00	0.000000