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Batch Production Using Dynamic Cellular Manufacturing Systems

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Vijay R. Kannan

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of the requirements for

Ph.D. degree in Operations Management

Soumen Ghosh
Major professor

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BATCH PRODUCTION USING

DYNAMIC CELLULAR MANUFACTURING SYSTEMS

By

Vijay R. Kannan

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
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ABSTRACT

BATCH PRODUCTION USING DYNAMIC CELLULAR MANUFACTURING SYSTEMS

By

Vijay R. Kannan

Demand patterns in the batch manufacturing environment are increasingly characterized by greater variety, frequent design changes, and lower volumes. These trends place a premium on short lead times and small batch sizes. Production methods that are commonly used in this environment, are limited in their ability to provide both the flexibility and efficiency needed to meet these needs. Job shops provide the flexibility to respond to changes in demand, but their use of frequent setups is not conducive to the repetitive production of small batches. Cellular manufacturing exploits similarities in production needs, but is inflexible due to its rigid physical layout.

Dynamic Cellular Manufacturing (DCM) systems allow cellular manufacturing to be operationalized without the layout constraints imposed by traditional cellular systems. Manufacturing cells are formed on a real time basis, based on prevailing production needs. These cells can evolve, expand, contract, or dissolve, depending on the needs of specific part families and machine availability. This allows the principles of family based production to be implemented with the flexibility required to meet current demand patterns. This is accomplished without physically changing an existing job shop.

The use of DCM is compared to that of traditional job shop and cellular production methods under a range of shop conditions. In addition, DCM is examined under a broader range of conditions in order to identify conditions that appear conducive to its use. The results show that the combination of flexibility and setup efficiency embodied in DCM, enables it to meet the needs of small/medium batch production more effectively than the other production methods. DCM outperforms these traditional production methods over a wider range of operating conditions than anticipated. It also appears to be more robust to certain kinds of variability than currently used production methods.

DEDICATED TO MY PARENTS

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CHAPTER 1

INTRODUCTION AND PROBLEM STATEMENT

1.1 INTRODUCTION

Between 60 and 80% of manufacturing takes place in a batch production environment (Chevalier, 1986). However, recent changes in the batch manufacturing environment have brought into question the use of the process layouts or job shops that are often used for this type of production. According to Hyer (1982), 60-80% of manufacturing in the U.S. takes place in shops that utilize a process layout. Such shops, organized as groups of functionally similar machines, provide routing flexibility by allowing any available machine of the required type to be used to process a part. In this environment, the ratio of setup times to processing times is typically large, making the use of frequent setups inefficient. In addition, jobs often encounter long delays waiting for machines to become idle and then be setup. Jobs spend as much as 95% of their flow times in queues and in transit between machines (Tersine, 1985). To reduce these inefficiencies, batch sizes are generally large, increasing work in process and finished goods inventories.

Increasingly however, demand is characterized by greater variety, lower volumes, frequent design changes and short cycle manufacturing. Demand is also more uncertain than in the past. These factors make reductions in lead times and batch sizes essential to improve responsiveness and competitiveness. This has been demonstrated by the performance of manufacturing systems based on the just in time philosophy. Quality and reliability are also major considerations given the increased level of competition. Greater diversity in materials, and higher material and energy costs add to the need for a more efficient production system.

Given the limitations of job shops, considerable attention has been paid recently to Cellular Manufacturing (CM). CM is one facet of Group Technology (GT). This is a philosophy of production based on the principle of exploiting similarities in part design and manufacture. CM specifically deals with the manufacture of families of parts, parts that have been grouped based on processing similarity, within manufacturing cells, sets of machines which have been dedicated to the manufacture of specific families. The suggested gains from this are:

- Improved control and monitoring of jobs, since they move within a limited physical area, and follow a clearly defined route
- Shorter lead times and work in process inventory, since the benefits of a flow line can be attained
- Faster quality feedback, since with the use of a flow line, the source of a problem can be detected more quickly
- Lower setup times and tooling requirements due to the greater homogeneity of parts produced within a cell
- Smaller lot sizes due to the ability of jobs to share setups
- Learning benefits due to repetitive processing and worker specialization
- Increased operator satisfaction due to the enlargement of job assignments to cover family processing.

Despite the potential however, the evidence increasingly suggests that CM is not the solution to the problems of small batch manufacturing. The anticipated gains from its use are more than offset by its limitations. The cost of physically re-organizing the shop floor and adding new equipment which often results, is high. In addition, there is a cost associated with lost production during the re-organization. Since re-organization is based on existing demand patterns, it may not be possible to absorb subsequent changes in demand without additional re-organization and/or investment. The dedication of equipment to cells reduces routing flexibility. Since cells are dedicated to individual families, demand patterns that create uneven cell workloads result in bottlenecks in some cells, and idleness in others. This leads to long queues and consequently increases the mean and variance of flow time. The evidence suggests that the range of conditions when a cellular layout performs at a comparable level to a process layout, is extremely limited. In summary, although production control and focus might be improved by effectively creating plants within plants consistent with Skinner's concept of focus (1974), shop performance is poorer.

1.2 PROBLEM STATEMENT

Based on the existing evidence, a need exists for greater manufacturing flexibility. Swamidass (1988) defined flexibility as

> "the capacity of a manufacturing system to adapt successfully to changing environmental conditions and process requirements" and "the ability of the production system to cope with the instability induced by the environment."

While traditional process layouts offer a high degree of flexibility, they are otherwise inefficient for part family production. CM improves efficiency, but at the cost of reduced flexibility. As an alternative to these extremes, this research operationalizes a manufacturing system for small/medium batch family production that offers a higher degree of flexibility than traditional CM without significantly compromising its efficiency. The system proposed is a hybrid between CM and job shop production that takes advantage of the benefits of each, yet attempts to minimize or eliminate their individual limitations. This is accomplished by manufacturing in an environment characterized by dynamically formed manufacturing cells, or Dynamic Cellular Manufacturing (DCM). It is envisioned that DCM will enable contemporary production needs to be met more effectively, by better managing the apparent tradeoff between flexibility and setup efficiency. Furthermore, higher flexibility in DCM is obtained without necessitating the high capital investment as in a FMS.

DCM focusses on current manufacturing trends, for example shorter product life cycles, frequent product revisions, and new product introduction. It does this by using the principles of CM, but without the physical shop re-organization. Scheduling mechanisms are used that recognize part family affiliations, and based on these, temporarily dedicate machines. The result is the formation of logical production cells based on need, that exist only as long as the need prevails. Since no permanent machine dedication is involved, the underlying flexibility of a process layout is maintained while simultaneously establishing the flow pattern dominance and family orientation of CM. This facilitates lower flow times and work in process, reduced bottlenecks, and more balanced utilization. Since there is no physical shop re-organization, there is no financial cost associated with the introduction of DCM, nor a need for either a total or partial shutdown of the production system. In addition to providing an alternative to traditional cellular and job shop manufacturing, DCM provides a vehicle for testing the appropriateness of CM in a given production environment.

This study compares the performance of DCM to that of a traditional job shop, and a shop organized using the principles of CM. The objective is to identify whether DCM can meet the needs of small/medium batch production more effectively, and if so, under what conditions. The questions to be addressed are :

a. Do setup conditions exist where DCM's use of the part family concept and efficient use of setups, is more beneficial than the flexibility of a traditional job shop. If so, what setup conditions are conducive to DCM.

b. Can the recognition of part families by DCM, make it more effective in dealing with different part mix compositions. If so, for what part mix characteristics is DCM preferable.

c. Can the greater flexibility of DCM allow it to overcome the setup efficiencies of permanent machine dedication in traditional CM, and if so, under what setup conditions.

d. Does the greater flexibility of DCM make it more responsive to changes in part mix than traditional CM, and if so, under what part mix conditions.

e. Does the information used to form dynamic cells affect their performance.

f. Does shop load have a significant impact on the effectiveness of DCM.

g. Is DCM sensitive to changes in job size.

h. Does job dispatching affect the performance of DCM.

A simulation model is used to compare the behavior of the three systems under various shop conditions, and to provide answers to these questions.

1.3 ORGANIZATION OF DISSERTATION

Chapter two discusses the literature that addresses the use and design of CM systems, evidence of their performance, and mechanisms used to improve their effectiveness. This will illustrate the shortcomings of CM for small/medium batch production, and address the need to incorporate greater flexibility into existing cellular production methods. Chapter three describes in more detail, the concept of DCM, how it differs from existing production methods, and the specific issues and questions to be addressed by this research. Chapter four describes in detail the experiments carried out, the methodology used, and the techniques used to answer the research questions. The results of the experiments and analysis of their implications are discussed in Chapter five, followed by a discussion of the conclusions of the study and directions for future research.

CHAPTER 2

BACKGROUND AND LITERATURE REVIEW

2.1 INTRODUCTION

Considerable attention has been paid recently to improving the performance of small/medium batch production systems. One attempt to deal with this problem has focussed on the principles of GT. One aspect of GT that has received particular attention is CM. A number of articles have discussed the advantages and disadvantages of CM (e.g., Greene & Sadowski, 1984, Suresh & Meredith, 1985). However, though case evidence suggests gains from the use of CM, a larger body of literature refutes this.

This chapter discusses the literature that has addressed the merits of CM and compared its use to that of a process layout. Mechanisms that have been proposed to overcome CM's limitations are identified and their impact examined. The results will demonstrate the need for a new approach to small/medium batch manufacturing. The literature on the formation of manufacturing cells is also discussed. This is an important issue in CM since cell formation is a key component in CM system design.

The chapter concludes by addressing the issue of manufacturing flexibility. As the evidence will show, it is CM's lack of flexibility in contrast to that of a process layout, that is the driving force behind the need for an alternative approach to small/medium batch production.

2.2 RESEARCH ON CELLULAR MANUFACTURING (GROUP TECHNOLOGY)

2.2.1 Comparative Studies of Cellular Manufacturing Performance

Evidence exists, primarily from surveys of CM users, that its use can significantly improve shop performance compared to that of a process layout (Hyer, 1982). However, several questions exist regarding the validity of these observations.

Leonard & Rathmill (1977) concluded that comparisons between cellular and process layouts are often made between efficiently organized and operated cellular layouts, and process layouts that were not optimized in the same way. This makes direct comparison of their performance inconclusive. Their research also suggested that contrary to expectations, CM yields lower utilization, more complex production control, and reduced job satisfaction. Craven (1977) drew attention to the fact that gains from the use of CM depend on a myriad of design considerations, constraints, and trade-offs. Flynn & Jacobs (1986) noted that during the time it takes to implement CM systems, other variables such as product mix, can change. This again makes comparison with the original process layout inappropriate.

Wemmerlov & Hyer (1987) stated that performance improvements arising from the conversion from a process to a cellular layout, do not reflect the cost and effort involved. In addition, CM typically co-exists with machines organized on a functional basis. Any gains from the use of the manufacturing cells may come at the expense of the functional component of the shop. They also suggested that one of the reasons for poor CM performance is the use of poor routing information in cell design. Morris & Tersine (1989) indicated that when CM is introduced, it is frequently accompanied by the addition of new equipment. This new equipment might have improved the performance of the existing process layout.

As well as the evidence from industry, several simulation studies have also concluded that CM performance is not superior to that of process layouts, and is in fact inferior on several dimensions.

2.2.1.1 Cellular Layouts vs. Process Layouts

Cummings (1980) study is the only one to consistently support the use of a cellular layout. It compared the performance of cellular and process layouts under different levels of utilization, and with no and low labor absenteeism. Results showed that absenteeism did not yield poorer performance when using a cellular layout except at very high utilization. However, when using the process layout, performance decreased as absenteeism increased at all levels of utilization. With or without absenteeism, the cellular layout performed considerably better, particularly as utilization increased. Despite these findings, the lack of recognition of family and setup characteristics, makes their value limited.

Flynn (1984), Flynn & Jacobs (1986, 1987) conducted several comparisons of process and cellular layouts. They compared four layouts; a process layout, a process layout with machines dedicated to specific parts, and two cellular layouts that differed in how machines were organized. They showed that although the shops using dedicated machines yielded improved performance with respect to setup, utilization and material handling, they performed poorly for most other measures, in particular flow time and queue related measures. Of the layouts using dedicated machines, the process layout performed the best for queue related measures. They concluded that it was the dedication of machines rather than the layout itself that led to differences in performance.

Flynn (1984) also considered two alternate routing strategies as a means of improving the performance of the cellular layouts. According to the first strategy, jobs had at most one alternate machine for a given operation, the machine that was physically closest to the primary machine. Jobs were re-routed to the alternate machine if there were more than twenty parts in the queue of the primary machine. Although this strategy generally led to improved performance, performance was still inferior to that of a process layout. The second strategy allowed work to be re-routed to any similar machine when the total work content at the primary machine exceeded a certain level, defined in terms of numbers of days of work. The results again showed that shop performance improved, but only when cells were designed based on material flows between machines and not cells. Larger critical queue lengths yielded better results, by increasing the accumulation of jobs in a queue and increasing the potential to share setups. Though this strategy outperformed the first, the improvement was again not enough to make the performance of the cellular layout comparable to that of a process layout.

Morris (1988), Morris & Tersine (1990) also found that the use of CM led to a degradation in shop performance. They sought to identify operating conditions that are conducive to CM. Results showed that a cellular layout performed at a comparable or superior level to a process layout only when setup and material handling times were very high, demand patterns stable, and job flow unidirectional. The difference in flow times under other conditions was large enough that even with a ten fold increase in material handling time, the process layout, which does not lend itself to material handling efficiencies, had lower flow times.

Suresh (1992) demonstrated using queuing theory that partitioning a job shop into cells necessarily leads to a decrease in flow time and work in process performance, and lower utilization. Only if setup times within the cells are significantly reduced can the cells generate improvements in performance. These conclusions were tested using a simulation study of a process layout and two cellular layouts that differed in size and number of families processed within each cell. Based on the batch size that yielded the most efficient process layout operation, the results showed that under high setup times, the cellular layouts were unstable at this or smaller batch sizes. Bottlenecks at even a single machine were enough to render the entire cell unstable. Reductions in setup times within the cells were necessary to induce stability. Further reductions enabled the cellular layouts to outperform the process layout. Using larger batch sizes, the cellular layouts were initially stable but yielded considerably poorer performance than the process layout operating with the optimal batch size. The performance of the cellular layouts again improved as setup times within the cells were reduced. When cells were larger, flow time performance was always better due to the reduction of bottlenecks. However, utilization was unchanged due to the increase in setup frequency.

The ability to move work between cells was also shown to yield improvements in performance. Inter-cell movement in the shop with small cells induced stability under conditions that were previously unstable. Performance improved but was still poorer than that when using the process layout. When batch sizes were small, smaller reductions in setup time were needed to obtain stability in the shop and to generate improved performance compared to that of the process layout. However, for large reductions in setup time, performance began to deteriorate as move times more than offset the gains from lower setup times.

2.2.1.2 Hybrid Cellular Layouts vs. Process Layouts

Hyer (1982) found that in shops using CM, none was organized entirely as cells. Shops contained a combination of cells and machines organized by function. Most users produced at least 45% of parts outside the cell. Burgess (1988) suggested that determining the extent to which cells should be used in such a hybrid layout was of greater importance than determining whether they should they be used at all.

Christy & Nandkeolyar (1986) investigated the percentage of jobs that must be completed within the cellular component of the shop in order for it to outperform a pure process layout. They showed that for percentages between 17.5 and 22.5%, the hybrid yielded lower flow times. Consistently however, the hybrid layout yielded higher mean tardiness. Utilization was generally higher within the cellular component of the shop. For the optimal proportion of jobs passing through the cell, the performance of the hybrid improved when setup, operation and material handling times were reduced by 60-65%, though greater reductions were needed to yield improvements in tardiness performance.

Using a labor constrained environment, Burgess (1988) showed that contrary to Christy & Nandkeolyar's results, the proportion of jobs passing through the cell in the hybrid layout had to exceed 40% in order for the hybrid layout to outperform the traditional process layout. This was true even when setup times in the process layout were reduced by as much as 25%. Reducing the proportion of jobs passing through the cell had a significant impact. For example, the process layout outperformed the hybrid layout if only 30% of jobs passed through the cell even when setup times in the cell were reduced by 90%. Burgess concluded that in such hybrid layouts, the relative allocation of resources between the two components of the shop has a significant impact on shop performance.

Queuing theory was used by Suresh (1991) to explain why shop performance must decrease when a job shop work center is partitioned into the kind of hybrids described above. Flow time and work in process were shown to increase due to the increase in queues that result from machine dedication. Smaller batch sizes were also shown to be infeasible within the cellular component of the shop. When setup times within the cellular component were reduced, not only were smaller batch sizes feasible, but the performance of this component of the shop was better than that of the original un-partitioned work center. However, performance of the shop as a whole was inferior due to the negative impact on the functional component of the shop. Conditions for effective partitioning were defined and confirmed using a simulation model. The results re-iterated the potential for machine dedication at low batch sizes if setup times are reduced, but also highlighted the need to resolve the difficulties this creates within the functional component of the shop.

2.2.2 Other Operational Issues in Cellular Manufacturing

Crookall & Lee (1977) and Lee (1985) showed that CM systems that utilized large cells, few families, and small batch sizes, generally yielded better performance than those that did not. The presence of multiple servers in large cells more than offset any increases in setup frequency. Fewer families decreased the need for setup changes. Smaller batch sizes allowed jobs to move through the shop faster, though the resulting increase in setups caused increases in utilization. A similar study was carried out by Gupta & Tompkins (1982) who used a simulation model to examine the tradeoffs between cell size, material movements, and number of inter-cell moves, and between batch size and setup times. Though intra-cell moves increase with larger cell size, these are generally preferable to inter-cell moves. They showed that as expected, larger cells yielded fewer inter-cell moves. Karmarkar et al. (1985b) showed analytically and using a simulation model that reductions in batch size reduced flow time and work in process. However, batch sizes that were too small yielded more frequent setups, increased queues, and poorer performance. Additional studies such as Sinha & Hollier (1984), and Wemmerlov & Hyer (1987), have addressed additional issues that can affect the performance of CM systems, but which have yet to be examined.

2.2.3 Extensions to Cellular Manufacturing Systems

Given the limitations of CM particularly with respect to flexibility, a number of approaches have been suggested to improve its performance. These fall into three main areas; group scheduling, repetitive lots, and alternate routing.

2.2.3.1 Group Scheduling

According to Mosier & Taube (1985), group scheduling is the least addressed topic related to CM. It refers to scheduling rules that exploit family processing similarities, primarily in setups, between jobs in a queue. Similar sequence-dependent scheduling rules have been used in job shops where part families were not explicitly considered.

One stream of group scheduling research is analytic in nature. A number of these studies consist of optimal family and job sequencing rules in a single machine facility. Hitomi & Ham (1978) used mathematical programming to maximize production rate. Foo & Wager (1983) developed a dynamic programming formulation to minimize setup time for a single part family with sequence-dependent job setup times. Ozden et al. (1985) used dynamic programming to minimize total setup cost where job and family setup times were sequence-dependent.

Analytic models have also been applied specifically in a cellular environment. A branch and bound solution to family and job sequencing was used by Hitomi & Ham (1977) to minimize makespan. A similar approach was used by Ham et al. (1979) to minimize makespan with the minimum number of tardy jobs. Sundaram (1983) developed two static heuristics to minimize makespan. The first heuristic selects the family to be processed next on a machine based on earliest family completion date at that machine. Within a family, a Gantt chart is used to schedule jobs to minimize makespan. According to the second heuristic, the family is selected based on shortest family processing time. Only on completion of family processing at the machine is the family loaded at the next machine. The second heuristic was shown to perform the better of the two, yielding an optimal solution for the data set used, though optimality is not guaranteed.

Most of the group scheduling research specific to cellular environments consists of heuristics applied in simulation studies of single job shop and flow shop cells. They are generally scheduling rules that use different criteria to select a family for processing, then process all jobs in the queue from this family prior to resetting the machine. This takes advantage of the similar setup needs of jobs from the same family, thereby reducing setup frequency.

2.2.3.1.1 <u>Group Scheduling in Job Shop Cells</u>

Vaithianathan & McRoberts (1982) defined five heuristics for family selection. These consider lowest slack/processing time ratio, lowest family slack, highest setup time, lowest setup time, and highest similarity of jobs (using similarity coefficients). Within a family, jobs are dispatched using the shortest processing time (SPT) rule. Compared to scheduling based on SPT alone, the heuristics yielded lower flow times and number of setups per job. However, due date performance was very poor.

Mosier (1983) and Mosier et al. (1984) compared three mechanisms for family selection. These select families based on highest family work content (WORK), highest average job priority (AVE, five dispatching rules were used to prioritize jobs), and the economic benefit of changing the current setup or continuing to use the existing setup (ECON). This rule makes it possible to change the setup even though jobs remain that require the existing setup. They showed that overall, WORK yielded the best performance followed by ECON. They also showed that family rules performed well with respect to mean flow time and mean lateness, but not for mean tardiness and percent tardy. Dispatching using either the SPT or minimum slack rule generally yielded the best results. Kelly at. al (1986) compared WORK and ECON to two cost based family selection rules. They showed that cost based heuristics performed poorly for flow time and tardiness measures.

Flynn (1987) applied the repetitive lots (RL) procedure (Jacobs & Bragg, 1988) in a multi-cell shop. This procedure, designed to minimize setups in job shop scheduling, is equivalent to FCFS family selection. Within a family, jobs are also dispatched using the FCFS criterion. Flynn also considered a truncated form of RL that limits the number of batches processed with the same setup, in order to prevent long waits for jobs from other families. The study compared the use of a cellular layout using both forms of RL, with a process layout, a process layout with machines dedicated to particular parts, and a cellular layout using FCFS dispatching alone. The results showed that in the cellular shop, both forms of the RL rule, though indistinguishable in their performance, outperformed FCFS dispatching for all performance measures. The relative performance of the three layouts when RL was used was similar to that of Flynn & Jacobs previous works (1986, 1987). The shops with dedicated machines performed better with respect to setup time and utilization, but poorer than the pure process layout on queue related measures and flow time. However, the difference in performance between the cellular and pure process layouts was significantly smaller. No differences in performance existed between the two layouts with dedicated machines. This further suggests that machine dedication rather than layout, has a more significant effect on performance.

Mahmoodi et al. (1990) considered three family selection rules. FCFAM selects the family containing the first job in the queue, DDFAM the family containing the job with the earliest due date, and MSFAM the family that minimizes future sequence-dependent family setups. They showed that MSFAM and DDFAM performed well for most performance measures. MSFAM performed poorly only for mean tardiness. Their relative performance depended on other conditions such as load and setup time/run time.

They also showed that dispatching jobs within a family using either the SPT rule or a processing time/slack hybrid (SI^x), yielded the best performance, similar to the findings of Mosier et al. (1984). Mahmoodi et al. (1988) also showed that the use of DDFAM and FCFAM in conjunction with SPT and FCFS job dispatching, always yielded superior flow time and tardiness performance than scheduling using the dispatching rules alone.

Mahmoodi & Dooley (1991) compared DDFAM and MSFAM, which they categorized as exhaustive rules, to two non-exhaustive rules that do not require all jobs using the current setup to be processed prior to a setup change. SLFAM processes jobs until the total slack of another family in the queue becomes negative. The setup is then changed to that of the more urgent family. If more than one family in the queue has negative slack, the family selected is that with the most jobs in the queue. DKFAM processes jobs until the time remaining until due date of the most urgent job, is more than C units greater than that of the most urgent job in another family in the queue. The setup is then changed to facilitate the new family. They showed that MSFAM always yielded the best flow time performance, and DKFAM the worst. DKFAM always performed as well as, if not better than the other rules for mean tardiness. MSFAM and SLFAM performed poorly. Proportion tardy was lowest for MSFAM, and highest for DKFAM. They again showed that dispatching using either the SPT or SI^x rules yielded the best overall performance. They concluded that although exhaustive rules as expected, generally perform better, there are benefits associated with non-exhaustive rules.

Ruben et al. (1993) examined factors that affect the performance of family scheduling heuristics. They showed that a rule that selects families based on minimum setup time and dispatches jobs based on SPT (MSSPT) performed better than existing family and non-family based scheduling rules. Significant gains in flow time performance were obtained by using group scheduling rules, though these were smaller for mean tardiness. The extent of gains depended on shop conditions, increasing with high utilization, setup/processing time ratio, and stable demand patterns. Though the $DDSI^x$ rule, which selects families based on most imminent job and dispatches using the SI^x rule yielded the best due date performance, scheduling using SI^x alone performed well, though this again depended on other conditions. MSSPT again performed best for proportion tardy, and FCFS based family scheduling for lateness. The authors concluded that by minimizing setups, group scheduling rules are in general more robust to shop load and setup/processing time ratio. However, they are also responsible for increases in tardiness when part families are large, by discriminating against parts from smaller families.

Wemmerlov (1992) conducted a comprehensive analysis of family and non-family based scheduling on a single machine. The study considered two family based rules, one equivalent to FCFAM, and one that selects families and jobs based on SPT. These were compared to scheduling using FCFS and SPT alone. The results showed that as the number of families was decreased, the resulting reduction in number of setups yielded improved flow time performance for all rules. However, at low setup times, the use of the SPT based family rule resulted in an increase in flow time. As the impact of setup times became less significant, the difference between this rule and the SPT dispatching rule increased. Unlike past studies, this demonstrated that when setup times are low, dispatching rules can outperform their family based counterparts. When demand was biased towards specific families, flow times were as expected lower, particularly when setup times were high and there were few families. Again, this was attributed to the increased ability to reduce setup frequency. Decreases in setup time were again shown to yield reductions in flow time, particularly at high utilization levels.

The research demonstrated the benefits of reducing variance. When processing time and arrival rate variance were reduced, the mean and variance of flow times were lower, as was the difference in performance between job and family based scheduling. In addition, greater benefit was obtained from reducing arrival rate variance, though failure to reduce processing time variance did on occasion lead to a degradation in performance of the two SPT based rules. The benefits of family scheduling rules also depended on the stability of the environment. When the environment was unstable, FCFAM performed better than FCFS. However, the SPT based family rule performed better than SPT only when processing time variance was reduced. Under unstable conditions, family scheduling rules were able to generate significant capacity increases and simultaneously improve flow time performance. In addition to instability, conditions of high utilization, setup times, and few families were shown to be most conducive to family based scheduling.

2.2.3.1.2 Group Scheduling in Flow Shop Cells

Hitomi et al. (1977) compared two group scheduling heuristics to traditional dispatching rules in a flow shop, job shop, and flow shop where flow patterns differed by family affiliation. The two heuristics select families based on minimum family setup time, and on the travelling salesman problem, where minimization of the sequence-dependent family setup times is the objective. Both rules performed well with respect to flow time measures, though not necessarily outperforming rules that did not recognize setups. However, their relative performance improved when utilization was high and the setup/processing time ratio large. For large ratios, they yielded the best performance. The interaction of utilization and setup/processing time ratio had a similar effect on flow time measures as the setup/processing time ratio. Heuristic methods were also used by Manivannan et al. (1987), and Abin & Mohamed (1987). Manivannan et al. developed a rule to minimize mean flow time given the optimal makespan. Abin & Mohamed developed a rule to minimize total setup time.

Wemmerlov & Vakharia (1992) compared a number of dynamic and static job scheduling rules to their family based counterparts. They confirmed that for each job based rule, the corresponding family based rule yielded superior performance. Of the family based procedures, minimum slack and FCFS based family selection generally yielded the best flow time and tardiness performance when used with FCFS dispatching. The performance of the FCFS based family selection rule is contrary to its performance in a job shop cell (Mahmoodi et al., 1990). As a group, family based rules outperformed job based rules though there was little discrimination between individual rules. In less that 40% of cases did the best job based rule perform significantly poorer than the worst family based rule. The gains from using family oriented rules were greater when utilization was high. This concurs with the results of Hitomi et al. (1977). Contrary to the evidence on job shop cells (e.g., Wemmerlov, 1992, Ruben et al., 1993), the number of part families did not affect the relative performance of job and family rules. This was significant only when both utilization and setup times were high. Similarly, the ratio of setup time to processing time was generally insignificant.

Mahmoodi et al. (1992) compared four family based scheduling rules to FCFS and SPT dispatching. They examined their performance under different shop load, setup/processing time ratio, due date tightness and inter-arrival time distribution conditions. Their results showed that for mean flow time, the MSSPT rule (Ruben et al., 1993) always yielded the best performance. Under certain conditions, this was matched by a rule that selects the next family based on job slack and dispatches jobs using SI'. This rule was shown to perform well in a job shop cell (Mahmoodi et al., 1990). As expected, this rule consistently performed best for due date measures. These two rules were also shown to be the most robust to changes in shop environment.

The ECON rule that had been shown to perform well in a job shop cell (Mosier, 1983, Mosier et al. 1984), performed poorly. It also proved to be the least robust of the family rules used. Contrary to Wemmerlov & Vakharia (1992), FCFAM also performed poorly.

The research indicated that for each performance measure, differences in performance between family heuristics were small when utilization was low, but increased at higher utilization. Consistent with past research on flow shop cells (Wemmerlov & Vakharia, 1992), and job shop cells (Mahmoodi et al., 1988), group scheduling rules yielded superior performance than their corresponding dispatching rules, particularly when utilization and variance were high.

Russell & Philipoom (1992) examined the effect of due date setting procedures on the performance of family scheduling rules. They showed that a procedure that considers how many setup changes occur before a job is processed, consistently yielded the best performance. They also demonstrated the importance of selecting scheduling mechanisms in conjunction with the due date setting procedure particularly when setup times were high. Overall, they showed that for flow time, the best scheduling rule was one that selects families based on lowest processing time per job, and dispatches jobs using the SPT rule. For this heuristic, no due date setting mechanism dominated. Mosier (1983), Mosier et al. (1984) showed that in a job shop cell, family selection based on average family priority tended to perform poorly. For other heuristics, relative performance did depend to a greater degree on which due date setting procedure was used, but again, none dominated.

For due date performance, the relative performance of the rules depended on setup times. When setup times were high, three heuristics generally performed best; FCFS family selection with slack based job dispatching (FCFS-SLK), due date dispatching where jobs not belonging to the current family have a constant added to their due date to penalize additional setup changes (EDD-T), and a rule that requires a setup change after a fixed amount of time has elapsed in addition to when no jobs with the current setup remain (Sawicki, 1973). For this rule (SAW-T), the authors showed that the best family and job selection rule depended on the performance measure of interest and the due date setting mechanism used. Overall however, FCFS family selection and slack based dispatching performed best. When setup times were low, performance was generally best for the EDD-T rule.

2.2.3.1.3 Sequence-Dependent Scheduling in Job Shops

In addition to the group scheduling literature, limited research exists on sequence-dependent scheduling in job shops. However, Wemmerlov (1992) makes the distinction that unlike group scheduling rules that attempt to avoid setups, sequence-dependent scheduling rules typically consider only that changeover times are dependent on the existing setup, and do not explicitly try to avoid setups.

Gavett (1965) considered the use of a scheduling rule that processes the job with the lowest setup time relative to the job just completed, as well as two variants of this rule. For a finite number of jobs, he showed that these rules performed significantly better than random rules, but were frequently not optimal. The gains from the use of these rules as well as their relative performance, depended on parameters such as distribution and variance of setup times, and batch size. Haynes et al. (1973) examined how these parameters caused the heuristics to perform differently to an optimal sequence. They showed that the rules yielded results closer to optimality when either a gamma or normal distribution was used for setup times, and when batch sizes were small. The use of a uniform distribution led to poor results.

Hollier (1968) compared a dispatching rule that selects the next job based on its using the current setup, to dispatching rules that do not recognize setups. This rule was shown to perform well for a number of measures, sometimes outperforming the other rules. Wilbrecht et al. (1969) evaluated three sequence-dependent scheduling heuristics. These select the job with the lowest setup time relative to that of the job just completed, the job with the lowest process time (setup time plus run time), and the job with the highest process time. They showed that for a number of performance measures, these rules performed as well as or better than rules that do not consider sequence dependencies. The first two rules exhibited particularly good performance.

White & Wilson (1977) developed a regression model that allows setup times to be predicted, based on the assumption that actual setup times are not always known. Given these predictions, a heuristic was used to sequence jobs in order to minimize the number of more time consuming setups, and total setup time. This heuristic was shown to generate good results even though actual setup times could not always be used.

The Repetitive Lots (RL) procedure (Jacobs & Bragg, 1988) proposes splitting jobs into transfer batches smaller than their original release quantity. This promotes more efficient material flow and scheduling by allowing transfer batches to move independently. At each machine, transfer batches using the existing setup are processed first on a FCFS basis. When no such jobs remain, the setup is changed to that required by the first remaining job in the queue. This is similar in principle to the FCFAM family scheduling rule. The use of RL was shown to yield significant improvements in flow time performance over a range of release and transfer batch sizes. In addition, for smaller release batch sizes, it induced stability in shops that were previously unstable.

2.2.3.2 Lot Splitting in Cellular Manufacturing

Lot splitting has been to used in CM to improve the efficiency of material handling and setup use similar to the principles of repetitive lots. Morris & Tersine (1989) considered splitting jobs into transfer batches of size one in conjunction with the use of cell loading (Mosier, 1983). A cell using cell loading processes a single job at any given time, unlike the more common machine loading, where a number of jobs compete for machines. Mosier showed that cell loading yielded low utilization and poor performance. Morris & Tersine however applied cell loading in conjunction with transfer batches. Their results indicated that at low utilization, cell loading yielded performance superior to that of a process layout and a cell using machine loading. However, as utilization increased, the shop using cell loading was more sensitive to increased congestion. The less efficient use of machines resulted in performance that was inferior to either of the two other layouts.

Sassani (1990) showed that reducing transfer batch size led to reductions in setup time and proportion tardy. However, the performance of individual cells was sensitive to the processing characteristics of jobs processed within them.

2.2.3.3 Alternate Routings in Cellular Manufacturing

Alternate routing has been proposed as a means of reducing problems in CM of bottlenecks and imbalances in cell utilization, by re-routing jobs from overloaded machines to less busy machines in other cells. However, this does result in an increase in inter-family setups and the complexity of material handling. Widespread use of alternate routing makes the operation of CM similar to that of a process layout, since the material handling and setup benefits of CM are lost. Typically 20% of parts encounter some inter-cell movement in practice (Wemmerlov & Hyer, 1987), though this may not be attributable solely to alternate routing.

Ang & Willey (1984) considered several alternate routing heuristics. In addition they considered routing work to idle machines from those that were not necessarily congested, in order to balance loads. Their results indicated that a number of these heuristics led to improved performance. In particular, a rule that transfers jobs from their primary machine if average workload at the machine is greater than a critical value, and sends them to the alternate machine with the lowest average workload that can process the job immediately, showed the greatest improvement. Mean flow time, standard deviation of lateness, and mean tardiness, all improved. However, performance gains decreased as the amount of re-routing increased. They also considered the impact of returning a transferred job to its primary machine after it had been processed at an alternate machine. Though this also led to performance improvements, these were not as large. Alternate routing led to performance gains regardless of which dispatching rule was used, shop configuration (i.e., number of cells, cell size), changes in product mix and demand patterns. The results showed that simple heuristics can yield significant performance improvements if used sparingly, and that the gains are more the result of balanced workload than re-routing itself. However, the time involved in re-routing was not explicitly considered nor was any comparison made to a process layout.

Garza (1990) and Garza & Smunt (1991) showed that limited alternate routing enabled CM to outperform a process layout. They showed that CM performance could better that of a process layout when batch sizes were small, setup times high, and run time variance low. They also showed that small ratios of minor (intra-family) to major (inter-family) setup time led to improved CM performance by increasing the impact of fewer major setups. In addition, they showed that when the impact of material handling in the process layout was large, the use of alternate routing was consistently beneficial, regardless of the extent of its use. Alternate routing was also examined by Flynn (1984) and Suresh (1992) in studies that compared CM using alternate routing to the use of process layouts (Section 2.2.2.1).

Though the literature on alternate routing in CM is limited, considerable evidence of its benefit in a job shop exists, e.g., Wayson (1965), Russo (1965), Goodman (1972), Tilak (1978), and Khatour & Moodie (1979). Bobrowski & Mabert (1988) investigated the effect of adding routing flexibility at the process planning stage. They showed that increased routing flexibility led to performance benefits, but that these followed the law of diminishing returns. With additional flexibility, a tradeoff exists due to the increased tooling and fixtures required.

2.2.4 Cell Formation Techniques in Cellular Manufacturing

In addition to the literature on the performance of CM, a significant body of research has examined the cell formation process. Cell formation involves the grouping of parts into families based on production similarity, and allocating machines to individual families to form cells. The current research is not concerned with traditional cell formation since permanent cells are not formed. However, the separation of parts into families is important since the existence of part families is the basis for forming dynamic cells.

A number of taxonomies exist for classifying approaches to cell formation (e.g., Wemmerlov & Hyer, 1986, Vakharia, 1986). These represent comprehensive surveys of the cell formation literature. The approach taken here is to briefly summarize some of the more significant contributions using a framework similar to that of Vakharia.

2.2.4.1 Non-Analytic Methods

2.2.4.1.1 Descriptive Methods

Wemmerlov & Hyer (1986) cited implementations of CM where part families were formed based on part name or function, i.e., a valve manufacturer might treat a valve stem as a part family. Categorization by visual inspection of shape or size is another means cited. Part coding, an important component of GT, can also be used to identify similar parts, by capturing shape, size and machining characteristics.

2.2.4.1.2 Manual Methods

Burbidge's (1975) Production Flow Analysis (PFA) uses the part/machine matrix that defines production requirements, and by manual re-arrangement, obtains clusters of mutually exclusive part/machine groupings along the diagonal. Groupings that do not yield precise partitions are used as the basis for the final cell configuration. Similar approaches have been suggested by El Essawy & Torrance (1972), de Beer et al. (1976), Malik & Dale (1977), and de Beer & de Witte (1978). El Essawy & Torrance's Component Flow Analysis sorts parts twice, based on the order in which they use machines and the minimum number of machines required. This sorting is the basis for forming machine groups, taking into consideration machine, part and shop constraints. Cells are formed around groups requiring the most machines. Detailed analysis of within cell flow patterns is carried out to ensure a feasible design. de Beer et al. and de Beer & de Witte defined Production Flow Synthesis in which families are formed in a similar manner to PFA, but operations defined also in terms of the number of machines that can be used to process them. Machine clusters are formed depending on how many machines can be used for a particular part. Malik & Dale suggested forming product groups based on processing requirements, and allocating the required number of machines to each group. Machines not allocated form a remainder cell.

Tilsley & Lewis's (1977) Flexible Production Cells also forms cells based on processing requirements, but also takes into account demand variability. It is based on computer analysis of routings to identify machines that occur together frequently. Burbidge (1977) also proposed Nuclear Synthesis, where machines used by only a few parts are identified and represent the nuclei of cells. Once these nuclei are identified, processing requirements of parts using them are analyzed, and parts with similar processing requirements added to the group. Corresponding machines are then allocated to the groups to form cells.

2.2.4.2 Analytic Methods

2.2.4.2.1 Similarity Coefficients/Cluster Analysis

Similarity coefficients, first proposed by Jaccard (Sokal & Sneath, 1973) numerically define the similarity between pairs of items. McAuley's Single Linkage Cluster Analysis (1972) defines the similarity between two machines as the ratio of number of parts using both machines to the number of parts using at least one. Cluster analysis is used to determine the optimal grouping of machines based on these similarities. Machines are added to a cluster if their similarity with existing machines in the cluster exceeds a threshold value. As fewer machines remain, a clustering algorithm is used to systematically reduce the threshold value until all machines are allocated. Similar to this approach is the Bond Energy Algorithm, (McCormick et al., 1972). Cells are identified by reordering the binary part/machine matrix based on bond energy, the product of adjacent element values, and maximizing total bond energy. Similarity coefficients were also used by de Witte (1980) in an extension of an earlier work.

Rajagopalan & Batra (1975) used graph theory to form cells. Arcs of the graph represent the strength of similarity between machines. These form cliques or groups of machines so that strong relationships exist within groups, and weak relationships between groups. Chandrasekharan & Rajagopalan (1986a, 1986b) formulated the problem as a bipartite graph and used a non-hierarchical clustering algorithm to obtain diagonal groupings within the part/machine matrix.

Carrie (1973) and Vakharia & Wemmerlov (1990) applied similarity coefficients to parts rather than machines. Carrie's method groups parts together if their similarity is above a threshold value, and a specified minimum number included in a family. This prevents the formation of unduly small cells. A clustering algorithm is used to systematically reduce the threshold value until all parts are allocated to a family. Vakharia & Wemmerlov explicitly considered intra-cell material flows and machine load in cell formation. Their algorithm distinguishes between parts based on the need for operation backtracks (non-sequential operations on the same machine) and number of operations.

In addition, it distinguishes between parts using the same machines in the same sequence, and those using the same machines in a different order. Operation sequence was also considered by Choobineh (1988).

Kusiak (1987) proposed the p-median problem in which cells are formed using an integer programming formulation, whose objective is to maximize total similarity. The maximum number of part families to be formed can be expressed as a constraint in this formulation. Kusiak also presented a formulation that allows alternate process plans for a part. Kusiak & Cho (1992) developed two formulations that consider alternate process plans both when there are and are not bottleneck parts or machines.

More comprehensive surveys of the literature regarding similarity coefficients and cluster analysis can be found in Chu (1988), and Shafer & Rogers (1993).

2.2.4.2.2 Block Diagonal Methods

Several algorithms form cells by re-ordering the binary part/machine matrix to yield mutually exclusive clusters along the diagonal of the matrix similar to Production Flow Analysis. King's (1979) Rank Order Clustering (ROC) re-orders the matrix by attributing binary values to the rows and columns of the matrix. These are converted to decimal equivalents and the rows and columns re-ordered based on decreasing decimal values. The process is repeated until no changes in the matrix occur. King (1980) modified this so that the rows and columns can be ordered directly from their binary values. King &

Nakornchai (1982) proposed ROC 2 which is similar to ROC but computationally less demanding. This algorithm places all rows with a '1' in the last column at the top of the matrix, then does the same with the columns, moving columns with a '1' in the last row to the left of the matrix. This is repeated until there are no further changes in the matrix. Chan & Milner's (1982) Direct Clustering Algorithm is similar to ROC 2 but re-orders rows and columns based on decreasing number of entries in the row or column.

Boe & Cheng (1991) and Askin et al. (1991) addressed the limitation of procedures based on ROC that they do not guarantee a diagonal matrix structure after re-ordering. They proposed new algorithms that do produce such a structure.

2.2.4.2.3 <u>Other Analytic Methods</u>

Combinatorial grouping and mathematical programming have been used by Purcheck (1974, 1975a, 1975b), and Oliva-Lopez & Purcheck (1979). Machines needed to process a part and any parts whose routing is a subset of its are identified. Based on constraints such as cell workload, groupings of sets of similar parts are found and merged. Corresponding machines are allocated to the merged sets to form cells. Mathematical programming was also used by Shtub (1989) who modelled the cell formation problem as a generalized assignment problem.

In addition to the traditional approaches to cell formation, newer approaches have been developed recently to overcome some of the limitations of existing methods (Chu, 1993).

Amongst these are neural networks (Kaparthi & Suresh, 1992, Chu, 1993), fuzzy clustering (Xu & Wang, 1989, Chu & Hayya, 1991), syntactic pattern recognition (Wu et al., 1989), expert systems (Kusiak, 1988), and simulated annealing (Boctor, 1990).

2.2.4.3 Other Studies on Cell Formation

Although several cell formation procedures exist, their impact on shop performance is largely unclear. Most procedures do not consider their impact on shop performance. Though some have been evaluated on the performance they yield, evidence of their relative performance is limited (e.g., Morris, 1988, Shafer, 1988, Shafer & Meredith, 1990, Chu & Tsai, 1990).

Several studies have incorporated information on additional shop characteristics as well as those of the parts and machines themselves. Vannelli & Kumar (1986) developed a heuristic that minimizes the number of bottleneck cells. Ballakur & Steudel (1987) considered the impact on cell formation of factors such as cell utilization and workload. Seifoddini (1987) and Balasubramaniam & Panneerselvam (1993) incorporated information on production volumes in cell formation. Nagi et al. (1990) formulated cells while incorporating multiple routings and capacity constraints. Rajamani et al. (1990) also considered the availability of alternate process plans. Sule (1991) developed a heuristic that considers capacity requirements as well as equipment costs and the costs associated with inter-cell material movements. The impact of operating costs, lot size and production planning, was also considered by Chakravarty & Shtub (1984). Rajamani et al. (1992) formulated a mixed integer programming model that evaluates the trade-off between investment in additional machines and setup costs where setups are sequence-dependent.

A number of articles have focussed on the issue of exceptional elements, parts that do not fit into identified cells. Surveys of CM users (e.g Pullen, 1976, Wemmerlov & Hyer, 1989) suggest that despite the intent of CM to obtain independent cells, most implementations have large numbers of parts requiring processing in multiple cells. Waghodekar & Sahu (1984) developed a heuristic to minimize the number of exceptional elements. Kumar & Vannelli (1987) developed a method for identifying parts that can be subcontracted so that those remaining belong to well defined cells. Wei & Gaither (1990) formulated an integer programming model that minimizes the opportunity cost associated with manufacturing exceptional parts. Kern & Wei (1991) and Shafer et al. (1992) developed models that consider the costs of eliminating exceptional elements (i.e., by inter-cell movement, machine duplication, or sub-contracting) once a cell configuration has been identified.

A number of formulations focus specifically on the issue of inter-cell movement of work and machine duplication. Harhalakis et al. (1990) and Wu & Salvendy (1993) minimized the number of inter-cell moves by combining cells using heuristic and network approaches respectively. Vohra et al. (1990) also formulated the cell formation problem as a network to minimize interactions between cells. Logendran (1990) considered the effects of both inter and intra-cell movement as well as workload imbalances within cells. This approach was extended (Logendran, 1991) to incorporate the impact of operation sequence and cell layout. Song & Hitomi (1992) developed a quadratic assignment problem to minimize inter-cell movement. Okogbaa et al. (1992) allow inter-cell movement so that the variance of busy times of identical machines is similar. Dahel & Smith (1993) formulated integer programming models to minimize inter-cell movement and to minimize inter-cell movement while simultaneously maximizing routing flexibility.

The issue of duplicate machines was considered by Seifoddini & Wolfe (1986), Seifoddini (1989), and Logendran (1992). Seifoddini & Wolfe developed a similarity coefficients approach to cell formation that duplicates bottleneck machines. Seifoddini's model evaluates the machine duplication decision based on the tradeoff between increased equipment cost and reduced material handling cost. Logendran formulated an integer programming model that explicitly considers budgetary constraints in permitting machine duplication.

2.2.5 Summary of Research on Cellular Manufacturing

Past research on CM allows a number of conclusions to be made about its effectiveness. It is evident that the process of machine dedication either in a cellular or process layout, leads to significantly reduced shop flexibility and severe utilization problems. The result is performance that is inferior to that yielded by a pure process layout. Only when non-processing components of flow time (i.e., setup, material handling) are large, does the potential exist for CM to outperform a process layout. Even the more common process/cell hybrid layout performs comparably to a process layout only under limited circumstances.

Of the three procedures outlined to improve CM performance, none is designed to overcome its inherent limitations. The objective of group scheduling is to take advantage of batch similarities with respect to setups. As currently implemented, it is not concerned with machine configuration or routing issues, and thus fails to address the issue of flexibility. Lot splitting, though improving the efficiency of material flows, suffers from the same limitations. Alternate routing, though to some degree alleviating problems of unbalanced utilization and reduced flexibility, does not overcome the problem of machine dedication that Flynn & Jacobs (1986) suggested is the primary cause of poor performance. Each approach is also short term and narrowly focussed in how it tries to improve performance. None adopts a long term perspective, taking into account the downstream consequences of their actions, nor do any address problems of changing product mix and volume.

Although these mechanisms enhance CM performance, the magnitude of the machine dedication problem appears too large to be overcome within a cellular layout. Though many approaches to cell formation have been proposed, they typically do not consider resulting shop performance. Those that do are faced with the problem of trying to satisfy often conflicting goals. The result is that the impact of cell formation on shop performance is not clear. Even if it were and cells formed accordingly, the fact that machines are dedicated implies that flexibility is lost. As long as this situation remains, so will limits on shop performance. As Lewis (1973) stated, the ability to use a production system to its best advantage is predetermined by how it is conceived and designed. Given the available experimental and case evidence, it is apparent that the processing of part families must be viewed from an alternative perspective that does not impose the restrictions placed by traditional CM.

2.3 FLEXIBILITY ISSUES IN MANUFACTURING

Based on the evidence, it is the loss of flexibility that limits the ability of CM systems to generate improvements in performance. Not only does this loss of flexibility compromise the production of existing products, but it makes it unresponsive to a changing environment. As Buffa (1984) stated, in the present manufacturing climate, there is a premium on flexibility. Harrigan (1985) suggested that organizations need to be flexible because of technologically driven shorter life cycles and global competition, and can be most responsive if facilities are designed with flexibility in mind. It is evident therefore that the flexibility of the manufacturing process is the key to the ability to respond to a uncertain environment.

Flexibility has been suggested to be a component of manufacturing strategy (Buffa, 1984, Wheelwright, 1984). It thus represents one of the distinctive competencies that can be used to obtain competitive advantage. Numerous definitions of flexibility in ma

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manufacturing exist (e.g., Mandelbaum, 1978, Hall, 1983, Swamidass & Newell, 1987, Swamidass, 1988). At the core of these is the ability of a production system to respond effectively to a changing environment. Mandelbaum (1978), and Buzacott (1982) additionally characterized flexibility as the ability to respond to change, and the ability to continue to perform despite the change. Slack (1987, 1990) made the distinction between range flexibility and response flexibility. Range flexibility refers to the breadth of change that can be accommodated. Response flexibility is the ease with which change can be made.

2.3.1 Types of Manufacturing Flexibility

The concept of flexibility in manufacturing has been used across the entire spectrum of the production process, from product design to processing to delivery. Swamidass (1988) identified twenty terms associated with flexibility in the operations management literature. A number of typologies exist that identify the aspects of manufacturing that flexibility must address. These include Mandelbaum (1978), Buzacott (1982), Zelenovic (1982), Gerwin (1983, 1987), Slack (1983), Browne et al. (1984), Swamidass (1988). These are summarized by Alder (1985). Common to a number of these frameworks as well as the perceptions of managers (Slack, 1987, 1990) are part, part mix, volume and routing flexibility. In order to be competitive, an organization needs to be responsive to changes in demand in terms of the types of parts it produces, their mix and volumes. To be consistent with these needs, the production system must possess the flexibility to meet new process plans, and to alter routings to accommodate changes in production schedules, capacity requirements and disturbances to the system such as machine breakdowns.

As Gerwin (1987) suggested, manufacturing flexibility can be considered at a number of levels. Amongst these are the flexibility of individual machines, the manufacturing process, or the manufacturing system as a whole. Slack's studies of managers (1987, 1990) indicated that managers are cognizant of the value of flexibility, but have a limited view of it. They also prefer to deal with only a limited amount of flexibility. Managers tend to view flexibility from a resource perspective, typically focussing on the flexibility of a single resource, rather than that of the production system as a whole. Flexibility is seen typically as a means towards an end rather than an end in itself. It is sought primarily to meet the specific needs identified earlier, the ability to produce new parts, modify part mix, change the level of output, and in addition, the ability to change delivery dates. The evidence suggests that managers are more concerned with response flexibility than range flexibility, particularly the time needed to bring about change. The limited evidence on the relationship of flexibility and performance from both empirical and simulation studies, confirms the importance and increasing recognition of flexibility as a competitive tool, an important shift away from the traditional focus on cost and productivity.

2.3.2 The Impact of Resource Flexibility

Consistent with the perceptions of managers (Slack, 1987, 1990), evidence from the literature suggests that resource flexibility, specifically machine and labor flexibility, is central to the discussion of manufacturing flexibility (Slack, 1990). Malhotra & Ritzman (1990) tested the hypothesis that increased resource flexibility in a multistage manufacturing environment, allows an organization to improve its performance when confronted with a changing environment. Machine flexibility was modelled by defining a shop with a fixed number of machines and changing the number of departments they were allocated to. Fewer departments implies departments must process a greater number of items with a larger number of more general purpose machines, making them more flexible. Labor flexibility was modelled by changing the number of machines a worker could operate. Two environments were examined, a benign environment characterized by small lot sizes and a large capacity cushion, and a hostile environment characterized by large lot sizes and a low capacity cushion.

Even with change limited to lot sizes and capacity, their results showed the value of flexibility. In the benign environment, greater machine flexibility led to modest improvements in customer service as measured by past due demand, but in the hostile environment, there were substantial gains. The effect on inventory was less significant in each environment. The benefits of increased labor flexibility were also lower in each case. When both forms of flexibility were introduced, the performance gains were only marginally greater than when only one existed. Machine flexibility is thus an important mechanism in responding to a changing environment, though there is a related cost in terms of the purchase of more flexible but less efficient general purpose machines.

These results are similar to those obtained by Bott & Ritzman (1983). They showed that in an MRP environment, the allocation of equipment to a few, large, general purpose departments rather than several, small, specialized departments led to significantly improved performance. Customer service, measured by past due demand, was significantly lower. Inventory and the occurrence of bottlenecks were also reduced. The impact of greater flexibility was of particular significance when demand was unstable.

2.3.3 Flexibility, Manufacturing Performance, and Competitiveness

Swamidass & Newell (1987) surveyed a number of managers as part of a study of the relationships between environmental uncertainty, manufacturing strategy and business performance. The organizations concerned all used small batch manufacturing processes. One of the issues investigated was the effect of flexibility. Using a path analytic model, they found there to be a strong positive correlation between flexibility and performance. The benefits associated with greater flexibility were also positively correlated with environmental uncertainty. The authors, commenting on the reported gains of Japanese producers who designed repetitive production lines with flexibility in mind (Schonberger, 1982), concluded that flexibility is important regardless of the manufacturing process being used.

Roth & Miller (1990) as part of a broader study into the relationships between manufacturing and managerial strengths and business performance, surveyed manufacturing executives about the strength of their competitive capabilities relative to their competitors. Using factor analysis, the authors identified five independent dimensions of manufacturing strength. One of these was flexibility, specifically, new product, volume and design change flexibility. They categorized companies as superstars, middlemen, and weaklings, based on their competitive strengths, and compared these groups with respect to the importance they placed on flexibility. The results showed that both superstars and middlemen placed greater importance on flexibility than weaklings, though there was no difference between superstars and middlemen. In addition, they categorized the companies as winners and losers based on economic performance, and again compared the two groups to determine whether differences in attitudes to flexibility existed. As expected, the winners were shown to place greater emphasis on flexibility than losers.

In a comparative study of Japanese, European and American manufacturing organizations, De Meyer et al. (1989) identified differences in competitive priorities and courses of action of organizations in each environment. European and American producers still consider quality, reliability, and to a lesser degree cost as their competitive priorities. However, the Japanese, having already addressed these issues, consider flexibility to be the top priority. Their ability to shift focus is made possible by the fact that they have attained what they consider to be appropriate levels of quality, cost and reliability, and now have a significant cushion relative to their competitors on these dimensions. This allows them to concentrate on what the authors call the next competitive battle. An important finding of the research is that actions taken by Japanese producers are consistent with their stated concerns and competitive priorities. This is increasingly true of American producers, but less so of Europeans. This consistency has been suggested to be a critical determinant of manufacturing success (Hill, 1989).

2.3.4 Summary of Research on Manufacturing Flexibility

The evidence on the effect of manufacturing flexibility on performance, though sparse, clearly demonstrates its value. Equally important is the finding that only a limited amount of flexibility is required to improve performance. Further increases in flexibility may have limited value. This is entirely consistent with results from studies that have implicitly, if not explicitly, considered the effect of increased flexibility (Bobrowski & Mabert, 1988, Ang & Willey, 1984). Given the costs associated with greater flexibility, this is significant.

CHAPTER 3

DYNAMIC CELLULAR MANUFACTURING (DCM)

3.1 INTRODUCTION

Given the limitations of CM, the value of resource flexibility, and the need for greater responsiveness to changing market demands, a need exists for a more flexible production system for small/medium batch production that allows the advantages of part family production to be attained. Such a system should not permanently dedicate machines but maintain flexibility in machine allocation. A system of this nature can be characterized by a layout in which cells are not viewed as a physical grouping of machines as they are in traditional CM. Instead, cells are temporary entities that are formed and destroyed on a continual basis by allocating machines to families based on current need and availability. The parts that constitute a family are those that have similar processing requirements, thus allowing the number of setups to be kept to a minimum.

The concept of a cell that is not a physical ordering of machines was initially suggested by McLean et al. (1982) and Simpson et al. (1982). They defined a 'virtual cell' to be a set of machines, which, though physically separated, exist together as a logical entity for scheduling purposes. In real time, virtual cells are created to meet current processing needs, then dissolved on completion. The virtual cell is a routing mechanism where the required machines are claimed before processing begins, and where machines are dedicated to a given processing requirement only as long as needed. Irani et al. (1993)

used the term virtual cell to refer to cells created by the sharing of machines in a shop physically organized as a cell/process hybrid layout similar to that described earlier. They proposed a shop layout in which cells with overlapping machine requirements are located physically adjacent to each other. Likewise, machines used by several cells are organized functionally and located physically close to the cells which require them. This physical organization facilitates machine sharing without the need for machine duplication or increasing the complexity of material handling. Individual parts can be processed outside their primary cell creating the illusion of a cell since machines outside the primary cell are temporarily dedicated to the corresponding family.

3.2 MANUFACTURING ENVIRONMENT FOR DCM

Dynamic cell formation involves examining the set of jobs awaiting processing at each process department, and identifying their part family affiliations. When machines in the department become available, they are temporarily allocated to families requiring them using family based scheduling rules. It is this temporary allocation of machines to families that creates the illusion of a cell. Machines allocated to a family define a path through the shop. While this path continues to exist, parts from the family are routed along it to the specific machines they require. Unlike traditional job shops where the allocation of machines to jobs is essentially random in nature, in DCM, machines are to a greater degree pre-assigned as they are in traditional manufacturing cells.

Cells formed in this way are dynamic and virtual. They are dynamic since they are formed on an ongoing basis based on current processing needs and machine availability. They are virtual since they cease to exist after the need for them passes. Over time, the machines making up a cell change based on machine availability. This yields a more efficient utilization of machines than in traditional CM. In addition, the size of a cell can change over time. A cell begins to evolve once a single machine is allocated to a part family. As parts from the family progress through the shop, machines from other process departments may be allocated to them, increasing the size of the cell. Eventually, machines from all departments visited by family members, may be held simultaneously. This represents the greatest length of the cell. Beyond this, the cell can expand only if multiple machines from the same process department are allocated to it. This can occur f the additional machines are not required by other families. The capacity of the cell can thus adjust to better meet the processing needs of the family without compromising the processing needs of other families. Conversely, machines no longer required by the family may be released, causing a contraction in the size of the cell. Cells may not always evolve to their maximum length if machines are released at a faster rate than they are added. Cells also need not consist of a continuous path if they do not contain machines in the interior of the routing. In this case, the cell exists as disjoint cell segments.

The primary benefit of forming cells in this manner is that family processing needs are met without the sacrifice of flexibility. Machines are constantly assigned or re-assigned to cells based on family need. This dynamic allocation overcomes the problem of unbalanced load in traditional CM. This in turn makes the configuration more responsive to changes in volume, family composition, and family size. In addition to offering an alternative mode for part family production, DCM makes it possible for a manufacturing concern considering conversion to a cellular layout, to investigate whether it can benefit from such a change. Since DCM applies the family concepts of CM, it can be used as a mechanism to study the potential gains from using a cellular layout before any physical change or investment takes place.

3.3 DCM vs. CELLULAR AND PROCESS LAYOUTS

3.3.1 Shop Layout

A major advantage of DCM is that it does not require the long term or permanent physical shop re-organization required by traditional CM. Traditional CM is founded upon physical re-organization of machines and their dedication to part families. This way, a line flow or similar simplified routings can be obtained within each cell. This in principle should yield improved control, lower work in process, and more efficient material handling. In addition, CM typically strives for cells to be independent with machines allocated to only a single cell. Consequently, additional equipment purchases are often needed to make this possible, adding to the cost of re-organization. Implicit is the fact that re-organization takes time, which will likely render the shop less than 100% operational. Morris (1988) suggested that the need to physically re-organize a shop may discourage product innovation in favor of process convenience.

Physically, DCM can use the existing process layout. The only physical difference is in the dedication of machines. Since DCM cells are not physical groupings of machines, there is no need to physically re-organize the shop floor. This is particularly significant with shorter product cycles, changes in part mix and the need for short lead times. Given time and cost considerations, modifications to a traditional cellular layout to accommodate such change may not be possible nor advisable. Since there are no physical cells, duplication of machinery to achieve cell independence is not an issue. The need for no additional investment is important not only in terms of dollars saved, but also given the current emphasis on short term financial decision making. As Voss (1986) suggested, investment decisions may not consider non-quantifiable factors such as increased flexibility and improved competitiveness. This alone may preclude investment in CM projects.

Since DCM cells are not fixed entities nor their machines located adjacent to each other, there is a loss of some of the benefits of CM. In particular, the material handling benefits of CM are lost, and production control is more complex. However, the benefits of more efficient machine utilization can be expected to more than offset these losses.

3.3.2 Routing Flexibility

With traditionally formed cells, all machines required by a part family are dedicated permanently to that family. The result is that at times, some machines in a cell may be idle, while functionally similar machines elsewhere may have long queues in front of them. The result is that jobs in congested cells may be delayed (unless alternate routing strategies are employed). The aim of DCM is to exploit the routing flexibility of a process layout. The process layout makes it possible for any machine of a given type to be used to process a job. However, in DCM, machines are dedicated to a part family for as long as it needs them. Once a machine is no longer needed, it can be assigned to a different cell. Since any available machines of the required type can be allocated to a cell, routing flexibility is increased. This eliminates the need for alternative routing strategies.

3.3.3 Setup Issues

In a process layout, each job requires a major setup at each machine in its routing (unless sequence-dependent scheduling is used). These setups cannot take place until the machine is assigned to the job, thus the job must wait while the machine is being setup. In traditional CM, since machines are dedicated to part families, once machines are initially setup for a family, no major setups are required. Only minor setups are required to recognize differences between jobs in the same family. With DCM, setup requirements lie between these two extremes. Since a dynamic cell is dedicated to a family, a major setup is required at each machine only when it is allocated to a family. After that, only minor setups are required, to recognize differences between parts within a family.

3.3.4 Part/Volume Mix (Demand Structure)

CM is inflexible to changes in part mix and volume. Since the shop is physical organized based on a particular part mix and workload, it cannot respond effectively or rapidly if new parts are introduced that do not fit into existing families, and thus an existing cell. Likewise, if the workload of a cell changes, the cell cannot adapt. Such changes may require the additional purchase of machinery or relocation of existing machinery, which as explained earlier, may not be possible. Alternatively, parts may have to be produced using a combination of cells. This compromises the ability to reap the benefits of CM.

With DCM, this problem is moot. Since cells are not rigid, there is no problem of matching new parts with existing cells. New families can be created and cells formed to meet their processing needs without compromising the shop layout. Available equipment can be assigned and re-assigned to cells as the needs of families change. Since machines within a process department are homogeneous and located physically adjacent to each other, routing jobs to a secondary machine does not result in the loss of control that might occur with physically separated cells.

3.4 LIMITATIONS OF DCM

From an operational standpoint, DCM does have certain limitations compared to existing production methods. Scheduling in the DCM environment is more complex than in traditional CM. In a traditional cellular environment, the scheduling problem is limited to jobs within a given cell. In DCM, the scheduling problem encompasses the entire shop

	Shop Configuration		
	Process Layout	Cellular Layout	DCM
Requires Shop Reorganization	No	Yes	No
Requires New Equipment	No	Possibly	No
Machine Dedication	None	Permanent	Temporary
Shop Floor Control	Highly Complex	Least Complex	Moderately Complex
Scheduling Complexity	High	Low	Medium
Routing Flexibility	High	Low	Medium
Material Handling	High	Low	High
Type of Setups	Major & Minor	Minor	Major & Minor
Frequency of Major Setups	One/Machine/Job	None	One/Machine/Cell
Responsive to Change	Yes	No	Yes

Figure 1 : Comparison of DCM, Process and Cellular Layouts

and all current jobs. However, since jobs can only be routed to machines that are idle or already setup for the corresponding family, scheduling effort is lower than in a process layout, where all machines of the same type must be considered. As previously mentioned, the material handling benefits of traditional cellular systems will also be lost, due to the machines in a cell being physically distant.

From a behavioral standpoint, whether DCM has particular merit depends on its implementation. One of the suggested gains of CM is that since parts are processed within a cell, operators, if allocated to a cell rather than a machine, have a wider variety of tasks. The result is greater job satisfaction, and improved quality. In DCM (and a job shop), the same benefits can be obtained if cross training exists, and operators allocated to jobs rather than machines. However, the scope of these benefits might be limited by the machines in a jobs routing not being physically adjacent as they are in traditional cells.

3.5 DCM vs. FLEXIBLE MANUFACTURING SYSTEMS (FMS's)

Flexible manufacturing systems (FMS's) attempt to obtain the same benefits as DCM, namely greater flexibility and higher utilization. However, though FMS's may be able to achieve these benefits more efficiently, they impose additional constraints. Specifically, FMS's are characterized by complex planning and scheduling environments. They require expensive machining centers, sophisticated tooling systems, and advanced material handling systems to provide the degree of automation sought. Overall control of the system is governed by complex and expensive computer hardware and software. The costs associated with investment in capital and training are significant. It also takes time to install and test the system. Investment and time are factors that make even traditional CM difficult to justify unless a successful implementation can be guaranteed. Given evidence from existing FMS implementations, this is far from certain. From an operational standpoint, FMS's are inappropriate in an environment with long setup times which is characteristic of the environment being considered here. The intent of FMS's is to take advantage of production flexibility in environments with short setup times and where tooling changes can be automated.

Although DCM may not be able to provide the same level of flexibility as FMS's, it can attain a significant degree of flexibility without physical reorganization of the shop floor or new asset acquisition. Furthermore, it can do so without the introduction of the complexity or cost associated with FMS's. Given this tradeoff, the problems associated with investment decision making described earlier, and the need for rapid introduction of flexibility, DCM offers an attractive alternative.

3.6 SUMMARY OF DCM

In summary, DCM offers the benefits of CM while using a process layout, by means of scheduling as opposed to machine layout. The investment, physical re-organization and permanent machine dedication associated with traditional cellular systems are eliminated. CM's recognition of family processing needs and linear routings are retained and

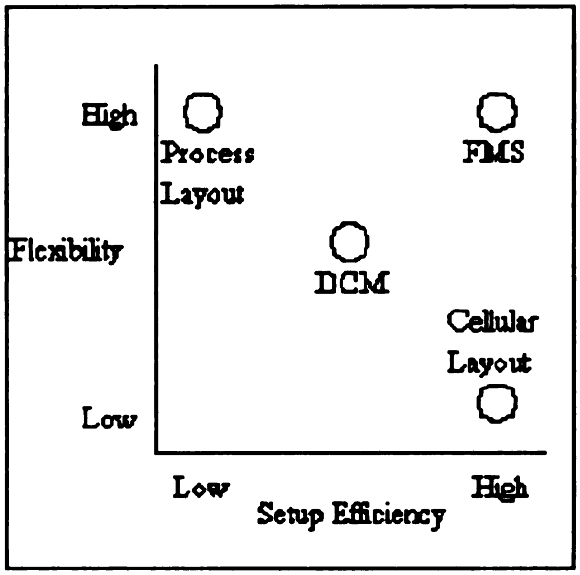


Figure 2. Tradeoffs Between Flexibility and Setup Efficiency

combined with the flexibility of a process layout. This allows the shop to respond more quickly and efficiently to changes in production needs. DCM represents a trade-off between the benefits of traditional CM and a process (or job shop) layout. It is also a tradeoff between flexibility and setup efficiency.

3.7 RESEARCH STATEMENT

This research examines the impact of DCM on small/medium batch production in a closed shop environment. In a closed shop with repeat orders for a standard set of parts, considerable scope exists for the application of CM. It is possible and beneficial to identify similarities in part processing requirements and to exploit these in the production process, particularly since these parts and families will exist over a period of time. In an open shop with different parts being produced without repetition, part families are less clearly defined. With the composition of demand constantly changing, the make-up of families also changes, making the application of traditional CM inefficient. Though there is less potential to exploit production similarities in an open shop, possibilities may still exist. One of the advantages of DCM is that since cells are not fixed entities, greater flexibility exists in defining families and thus cells. Unlike traditional CM, DCM may thus have applicability in an open shop. Even if a family consists of a single part, loading the corresponding cell is equivalent to cell loading. Though cell loading in a traditional cell was shown to yield poor performance (Mosier, 1983), the increased flexibility and utilization of DCM can be expected to make cell loading more attractive.

The research addresses a number of questions regarding the potential of DCM. These address two major issues. The first is the tradeoff that DCM represents between the flexibility of a process layout, and the family processing and setup efficiency of traditional CM. Five questions relating to this issue are investigated using specific hypotheses:

a. Do setup conditions exist where DCM's use of the part family concept and efficient use of setups, is more beneficial than the flexibility of a traditional job shop. If so, what setup conditions are conducive to DCM.

b. Can the recognition of part families by DCM, make it more effective in dealing with different part mix compositions. If so, for what part mix characteristics is DCM preferable.

c. Can the greater flexibility of DCM allow it to overcome the setup benefits of permanent machine dedication in traditional cellular manufacturing, and if so, under what setup conditions.

d. Does the greater flexibility of DCM make it more responsive to changes in part mix than traditional cellular manufacturing, and if so, under what part mix conditions.

e. Does the information used to form dynamic cells affect their performance.

The second issue is the robustness to change of a production system that physically has a process orientation, but is operated as if it had a product orientation. Three additional questions are examined:

f. Does shop load have a significant impact on the performance of DCM.

g. Is DCM sensitive to changes in job size.

h. Does job dispatching affect the performance of DCM.

These questions are addressed by first comparing the performance of DCM to that of a traditional process and cellular layout, and then examining the behavior of DCM in greater detail. The next chapter explains the research design used to carry out these studies.

CHAPTER 4

RESEARCH DESIGN

4.1 INTRODUCTION

The research is conducted in two stages. DCM is first compared to production using traditional process and cellular layout methods. The objective is to identify whether DCM yields better performance with respect to throughput and due date measures, and under what conditions its use might be appropriate. Stage two investigates DCM in more detail by examining other conditions that influence its performance and suggest potential for its use. This permits a better understanding of DCM and a greater awareness of when it might be used or when other alternatives are more appropriate.

4.2 RESEARCH METHODOLOGY

The research is conducted using computer simulation models. Simulation is a commonly used tool in research of this kind. It enables research to be conducted under controlled conditions defined by the researcher. This eliminates the risk of other factors affecting the validity of conclusions. Cook & Campbell (1979) refer to this as internal validity. Simulation also facilitates replication of an experiment. This allows sufficient data to be collected for statistical conclusions to be made with an appropriate degree of certainty, or statistical conclusion validity (Cook & Campbell, 1979).

4.2.1 Statistical Issues in Simulation

Five issues need to be addressed in simulation research to ensure its statistical validity. These are initialization bias, independence and normality of observations, sample size, and variance reduction. In non-terminating simulations such as those used in this research, the system being modelled begins in a state of no activity. However, the system is evaluated once it has reached steady state, or its long run level of activity. Observations collected prior to the system reaching steady state have a biasing effect since the system behaves differently initially compared to when it reaches steady state. To eliminate this initialization bias, the time at which steady state has been reached must be identified and observations prior to this point discarded.

Each time the simulation is run from start, observations collected during the initialization period must be discarded. This results in a large number of discarded observations. To reduce this, one long run can be carried out and batch sampling used. This leads to the problem of autocorrelation. To be valid measures, observations must be independent. The progress of a job is affected by that of jobs in the system at the same time, since they affect shop load, queue sizes, etc. However, jobs separated by a large enough time lag are not affected in this way. If the batch size is large enough, the mean response of adjacent batches can be shown to be independent (Kleijnen, 1987). This batch size must be determined.

In order to meet the assumptions of the statistical tests to be used in data analysis, the distribution of batch means must be approximately normal. The central limit theorem states that for large sample sizes ($n \geq 30$), the distribution of sample means is approximately normal even for non-normally distributed populations (Law & Kelton, 1982). However, the quality of the approximation depends on the population distribution. Larger batch sizes improve the quality of the approximation. An appropriate batch size must therefore be identified.

For statistical tests to be carried out with a high degree of power, a large enough sample size must be obtained. An appropriate number of batches must therefore be run for each treatment. Finally, the validity of statistical conclusions is compromised by the introduction of variance other than that due to the experimental treatments themselves. Additional sources of variation must therefore be minimized or eliminated.

4.2.1.1 Initialization Bias

The method used here is that of Schruben et al. (1983). If there is no significant difference between the mean of N observations, and the mean of the first k ($k < N$), a steady state response has been obtained. They defined a test statistic for this difference based on the t distribution. Since initialization bias is likely to cause an under-estimate of the steady state response, a one-sided hypothesis for mean difference is tested. If steady state is not reached within the first k observations, k is increased and the test repeated.

4.2.1.2 Autocorrelation

The procedure used here is the Von Neumann statistic (q) whose use is suggested by Kleijnen (1987). If batch means are independent and normally distributed, the expected value of q is known and its variance can be computed as a function of n, the number of batch means used to compute q. The statistic q is distributed normally. Kleijnen et al. (1982) suggest n be at least 100 since for small n the test has low power. A value of n = 100 is thus used. If the null hypothesis of independence is not accepted, the batch size is increased and the test repeated. In this research, an initial batch size of one hundred is arbitrarily selected and the batch size increased by one hundred each time the null hypothesis is not accepted.

4.2.1.3 Normality

An assumption of analysis of variance (ANOVA) which is used to analyze the data is that observations are normally distributed. However, Neter et al. (1990) state that ANOVA is robust to small departures from normality. In order to establish whether batch sample means are approximately normal, the Probability Plot Correlation Coefficient Test is used (Filliben, 1975). This computes the correlation between the ordered batch means and the order statistic medians from a standard normal distribution. If the distribution of means is normal, the correlation coefficient should be close to one. The significance of the correlation is evaluated by comparison with percent points of the normal probability plot correlation coefficient. If the hypothesis of normality is not accepted, the batch size is increased and the test repeated. In this study, the initial batch size is that which satisfies the assumption of independence. Increments in batch size of one hundred are used if normality is not obtained.

4.2.1.4 Sample Size

Assuming a normal distribution of sample means, the sample size required to obtain a confidence interval for the mean response can be computed as a function of the population variance, and the half width of the required interval. Pilot runs are conducted to estimate the mean and variance of flow time for each treatment. These are used to establish the sample size required to obtain non-overlapping confidence intervals for all treatment means. Schmeiser (1982) suggests using between ten and twenty batch means to estimate the confidence interval. Twenty batch means are therefore used.

4.2.1.5 Variance Reduction

In order to eliminate variance other than that due to the treatments, common random numbers are used (Kleijnen, 1987). For each treatment, the same random number stream is used for the corresponding input process. This ensures that the random numbers are not a source of variance. Glasserman & Yao (1992) demonstrated that the use of common random numbers guarantees variance reduction and is optimal for a wider class of simulation models than previously assumed. One random number stream is not synchronized. This ensures that samples are independent (Mihram, 1974) which is an assumption of the procedures to be used to analyze data.

4.2.2 Pilot Runs

In order to conduct the above tests, pilot runs are carried out for each treatment of the two stages of the research. These identify the initialization period and batch sizes to meet assumptions of autocorrelation and normality. For each stage of the research, the initialization period used during actual experiments is the longest identified from the corresponding pilot runs. Likewise, the batch size used is the smallest required to meet the assumptions for all corresponding treatments.

4.3 SIMULATION ENVIRONMENT

To facilitate comparison, the simulation environment used here is similar to that used by Morris (1988). This also allows the simulation models to be validated. However, for experimental purposes, certain parameters are changed to create a more suitable research environment. This section describes shop features common to both stages of the research.

A total of forty part types, partitioned into five families, are considered (Figure 3). Each

Family	Part Numbers
1	33, 34, 35, 36, 37, 38, 39, 40
2	19, 20, 21, 22, 23, 24, 25, 26
3	27, 28, 29, 30, 31, 32
4	9, 10, 11, 12, 13, 14, 15, 16, 17, 18
5	1, 2, 3, 4, 5, 6, 7, 8

Figure 3. Part Family Affiliations

family contains between six and ten parts. Parts have between four and six operations. Jobs arrive according to a poisson process, with inter-arrival times exponentially distributed. This is a commonly used arrival process in job shops (Law and Kelton, 1982). Jobs are for a single part type. Operation processing times consist of a constant and a stochastic component. These are 33.33 and Normal (1, 0.25) minutes per batch of size 100. Due dates are set using the Total Work Content (TWK) rule (Conway et al., 1967). This defines due dates as the arrival time of the job plus a multiple, k, of the job processing time. Baker (1984) has shown this to be an effective procedure with respect to tardiness performance over a range of conditions. Similar to Morris, $k = 3$ is used here. Weeks and Fryer (1977) showed that for a range of conditions, k values between 2.5 and 2.75 were optimal but that for small departures from optimality, performance did not change significantly.

A total of thirty machines are used. According to Baker (1974), no conclusive evidence exists to suggest that the number of machines in a shop affects its performance. The shop floor covers an area of 10,000 (100 x 100) square feet, each machine allocated an area of 225 (15 x 15) square feet. Layouts are defined using the CRAFT algorithm (Buffa et al., 1964). Forklift trucks are available for material handling purposes. These move at five miles per hour and are an unconstrained resource. Loading and unloading times are uniformly distributed in the interval 1 to 5 minutes.

4.4 PERFORMANCE MEASURES

Any comparative study of production systems must consider the effect they have on throughput performance and the ability to meet due dates. These determine the ability of the system to complete orders in a timely fashion. To accomplish this, mean flow time and mean tardiness are measured. In addition, the mean and standard deviation of work in process (WIP) are measured. WIP is defined in terms of number of minutes of work. WIP provides a surrogate measure for shop congestion. Changes in WIP can also be expected to correlate positively with flow time variance, which in turn affects tardiness variance. These are the primary performance measures due to their combined effect of appropriately gauging the overall performance of the system.

To more fully understand shop behavior, average utilization, proportion of time jobs spend during setups and in queues, and the proportion of tardy jobs are also measured. The intent of DCM is to reduce the impact of setup times relative to a traditional process layout, and to overcome problems caused by unbalanced utilization and long queues in a cellular layout. The secondary measures are used to identify if these objectives are met.

4.5 EXPERIMENTAL STAGE I

4.5.1 Experimental Factors

Stage one compares production using DCM to that using traditional process and cellular layout methods. The intent is to identify whether DCM performance differs from that obtained when using these layouts, and to determine when DCM might be preferred.

Number of Machines	30
Number of Parts	40
Number of Operations/Part	4-6
Job Arrivals	Exponential
Due Date	TWK, k = 3
Operation Processing Times	33.33 + Normal (1,0.25) minutes / batch size 100
Loading/Unloading Times	Uniform (1,5)
Material Handling	Forklift Truck, 5 mph
Performance Measures	Mean Flow Time, Mean Tardiness, Mean WIP, Standard Deviation of WIP Mean Utilization, Proportion Tardy, Setup Time Proportion, Queue Time Proportion

Figure 4 : Simulation Environment and Performance Measures

Three factors are examined: shop configuration, setup times, and part mix variability.

4.5.1.1 Shop Configuration

Seven shop configurations are examined, a traditional process layout, traditional cellular layout, and five configurations based on DCM. As described earlier, each shop consists of thirty machines. The traditional cellular layout consists of five cells, each containing between four and eight machines (Figure 5). Cell sizes are consistent with evidence of actual CM implementations (Wemmerlov & Hyer, 1989). Within cells, no machine duplication exists. Parts are fully processed within a single cell. Material handling times are not considered since cellular layouts are designed to make material handling inconsequential.

Cell/Family	Machines	Part No.	Routing
1	18, 25, 13, 3, 23, 10, 16	34	18, 25, 13, 3, 23, 10
		40	18, 25, 3, 23, 16
		38	18, 25, 3, 23
		39	25, 13, 23, 10
		33	25, 3, 10
		36	13, 3, 23, 10, 16
		37	13, 23, 10, 16
		35	13, 10, 16
2	26, 2, 15, 7, 17, 4, 20, 12	24	26, 2, 15, 7, 17, 4
		20	26, 2, 15, 7, 17, 4
		19	26, 7, 20, 12
		23	26, 20, 12
		26	2, 15, 7, 17, 4
		22	2, 15, 7, 17, 4
		21	2, 17, 4, 20, 12
		25	17, 4, 20, 12
3	22, 8, 28, 24, 9, 21	32	22, 8, 28, 24, 9
		30	22, 8, 28, 24, 9
		27	22, 28, 24, 9
		31	22, 28, 24
		28	8, 28, 24, 9, 21
		29	8, 9, 21
4	29, 14, 6, 19, 27	17	29, 14, 6, 19
		15	29, 6, 19, 27
		13	29, 19, 27
		9	29, 19, 27
		18	14, 27
		16	14, 27
		12	14, 27
		10	6, 19, 27
		14	6, 19
		11	6, 19
5	11, 1, 30, 5	7	11, 1, 30, 5
		6	11, 1, 5
		4	11, 30, 5
		2	11, 1, 30
		3	11, 1
		8	1, 30, 5
		5	30, 5
		1	30, 5

Figure 5 : Configuration of Cellular Layout

The process layout consists of eight process departments (Figure 6). Each contains three

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

Figure 6 : Configuration of Process Layout

or four machines. Routings using the process layout are defined in Figure 7. In addition, both shops contain a shipping and receiving department.

The configurations based on DCM have the same physical layout as the process layout. It is the temporary dedication of machines to families that distinguishes DCM from the process layout. Machines could be allocated to families using the group scheduling rules described earlier. However, these are typically local in nature. Most of these rules consider processing characteristics of families only at the machine of interest, and not elsewhere in the shop. In addition, they focus solely on exploiting sequence dependencies in scheduling decisions, giving the appearance of a job shop using sequence-dependent scheduling.

Part No.	Process Departments Visited
1	5,6
2	3,4,5
3	3,4
4	3,5,6
5	5,6
6	3,4,6
7	3,4,5,6
8	4,5,6
9	1,2,6
10	1,2,8
11	1,8
12	2,7
13	1,2,6
14	1,8
15	1,2,6,8
16	2,7
17	1,6,7,8
18	2,7
19	1,4,7,8
20	1,2,3,4,5,6
21	2,5,6,7,8
22	2,3,4,5,6
23	1,7,8
24	1,2,3,4,5,6
25	5,6,7,8
26	2,3,4,5,6
27	2,3,4,8
28	1,2,3,4,5
29	1,4,5
30	1,2,3,4,8
31	2,3,8
32	1,2,3,4,8
33	2,4,6
34	1,2,3,4,5,6
35	3,6,7
36	3,4,5,6,7
37	3,5,6,7
38	1,2,4,5
39	2,3,5,6
40	1,2,4,5

Figure 7 : Routings in Process Layout

In order to address this limitation, three selection rules that consider family processing needs at machines other than the machine to be assigned, are considered, in addition to two traditional family selection heuristics. These new rules embrace the intent of DCM to consciously create complete, continuous cells. This way, dynamically formed cells more closely resemble traditional cells in which all machines required by a family are available for its use, and form a clearly defined routing. Each rule is first applied to families without access to a machine in the process department in question. If no such families exist, all remaining families are considered. This promotes the development of multiple cells and the simultaneous processing of all families. In addition, it minimizes the risk of some cells not having access to a machine of a given type, while others have multiple machines of the same type.

The family selection rules based on past research are :

DCM 1 : The family with the lowest average job slack. This is similar to the DDFAM rule of Mahmoodi et al. (1988) that selects the family containing the job with the earliest due date, but explicitly considers remaining processing time and the urgency of the family as a whole (Mosier, 1984).

DCM 2 : The family containing the most jobs in the queue. This is similar to the WORK rule of Mosier et al. (1984), that selects the family with the greatest work content. This facilitates families with the greatest ability to minimize major setups.

The rules that incorporate information on family processing elsewhere in the shop are:

DCM 3 : A family is selected which also has parts currently being processed at its immediate predecessor departments. If more than one such family exists, the family with the most jobs in the current queue is selected. This rule facilitates the incremental building of cells, thereby reducing potential setups and queuing delays.

DCM 4 : The family requiring the fewest machines to complete a cell is selected. Similar to DCM 3, this facilitates the formation of complete cells, and reduces potential major setups and queuing delays.

DCM 5 : When no jobs remain from the family currently using the machine, the immediate predecessor departments of this family are examined to determine whether jobs from the family are currently being processed there. If they are, the machine is not re-assigned to a new family, but remains idle so that these jobs can use it without incurring an additional major setup. If there are no such jobs, the machine is assigned to the family with the most jobs in the current queue. This rule goes further in maintaining the structure of a cell once it has begun to evolve.

The family selection rules differentiate the five DCM shop structures among themselves, and also from the process and traditional cellular layouts.

4.5.1.2 Setup Time

Setup time can be expected to affect the relative performance of DCM and traditional process and cellular layouts. As demonstrated in past comparisons of CM and process layouts (e.g., Morris, 1988) and in other work on setup times (e.g., Karmarkar et al., 1985a), setup times have an important effect on shop performance. Setups require machines to be busy but do not themselves add value to manufactured products. Any delays due to setups therefore reduce the capacity of the production system. As described earlier, it is the frequency of major setups when using a process layout, that makes its use inefficient. Likewise, it is their avoidance when using a cellular layout, that makes CM more efficient. In the context of the present study, it is the ability of DCM to minimize the frequency of major setups without significantly compromising flexibility, that gives it a potential advantage.

Both major and minor setups are considered. Major setups between families are typically more time consuming. Minor setups between parts in the same family are generally of shorter duration and require less extensive tooling change. Both major and minor setups are assumed to be sequence independent. This is a common assumption in research of this kind. Two factor levels are considered. At the low setting, major setup time is one third of the processing time, and at the high setting, two thirds (Mahmoodi et al., 1992). These yield setup times of 11.33 and 22.66 minutes. Minor setup time is one quarter of the major setup time (Flynn, 1984). This is consistent with evidence from users of cellular systems (Wemmerlov & Hyer, 1989). The ratio of minor to major setups is not an experimental factor in this study. There is no setup time between jobs that are for the same part type.

4.5.1.3 Part Mix Variability

The primary property of a process layout that allows it to perform well is its flexibility. This also allows it to respond effectively to changes in the mix of parts to be produced, since a machine's use has not been pre-determined. CM is unable to respond effectively to such change since cells are designed to meet expectations of a given part mix. If the mix changes, shop performance deteriorates since jobs are required to be processed in specific cells which may not be designed to handle more than a certain load. Since it makes less rigid assignments of machines to families, DCM offsets this loss of flexibility while retaining the family recognition property of CM. Though a closed shop is being examined, the mechanism generating actual orders may create a variable part mix environment, for example MRP.

Two levels of this factor are considered. Under balanced part mix conditions, each family has the same demand probability (0.20). Within a family, parts have the same demand probability. This mix is consistent with the design of the cellular layout in that the workload of each cell is proportional to the number of machines it has. Under unbalanced part mix conditions, three families have a combined demand probability of 0.70, equally distributed between the families. The remaining two have a combined demand probability of 0.3, again equally distributed between the families. Within each family, individual parts have the same demand probabilities. Though no basis for this specific partitioning of demand between families exists, a similar approach was used by Wemmerlov (1992).

4.5.2 Simulation Environment

In this stage of the research, mean inter-arrival times are set in order to obtain a load of approximately 80% when using the traditional process layout. This is a load that has been used in past research, and that is found commonly in practice (Baker, 1974). Jobs are dispatched using the minimum job slack rule. This has been shown in past research to yield good flow time and tardiness performance in both process (Conway et al., 1967) and cellular shops (Mosier et al., 1984) if due dates have been established in an appropriate manner. It is also representative of rules used in research and in practice.

The rule is slightly modified for use in the process layout by first giving priority to jobs that are identical to those just completed. If there are no such jobs, job selection is then based on minimum job slack. Cellular approaches to manufacturing have a built in mechanism to recognize inter-family sequence dependencies. This modification compensates for the minimum slack rule failing to recognize sequence dependencies, and makes the implementation of the rule in the process layout more representative of actual use. The focus of this stage of the research is on shop configurations rather than scheduling issues.

4.5.3 Experimental Design & Research Hypotheses

Stage one of the research is carried out using a full factorial design with twenty eight (7 x 2 x 2) treatments. These are defined in Figure 8. The objective of the research is to identify conditions when DCM shows potential as an alternative to production using traditional job shop and cellular methods. The intent is not to predict the behavior of DCM in different environments. To accomplish this objective, stage one of the research investigates nine a priori hypotheses. These are formulated as non-orthogonal linear contrasts and are evaluated using ANOVA and paired comparisons. This is an appropriate approach to use since only the presence of effects and not their magnitudes is of interest.

ANOVA is first conducted to identify the presence of significant main and interaction effects. If there are significant main effects and no significant higher order interactions,

Setup Time		Low		High	
Part Mix		Balanced	Unbalanced	Balanced	Unbalanced
Shop Config.	DCM 1	1	8	15	22
	DCM 2	2	9	16	23
	DCM 3	3	10	17	24
	DCM 4	4	11	18	25
	DCM 5	5	12	19	26
	Process Layout	6	13	20	27
	Cellular Layout	7	14	21	28

Legend : 1 - 28 = Treatment Numbers
Low Setup Time = 11.33 minutes, High Setup Time = 22.66 minutes
Balanced Part Mix = Part families have equal demand probabilities
Unbalanced Part Mix = Three part families have demand probabilities of .233, two have demand probabilities of .15

Figure 8. Stage I Experimental Design

Kirk (1982) suggests the use of the Bonferroni procedure (Dunn, 1961) to test the significance of the contrasts. This test guarantees that if the error rate when testing each of C contrasts is α/C, the error rate for all C contrasts cannot exceed α. Neter et al. (1990) suggest that when only a small subset of all main effect contrasts is of interest, this test is more powerful than other tests such as the Scheffe or Tukey tests.

If significant higher order interactions exist, contrasts are no longer meaningful, since factor effects differ at different levels of other factors (Kirk, 1982). Under these conditions, the hypotheses are examined using paired comparisons of all treatment means using the Tukey method (Neter et al., 1990). Neter et al. suggest that this is a more powerful test to use when the number of comparisons is large. The inability to utilize the contrasts does however mean that any conclusions regarding factor effects must be viewed taking into account the effect of interactions.

The following are the nine a priori hypotheses to be investigated. Treatment means are defined in Figure 9.

Setup Time		Low		High	
Part Mix		Balanced	Unbalanced	Balanced	Unbalanced
Shop Config.	DCM 1	11	12	13	14
	DCM 2	21	22	23	24
	DCM 3	31	32	33	34
	DCM 4	41	42	43	44
	DCM 5	51	52	53	54
	Process Layout	61	62	63	64
	Cellular Layout	71	72	73	74

Figure 9. Stage I Treatment Means

(μ_{ij})

1. When setup time is low, the process layout outperforms DCM.

$$H_0: \Phi_1 = \sum_{i=1}^{5} \sum_{j=1}^{2} \frac{\mu_{ij}}{10} - \sum_{j=1}^{2} \frac{\mu_{6j}}{2} \leq 0$$

$$H_a: \Phi_1 > 0$$

Since the time associated with each major setup is low, the effect of greater setup frequency when using the process layout is relatively small. Under these conditions, the greater flexibility of the process layout should enable it to compensate for the increase in setup frequency that it incurs. Acceptance of the null hypothesis suggests that DCM overcomes this flexibility premium even when setup times are not expected to be critical.

2. When setup time is high, DCM outperforms the process layout.

$$H_0:\phi_2=\sum_{i=1}^{5}\sum_{j=3}^{4}\frac{\mu_{ij}}{10}-\sum_{j=3}^{4}\frac{\mu_{6j}}{2}\geq 0$$

$$H_a:\phi_2<0$$

The primary benefit of DCM over the process layout is that it reduces the frequency of major setups. When setup time is high, the benefit of fewer major setups is greater. Acceptance of the null hypothesis suggests that the minimization of setups cannot compensate for the reduced flexibility of DCM.

3. When part mix is balanced, the process layout outperforms DCM.

$$H_0:\phi_3=\frac{(\sum_{i=1}^{5}\mu_{i1}+\sum_{i=1}^{5}\mu_{i3})}{10}-\frac{(\mu_{61}+\mu_{63})}{2}\leq 0$$

$$H_a:\phi_3>0$$

When part mix is balanced, there are fewer parts from the same family and thus less scope to share setups. Under these conditions, the inability of the process layout to do this should not compromise its performance. Its greater flexibility should continue to give it an advantage. Acceptance of the null hypothesis indicates that even under conditions less suited to family recognition, DCM performs better.

4. When part mix is unbalanced, DCM performs better than the process layout.

$$H_0:\phi_4=\frac{(\sum_{i=1}^{5}\mu_{i2}+\sum_{i=1}^{5}\mu_{i4})}{10}-\frac{(\mu_{62}+\mu_{64})}{2}\geq 0$$

$$H_a:\phi_4<0$$

When part mix is biased towards certain families, there is greater scope to share setups. By reducing the number of major setups, DCM is in a better position to take advantage of these conditions. Acceptance of the null hypothesis indicates that this setup reduction is not sufficient to overcome the lower flexibility of DCM.

5. When setup time is low, DCM outperforms the cellular layout.

$$H_o: \phi_5 = \sum_{i=1}^{5} \sum_{j=1}^{2} \frac{\mu_{ij}}{10} - \sum_{j=1}^{2} \frac{\mu_{7j}}{2} \geq 0$$

$$H_a: \phi_5 < 0$$

When setup time is low, the greater number of major setups incurred by DCM has a relatively small effect. Under these conditions, DCM's greater flexibility should give it an advantage over the cellular layout. Acceptance of the null hypothesis suggests that this increased flexibility is insufficient to compensate for the elimination of major setups in the cellular layout.

6. When setup time is high, the cellular layout outperforms DCM.

$$H_o: \phi_6 = \sum_{i=1}^{5} \sum_{j=3}^{4} \frac{\mu_{ij}}{10} - \sum_{j=3}^{4} \frac{\mu_{7j}}{2} \leq 0$$

$$H_a: \phi_6 > 0$$

When setup time is high, DCM's need to use major setups has a greater adverse effect. By eliminating the need for major setups, the cellular layout is less affected by high setup time. Acceptance of the null hypothesis suggests that DCM's greater flexibility more than offsets the effect of high setup time.

7. When part mix is balanced, DCM outperforms the cellular layout.

$$H_0: \phi_7 = \frac{(\sum_{i=1}^{5} \mu_{i1} + \sum_{i=1}^{5} \mu_{i3})}{10} - \frac{(\mu_{71} + \mu_{73})}{2} \geq 0$$

$$H_a: \phi_7 < 0$$

8. When part mix is unbalanced, DCM outperforms the cellular layout.

$$H_0: \phi_8 = \frac{(\sum_{i=1}^{5} \mu_{i2} + \sum_{i=1}^{5} \mu_{i4})}{10} - \frac{(\mu_{72} + \mu_{74})}{2} \geq 0$$

$$H_a: \phi_8 < 0$$

Cellular layouts are unable to respond to change in part mix and perform well only if cell workload is consistent with cell capacity. Even when part mix is balanced, DCM has the flexibility to adjust to short term imbalances in workload distribution. Acceptance of the null hypotheses for hypotheses 7 and 8 suggests that this flexibility is not able to compensate for the increase in setups incurred by DCM.

9. Dynamically formed cells that recognize work flow patterns are more effective than those that do not.

$$H_0: \phi_9 = \frac{(\sum_{i=3}^{5} \sum_{j=1}^{4} \mu_{ij})}{12} - \frac{(\sum_{i=1}^{2} \sum_{j=1}^{4} \mu_{ij})}{8} \geq 0$$

$$H_a: \phi_9 < 0$$

The intent of DCM is to provide the benefits of part family production within a process layout. It also aims to make production more responsive to prevailing work patterns. Cell formation that explicitly considers the flow of work should therefore be more effective.

4.6 EXPERIMENTAL STAGE II

4.6.1 Experimental Factors

Unlike stage one whose purpose is to compare the performance of DCM to other small/medium batch production methods, the objective of stage two is a more detailed sensitivity analysis of DCM alone. Stage two examines the effect of factors, which, based on evidence from existing studies of small/medium batch production, may affect its performance. This extends the understanding of the appropriateness of DCM in different production environments. It also allows the behavior of DCM to be contrasted more fully with what is known about production using traditional job shop and cellular methods. The factors included are utilization, job dispatching, volume mix variability, and part mix variability.

4.6.1.1 Utilization

Past research on job shops (e.g., Baker, 1984) and CM (e.g., Hitomi et al., 1977) have shown shop performance to depend on utilization. As utilization increases, queues build up at machines. This increases the delays encountered by jobs, thus increasing flow times and leading to reduced on-time job completion. Job shops face the additional problem that increases in the arrival rate of jobs also increases the frequency of setups. This adds further to the problem of delays. CM faces a problem of low overall utilization due to the uneven distribution of work between machines. It is reasonable to expect that utilization will also affect DCM. However, given DCM's particular characteristics, it may respond differently.

Three levels of utilization will be considered, 70%, 80% and 90%. As described earlier, 80% utilization is common in practice and in prior job shop research. The remaining two levels have also been used in past job shop research (e.g., Baker, 1984) and allow the shop to be operated under conditions of lesser and greater congestion.

4.6.1.2 Job Dispatching

Past research on job shop scheduling (e.g., Conway et al., 1967) and scheduling in CM (e.g., Mosier et al., 1984) has demonstrated the impact of dispatching rules on shop performance. The order in which jobs are processed at a machine affects the extent to which queues build. It also determines the extent to which individual jobs are made to wait. To examine the impact of dispatching on DCM, three rules common in practice and in past research are examined. These prioritize jobs based on a range of characteristics that have been shown to have an objective rationale.

FCFS : Jobs are dispatched based on earliest arrival time at the machine or process department. This is used frequently in practice (Conway et al., 1967) based on its intuitive fairness.

SPT : Jobs are dispatched based on minimum operation processing time. SPT is an example of a processing time based rule. It has been shown in the past to yield good mean flow time performance (Conway et al., 1967). SPT reduces the build up of queues by processing jobs that can be completed quickly.

MINSLK : Jobs are dispatched based on minimum job slack. This is an example of a due date based rule. It has been shown in the past to yield good performance, particularly for due date measures (Conway et al., 1967). MINSLK explicitly tries to process jobs whose on time completion is compromised.

4.6.1.3 Volume Mix Variability

Changes in size of incoming jobs directly affects the stability of dynamically formed cells. Smaller jobs implies that there are more jobs in the system simultaneously. For the same utilization level, this suggests that a greater proportion of time is spent by machines while they incur setups. This reduces the extent to which individual cells are utilized. Likewise, greater variance in job size increases the variance of cell life, and thus the extent to which the benefits of the cellular structure can be exploited. While one of the benefits of DCM is the flexibility it introduces to CM, a trade-off exists with setup frequency. If the potential for cells to change is too great, this may offset the benefits of increased flexibility.

These effects are examined by defining three levels of this factor. The first level corresponds to the scenario in stage one where jobs have a constant batch size of one hundred (Morris, 1988). The effect of variance is captured by defining batch sizes to be normally distributed, with a mean of 100, and a coefficient of variation of 0.1 (Bott & Ritzman, 1983, Krajewski et al., 1987). A batch size of 100 is characterized as a large batch size. The impact of small job size is represented by jobs with a constant batch size of fifty, and a corresponding increase in arrival rate.

4.6.1.4 Part Mix Variability

Part mix variability is carried over from stage one due to the potential interaction it has with volume mix variability. Both affect cell workload and in turn the stability of cells, frequency of setups and productive capacity. The factor is defined the same way as in stage one. Part mix is either balanced in which case all families have the same demand, or it is unbalanced and demand skewed in favor of three families.

4.6.2 Simulation Environment

Only one DCM implementation, DCM 4, is included in stage two. This is one of the better performing implementations based on the results of stage one, and one that embraces the intent of DCM to consciously create complete cells. Setup times are not included as an experimental factor. Setup times are fixed at the low level from stage one, or 11.33 minutes per major setup. Utilization levels are based on the balanced part mix, minimum slack dispatching scenario.

4.6.3 Experimental Design

Stage two is carried out using a full factorial design with fifty four (3 x 3 x 3 x 2) treatments. These are defined in Figure 10. As described earlier, stage two of the research is exploratory in nature. No specific hypotheses are tested. ANOVA is used to identify the presence of significant main and interaction effects. Tukey multiple comparisons are used to identify the source of specific differences.

4.7 SUMMARY OF RESEARCH DESIGN

The study uses computer simulation models to show whether DCM is a viable alternative to production compared to traditional process and cellular layout methods. This is

	Volume Mix	100			N(100,10)			50		
	Utilization (%)	70	80	90	70	80	90	70	80	90
Disp. Rule	Part Mix									
FCFS	Balanced	1	7	13	19	25	31	37	43	49
	Unbalanced	2	8	14	20	26	32	38	44	50
SPT	Balanced	3	9	15	21	27	33	39	45	51
	Unbalanced	4	10	16	22	28	34	40	46	52
MINSLK	Balanced	5	11	17	23	29	35	41	47	53
	Unbalanced	6	12	18	24	30	36	42	48	54

Legend : 1 - 54 : Treatment Numbers
Dispatching Rule : FCFS - First Come First Served, SPT - Shortest Processing Time, Minslk - Minimum Job Slack
Volume Mix : 100 - Job Size = 100, N(100,10) - Job Size = N(100,10), 50 - Job Size = 50
Balanced Part Mix : Part families have equal demand probabilities
Unbalanced Part Mix : Three part families have demand probabilities of .233, two have demand probabilities of .15)

Figure 10. Stage II Experimental Design

accomplished by comparing the different shop configurations under a range of shop conditions, then examining additional factors expected to influence DCM performance. The research questions posed are examined using ANOVA, linear contrasts, and multiple comparisons. The results of these analyses are discussed in the next chapter.

CHAPTER 5

EXPERIMENTAL RESULTS

5.1 INTRODUCTION

The data collected from the simulation runs was analyzed in several stages. For each of the primary performance measures, analyses of variance were conducted to identify the presence of significant main and interaction effects. In each analysis, data were blocked by replication number. This allows the independence of samples to be verified since common random numbers were used (Mihram, 1974). Residual analysis was used to verify the assumptions of normality and homogeneous residual variances underlying the use and validity of ANOVA. The sources of specific differences associated with the significant main and interaction effects were evaluated using Tukey multiple comparisons. Since significant interactions were found in the stage one data for all primary performance measures, the nine a priori hypotheses were analyzed using Tukey multiple comparisons of treatment means. All statistical analysis was carried out using SAS (SAS Institute) and SYSTAT (SYSTAT Inc.) statistical software. Statistical tests were carried out at the $\alpha = .05$ level.

5.2 APPROPRIATENESS OF ANALYSIS OF VARIANCE

The appropriateness of ANOVA models was evaluated by examining whether assumptions of normally distributed residuals and homogeneous residual variances were met. Neter et al. (1990) state that minor violations of these assumptions does not necessarily compromise the validity of ANOVA. The impact of non-normally distributed residuals is to marginally increase the actual significance level and marginally decrease the power of the test. This is defined to be the probability of correctly failing to accept a false hypothesis. This effect is not significant for large sample sizes. The effect of non-homogeneous residual variances is the same as long as sample sizes are equal. Neter et al. (1990) suggest that data transformations be used to reduce or eliminate more substantial violations of these assumptions. Specifically they suggest the use of log, square root and reciprocal transformations, depending on the nature of the violation.

The implication for this research is that since sample sizes are large and balanced, inferences based on ANOVA can be assumed to be valid even in the presence of minor violations of assumptions, except where observed p values are close to 0.05.

The assumption of normally distributed residuals was tested using the Probability Correlation Coefficient Test (PCCT) described in Chapter 4. Homogeneity of variances was tested using the Hartley test (Neter et al., 1990). This considers the ratio between the maximum and minimum treatment residual variances and accepts the hypothesis of homogeneity if the ratio is not significantly different from one. Neter et al. (1990) state that small significance levels are justified when using this test. A significance level of $\alpha = .01$ was therefore used.

5.3 ANALYSIS OF STAGE I DATA

5.3.1 Introduction

The twenty-eight treatments in stage one are shown again for convenience.

Setup Time		Low		High	
Part Mix		Balanced	Unbalanced	Balanced	Unbalanced
Shop Config.	DCM 1	1	8	15	22
	DCM 2	2	9	16	23
	DCM 3	3	10	17	24
	DCM 4	4	11	18	25
	DCM 5	5	12	19	26
	Process Layout	6	13	20	27
	Cellular Layout	7	14	21	28

Legend : 1 - 28 = Treatment Numbers
Low Setup Time = 680 minutes, High Setup Time = 1360 minutes
Balanced Part Mix = Part families have equal demand probabilities
Unbalanced Part Mix = Three part families have demand probabilities of .233, two have demand probabilities of .15)

Figure 11. Stage I Treatments

5.3.2 Residual Analysis

For mean flow time and work in process, there was a good fit between the data and the ANOVA models. For mean flow time, though only ten of the twenty-eight treatments had normally distributed residuals, all but one (Treatment 7) yielded PCCT values within 4% of that required to accept the hypothesis of normality. The remaining treatment was within 7%. Nineteen of the treatments had residual variances that were homogeneous.

Of the remaining nine (Treatments 3,5,7,12,14,17,20,21,28), three were treatments whose variances were outliers (Treatments 7,14,28). None of the nine were amongst the better performing treatments.

For mean work in process, eleven treatments had normally distributed residuals. All but three had PCCT values within 2% of that required to accept the hypothesis of normality (Treatments 7, 14, 28). These were within 6% of the critical value. Nineteen of the treatments had homogeneous residual variances. The heterogeneous variances again came from poorer performing treatments (Treatments 3, 5, 6, 7, 12, 14, 20, 23, 24).

For mean tardiness none of the treatments yielded normally distributed residuals and only nine had homogeneous residual variances. In order to overcome this, the three transformations suggested earlier (log, square root, and reciprocal) were used. The log transformation significantly improved the fit of the data with the assumptions of ANOVA. All but four treatments (Treatments 1, 2, 8, 9) yielded PCCT values within 6% of that required to accept the hypothesis of normality. Nineteen treatments had homogeneous residual variances. Again, treatments with non-homogeneous residual variances were either outliers or other poor performing treatments (Treatments 3, 7, 10, 12, 14, 21, 24, 27, 28).

For the standard deviation of work in process, though all but three treatments had PCCT values within 7% of the critical value and eighteen had homogeneous residual variances, a log transformation significantly improved the fit of the model. All treatment residuals yielded PCCT values within 4% of the critical value, and twenty-five of twenty-eight had homogeneous residual variances. Again, treatments with heterogeneous residual variances were poorer performing treatments (Treatments 3, 5, 14).

5.3.3 Analysis of Effects

5.3.3.1 Mean Flow Time

ANOVA results for mean flow time are reported in Table 1. Since all higher order

Table 1. Analysis of Variance for Mean Flow Time

SOURCE	DF	SS	MS	F	p
Random Numbers	99	731960	7394	3.03	0.0001
Shop Configuration	6	11375365	1895894	777.75	0.0001
Setup Time	1	80978	80978	33.22	0.0001
Part Mix	1	293933	293933	120.58	0.0001
Shop * Setup	6	7437319	1239553	508.50	0.0001
Shop * Mix	6	5330985	888497	364.49	0.0001
Setup * Mix	1	551862	551862	226.39	0.0001
Shop * Setup * Mix	6	3165604	527601	216.44	0.0001
Error	2673	6515853	2438		

$R^2 = 0.82$

interactions are significant, Tukey multiple comparisons were carried out for each shop configuration for the four combinations of setup time and part mix. The rationale for this is the fact that over a short time horizon, setup time and part mix are factors that management can exercise some control over through the planning system. Only over a longer time horizon can management exercise control over the shop configuration. Treatment means are reported in Table 2.

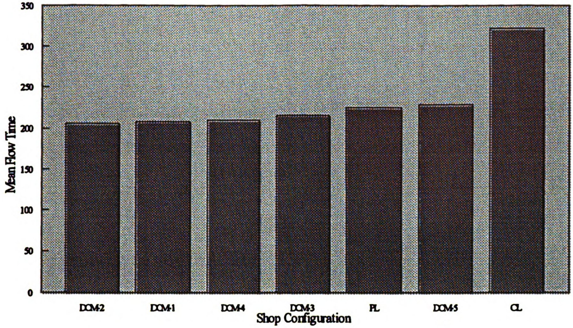
Table 2. Treatment Means for Mean Flow Time

Setup Time		Low		High	
Part Mix		Balanced	Unbalanced	Balanced	Unbalanced
Shop Config.	DCM 1	206.67	193.77	237.58	223.67
	DCM 2	205.76	193.42	236.07	222.66
	DCM 3	214.77	200.08	249.93	232.39
	DCM 4	208.51	196.30	240.50	227.04
	DCM 5	228.71	210.86	249.00	232.98
	Process Layout	225.47	208.44	268.15	247.98
	Cellular Layout	322.11	749.10	252.01	293.42

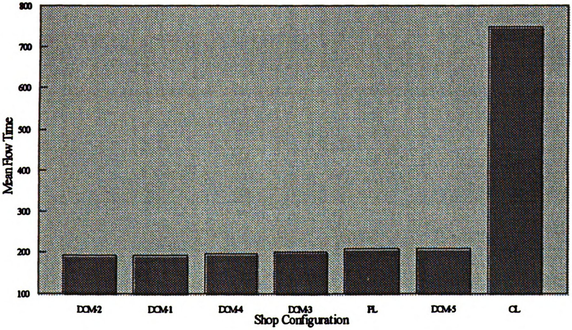
When setup time is low and part mix balanced, the best performance is yielded by DCM 1-4 (Figures 12, 13a). No significant differences exist between these configurations. The performance of the process layout is similar to that of DCM 5, even though DCM 5 is the most far-sighted of the DCM implementations. The performance of the cellular layout is poorer than that of the other configurations. When setup time is low and part mix unbalanced, performance is indistinguishable between all implementations of DCM and the process layout (Figures 12, 13b). Performance of the cellular layout is extremely poor. When setup time is high and part mix balanced, DCM 1, 2 and 4 yield the lowest flow times (Figures 12, 13c). DCM 3 and 5 and the cellular layout yield similar

Setup Time	Low		High	
Part Mix	Balanced	Unbalanced	Balanced	Unbalanced
Mean Flow Time	DCM 2 DCM 1 DCM 4 DCM 3 Process DCM 5 Cellular	DCM 2 DCM 1 DCM 4 DCM 3 Process DCM 5 Cellular	DCM 2 DCM 1 DCM 4 DCM 5 DCM 3 Cellular Process	DCM 2 DCM 1 DCM 4 DCM 3 DCM 5 Process Cellular
Log Mean Tardiness	DCM 2 DCM 1 DCM 4 DCM 3 Process DCM 5 Cellular	DCM 2 DCM 1 DCM 4 DCM 3 DCM 5 Process Cellular	DCM 2 DCM 1 DCM 4 DCM 5 DCM 3 Process Cellular	DCM 2 DCM 1 DCM 4 DCM 5 DCM 3 Process Cellular
Mean Work in Process	DCM 2 DCM 1 DCM 4 DCM 3 Process DCM 5 Cellular	DCM 2 DCM 1 DCM 4 DCM 3 Process DCM 5 Cellular	DCM 2 DCM 1 DCM 4 DCM 3 Cellular DCM 5 Process	DCM 2 DCM 1 DCM 4 DCM 3 DCM 5 Process Cellular
Log Standard Deviation of WIP	DCM 2 DCM 1 DCM 4 DCM 3 DCM 5 Process Cellular	DCM 2 DCM 1 DCM 4 DCM 3 DCM 5 Process Cellular	DCM 2 DCM 1 DCM 4 DCM 5 DCM 3 Cellular Process	DCM 2 DCM 1 DCM 4 DCM 5 DCM 3 Process Cellular

Figure 12. Tukey Multiple Comparisons of Shop Configuration
by Setup Time x Part Mix

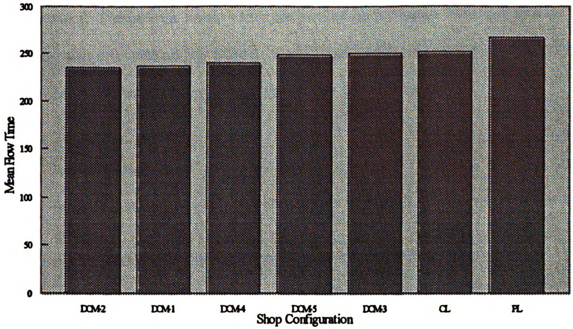


a. Low Setup Time, Balanced Part Mix

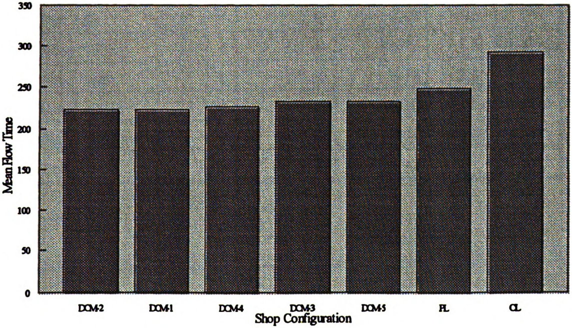


b. Low Setup Time, Unbalanced Part Mix

Figure 13. Mean Flow Time by Setup Time x Part Mix



c. High Setup Time, Balanced Part Mix



d. High Setup Time, Unbalanced Part Mix

Figure 13. (cont'd)

performance. The process layout yields the poorest performance. When setup time is high and part mix unbalanced, DCM 1, 2 and 4 again perform best (Figures 12, 13d). All DCM implementations outperform the process and cellular layouts.

5.3.3.2 Mean Tardiness

ANOVA results for log mean tardiness are reported in Table 3. Treatment means for the

Table 3. Analysis of Variance for Log Mean Tardiness

SOURCE	DF	SS	MS	F	p
Random Numbers	99	980.28	9.90	6.72	0.0001
Shop Configuration	6	902.58	150.43	102.06	0.0001
Setup Time	1	582.07	582.07	394.89	0.0001
Part Mix	1	3.83	3.83	2.60	0.1069
Shop * Setup	6	412.24	68.71	46.61	0.0001
Shop * Mix	6	22.60	3.77	2.56	0.0180
Setup * Mix	1	0.33	0.33	0.22	0.6378
Shop * Setup * Mix	6	12.25	2.04	1.39	0.2165
Error	2673	3939.97	1.47		

$R^2 = 0.42$

untransformed data are reported in Table 4. Pairwise comparison of shops by setup time/part mix conditions show that for low setup time, balanced part mix conditions, DCM implementations 1, 2, and 4 yield the best tardiness performance, followed by DCM 3 (Figures 12, 14a). Similar to the result for mean flow time, the performance of DCM 5 and the process layout is indistinguishable, and the cellular layout yields the

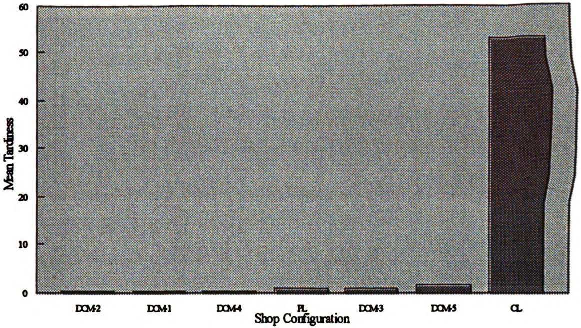
Table 4. Treatment Means for Mean Tardiness

Setup Time		Low		High	
Part Mix		Balanced	Unbalanced	Balanced	Unbalanced
Shop Config.	DCM 1	0.183	0.137	0.299	0.237
	DCM 2	0.152	0.142	0.231	0.191
	DCM 3	1.012	0.686	2.181	1.431
	DCM 4	0.318	0.426	0.629	0.636
	DCM 5	1.468	0.758	1.312	0.917
	Process Layout	0.950	0.635	3.570	2.465
	Cellular Layout	53.176	463.857	10.787	43.193

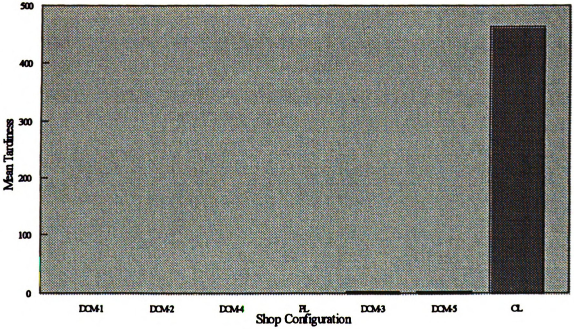
highest tardiness. For low setup time, unbalanced part mix conditions, DCM 1 and 2 outperform other DCM implementations (Figures 12, 14b). The process layout again performs poorly as does DCM 5, but not as poorly as the cellular layout. For both high setup time scenarios, DCM 1 and 2 again perform best, followed by DCM 4 (Figures 12, 14c, 14d). The process and cellular layouts perform poorer than all DCM implementations.

5.3.3.3 Mean Work In Process

ANOVA results for mean work in process are reported in Table 5. Treatment means are reported in Table 6. Multiple comparison results are, as expected, largely similar to those for mean flow time. The exceptions are that the performances of DCM 2 and 3 are not indistinguishable when setup time is low and part mix balanced, and DCM 4 and 5 perform differently when setup time is high and part mix unbalanced (Figures 12, 15a-d).

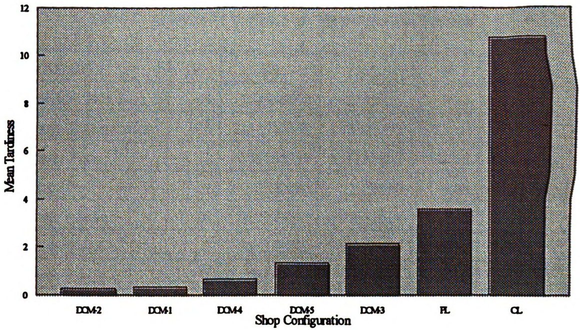


a. Low Setup Time, Balanced Part Mix

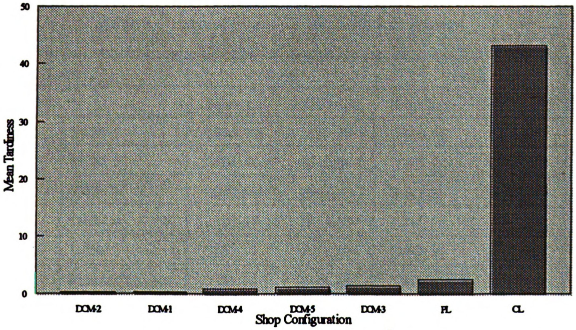


b. Low Setup Time, Unbalanced Part Mix

Figure 14. Mean Tardiness by Setup Time x Part Mix



c. High Setup Time, Balanced Part Mix



d. High Setup Time, Unbalanced Part Mix

Figure 14. (cont'd)

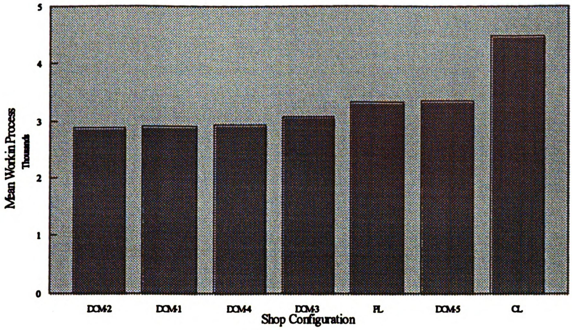
Table 5. Analysis of Variance for Mean Work in Process

SOURCE	DF	SS	MS	F	p
Random Numbers	99	223048038	2253010	8.44	0.0001
Shop Configuration	6	1158547167	193091195	723.67	0.0001
Setup Time	1	195185982	195185892	731.52	0.0001
Part Mix	1	22896	22896	0.09	0.7696
Shop * Setup	6	807971467	134661911	504.69	0.0001
Shop * Mix	6	386391299	64398550	241.35	0.0001
Setup * Mix	1	36492126	36492126	136.77	0.0001
Shop * Setup * Mix	6	249934824	41655804	156.12	0.0001
Error	2673	713214803	266822		

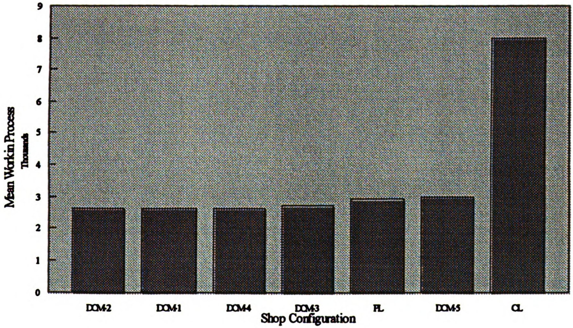
$R^2 = 0.81$

Table 6. Treatment Means for Mean Work in Process

Setup Time		Low		High	
Part Mix		Balanced	Unbalanced	Balanced	Unbalanced
Shop Config.	DCM 1	2916.70	2630.50	2816.46	2563.98
	DCM 2	2884.44	2611.62	2785.34	2541.40
	DCM 3	3083.43	2752.23	3012.25	2685.35
	DCM 4	2926.47	2653.40	2841.66	2593.50
	DCM 5	3362.13	2970.69	3062.79	2765.63
	Process Layout	3331.16	2941.83	3349.51	2960.70
	Cellular Layout	4487.57	7989.86	3025.80	3144.96

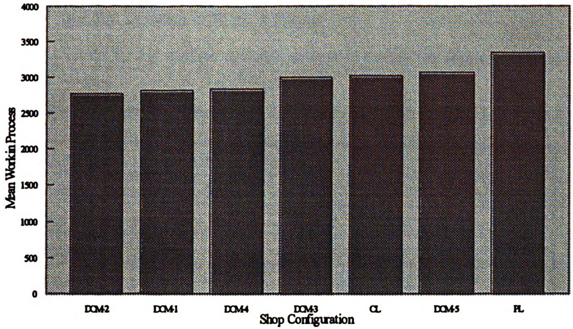


a. Low Setup Time, Balanced Part Mix

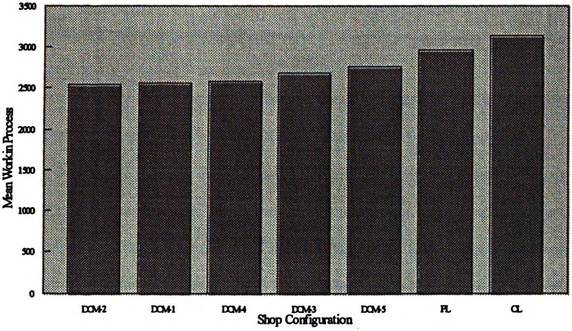


b. Low Setup Time, Unbalanced Part Mix

Figure 15. Mean Work in Process by Setup Time x Part Mix



c. High Setup Time, Balanced Part Mix



d. High Setup Time, Unbalanced Part Mix

Figure 15. (cont'd)

5.3.3.4 Standard Deviation of Work in Process

ANOVA results for log standard deviation of work in process are reported in Table 7.

Table 7. Analysis of Variance for Log Standard Deviation of Work in Process

SOURCE	DF	SS	MS	F	p
Random Numbers	99	10.69	0.11	45.88	0.0001
Shop Configuration	6	11.31	1.88	800.58	0.0001
Setup Time	1	1.59	1.59	673.75	0.0001
Part Mix	1	0.35	0.35	147.57	0.0001
Shop * Setup	6	4.31	0.72	305.37	0.0001
Shop * Mix	6	1.42	0.24	100.20	0.0001
Setup * Mix	1	0.03	0.03	11.08	0.0009
Shop * Setup * Mix	6	0.71	0.12	50.13	0.0001
Error	2673	6.29	0.002		

$R^2 = 0.83$

Treatment means for the untransformed data are reported in Table 8. For both low setup time scenarios, the best performance is obtained when DCM 1-4 are used followed by DCM 5 (Figures 12, 16a,b). The poorest performance is obtained when the cellular layout is used. When setup time is high and part mix balanced, DCM 1, 2 and 4 perform best followed by DCM 3 and 5 (Figures 12, 16c). The process layout performs poorest. The result is the same when setup time is high and part mix unbalanced except that the cellular layout performs poorer than DCM 5 but similar to the process layout (Figures 12, 16d).

Table 8. Treatment Means for Standard Deviation of Work in Process

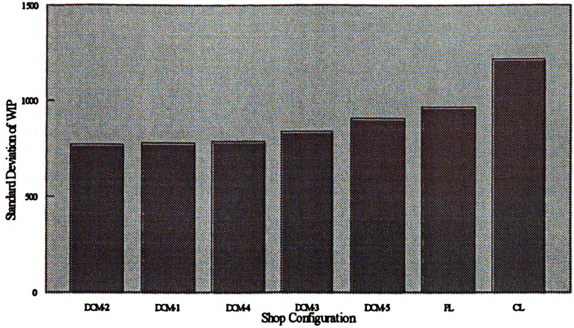
Setup Time		Low		High	
Part Mix		Balanced	Unbalanced	Balanced	Unbalanced
Shop Config.	DCM 1	778.53	700.87	744.73	684.23
	DCM 2	768.60	694.20	732.26	675.09
	DCM 3	841.63	745.55	815.09	747.38
	DCM 4	782.64	710.30	753.59	693.47
	DCM 5	906.37	798.93	810.45	743.17
	Process Layout	966.18	843.08	902.74	840.25
	Cellular Layout	1221.00	1843.26	850.83	854.20

5.3.4 Summary of ANOVA Results

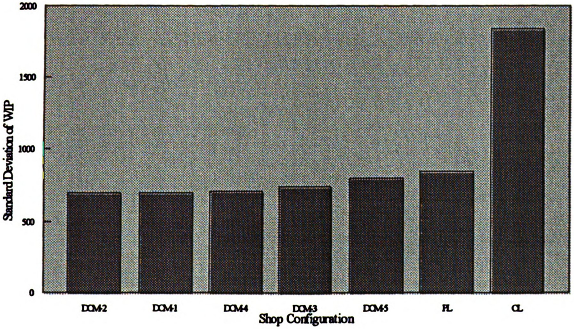
The ANOVA results indicate that the relative performance of the shop configurations depends on specific setup time and part mix conditions. They also show that under each set of conditions examined, DCM generally performs better than the process and cellular layouts. Only under one set of conditions is there no distinct advantage to be obtained by using DCM. The relative performance of different DCM implementations remains largely unchanged as shop conditions change, DCM 1, 2 and 4 generally performing best.

5.3.5 Analysis of A Priori Hypotheses

As described earlier, the presence of higher order interactions makes the interpretation of linear contrasts inappropriate. Instead, the a priori hypotheses were evaluated using Tukey multiple comparisons of treatment means. This was done by identifying those

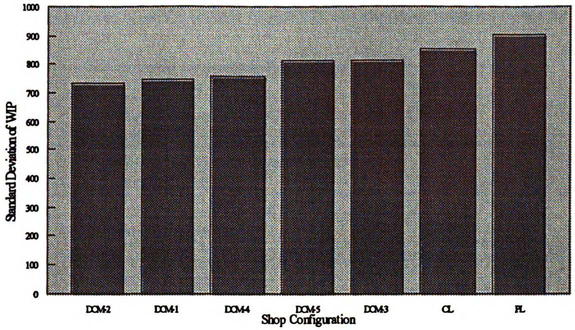


a. Low Setup Time, Balanced Part Mix

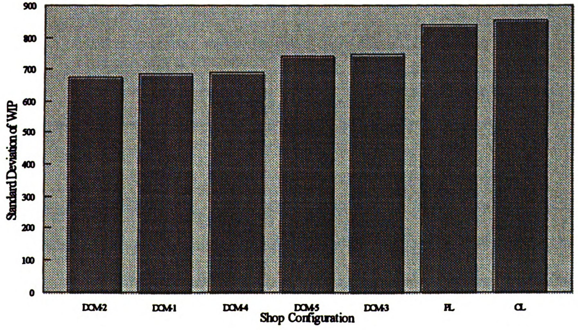


b. Low Setup Time, Unbalanced Part Mix

Figure 16. Standard Deviation of Work in Process by Setup x Part Mix



c. High Setup Time, Balanced Part Mix



d. High Setup Time, Unbalanced Part Mix

Figure 16. (cont'd)

treatments included in each hypothesis (Figure 17), and comparing treatment means for

Hypothesis		Treatments
1.	Process layout outperforms DCM when setup time is low.	1 - 6, 8 - 13
2.	DCM outperforms process layout when setup time is high.	15 - 20, 22 - 27
3.	Process layout outperforms DCM when part mix is balanced.	1 - 6, 15 - 20
4.	DCM outperforms process layout when part mix is unbalanced.	8 - 13, 22 - 27
5.	DCM outperforms cellular layout when setup time is low.	1 - 5, 7 - 12, 14
6.	Cellular layout outperforms DCM when setup time is high.	15 - 19, 21 - 26, 28
7.	DCM outperforms cellular layout when part mix is balanced.	1 - 5, 7, 15 - 19, 21
8.	DCM outperforms cellular layout when part mix is unbalanced.	8 - 12, 14, 22 - 26, 28
9.	DCM that recognizes material flows outperforms DCM that does not.	1 - 5, 8 - 12, 15 - 19, 22 - 26

Figure 17. Treatment Numbers by Hypothesis

all appropriate treatments (e.g., Hypothesis 1, Treatments 1-6, 8-13). The significance or otherwise of multiple comparisons can provide evidence to make certain conclusions regarding the hypotheses. If not, they can still yield information regarding underlying trends contained within the data.

5.3.5.1 Hypothesis 1

Hypothesis 1 states that when setup time is low, the process layout outperforms DCM. The data does not support this (Figures 18, 19a-d). DCM always performs at least as

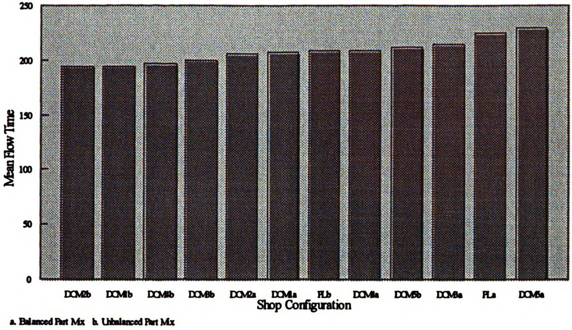
Mean Flow Time	Log Mean Tardiness	Mean Work in Process	Log Std. Dev. of WIP
DCM2/Unbal	DCM2/Unbal	DCM2/Unbal	DCM2/Unbal
DCM1/Unbal	DCM1/Unbal	DCM1/Unbal	DCM1/Unbal
DCM4/Unbal	DCM2/Bal	DCM4/Unbal	DCM4/Unbal
DCM3/Unbal	DCM1/Bal	DCM3/Unbal	DCM3/Unbal
DCM2/Bal	DCM4/Bal	DCM2/Bal	DCM2/Bal
DCM1/Bal	DCM4/Unbal	DCM1/Bal	DCM1/Bal
Process/Unbal	DCM3/Unbal	DCM4/Bal	DCM4/Bal
DCM4/Bal	DCM3/Bal	Process/Unbal	DCM5/Unbal
DCM5/Unbal	DCM5/Unbal	DCM5/Unbal	DCM3/Bal
DCM3/Bal	Process/Unbal	DCM3/Bal	Process/Unbal
Process/Bal	Process/Bal	Process/Bal	DCM5/Bal
DCM5/Bal	DCM5/Bal	DCM5/Bal	Process/Bal

Figure 18. Tukey Multiple Comparisons for Hypothesis 1

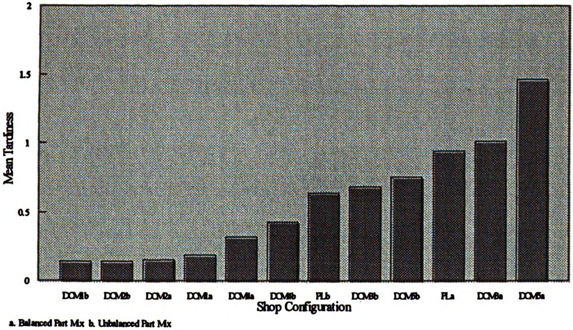
well as the process layout with the exception of the flow time performances of DCM 3 and 5, and the mean work in process performance of DCM 5. DCM 1, 2 and 4 always outperform the process layout for mean tardiness. DCM 2 also outperforms the process layout for the log of the standard deviation of work in process.

5.3.5.2 Hypothesis 2

Hypothesis 2 states that when setup time is high, DCM outperforms the process layout. The results support this for DCM 1, 2 and 4, and for the tardiness performance of DCM 5 (Figures 20, 21a-d). DCM 3 and 5 never perform poorer than the process layout.

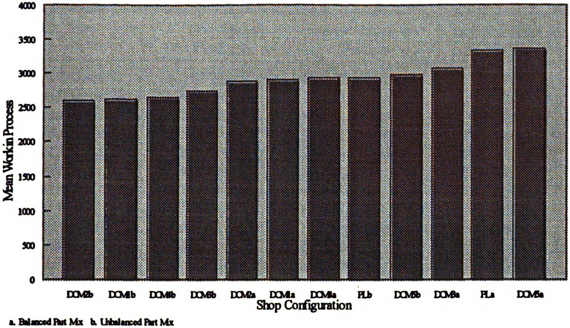


a. Mean Flow Time

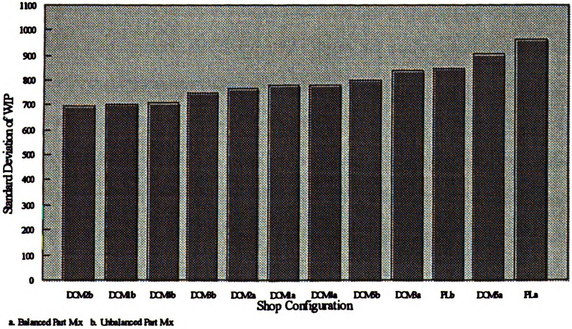


b. Mean Tardiness

Figure 19. Shop Performance for Hypothesis 1



c. Mean Work in Process



d. Standard Deviation of Work in Process

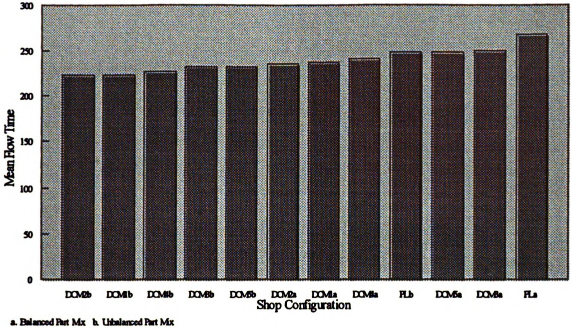
Figure 19. (cont'd)

Mean Flow Time	Log Mean Tardiness	Mean Work in Process	Log Std. Dev. of WIP
DCM2/Unbal	DCM2/Unbal	DCM2/Unbal	DCM2/Unbal
DCM1/Unbal	DCM1/Unbal	DCM1/Unbal	DCM1/Unbal
DCM4/Unbal	DCM2/Bal	DCM4/Unbal	DCM4/Unbal
DCM3/Unbal	DCM1/Bal	DCM3/Unbal	DCM2/Bal
DCM5/Unbal	DCM4/Unbal	DCM5/Unbal	DCM5/Unbal
DCM2/Bal	DCM4/Bal	DCM2/Bal	DCM1/Bal
DCM1/Bal	DCM5/Unbal	DCM1/Bal	DCM3/Unbal
DCM4/Bal	DCM5/Bal	DCM4/Bal	DCM4/Bal
Process/Unbal	DCM3/Unbal	Process/Unbal	DCM3/Bal
DCM5/Bal	DCM3/Bal	DCM3/Bal	DCM5/Bal
DCM3/Bal	Process/Unbal	DCM5/Bal	Process/Unbal
Process/Bal	Process/Bal	Process/Bal	Process/Bal

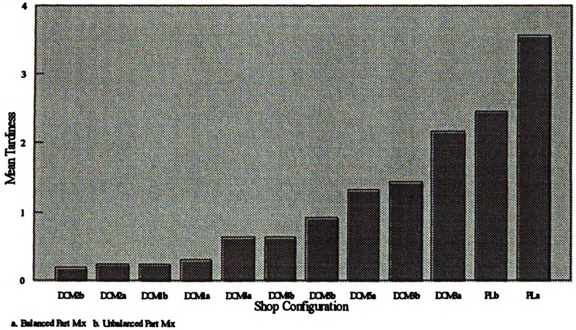
Figure 20. Tukey Multiple Comparisons for Hypothesis 2

5.3.5.3 Hypothesis 3

Hypothesis 3 states that when part mix is balanced, the process layout outperforms DCM. The results do not support this (Figures 22, 23a-d). For mean flow time, the process layout never outperforms any DCM implementation under the same setup time condition, being outperformed in all but one case (DCM 5 under low setup time conditions). The tardiness performance of DCM 1 and 2 is always better than that of the process layout. DCM 4 always performs at least as well as the process layout and DCM 5 never poorer than the process layout. DCM 1, 2 and 4 always yield better work in process performance than the process layout. DCM 3 also yields lower mean work in process. DCM never yields poorer work in process performance than the process layout.

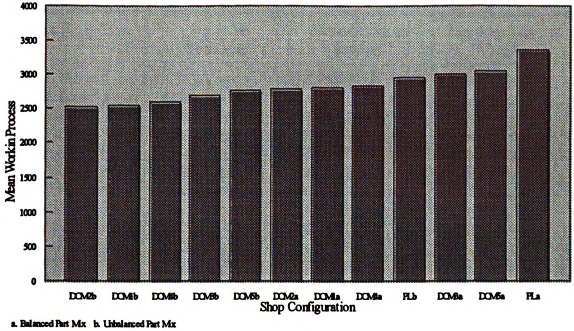


a. Mean Flow Time

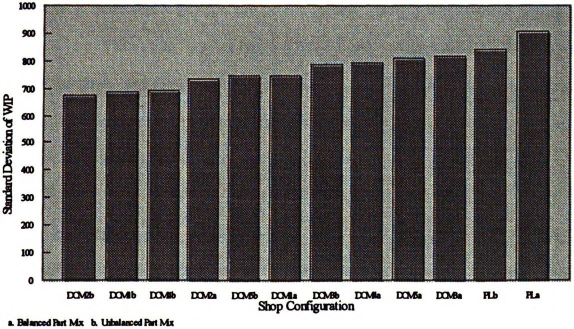


b. Mean Tardiness

Figure 21. Shop Performance for Hypothesis 2



c. Mean Work in Process



d. Standard Deviation of Work in Process

Figure 21. (cont'd)

Mean Flow Time	Log Mean Tardiness	Mean Work in Process	Log Std. Dev. of WIP
DCM2/Low	DCM2/Low	DCM2/High	DCM2/High
DCM1/Low	DCM1/Low	DCM1/High	DCM1/High
DCM4/Low	DCM4/Low	DCM4/High	DCM4/High
DCM3/Low	DCM2/High	DCM2/Low	DCM2/Low
Process/Low	DCM1/High	DCM1/Low	DCM1/Low
DCM5/Low	DCM3/Low	DCM4/Low	DCM4/Low
DCM2/High	DCM4/High	DCM3/High	DCM5/High
DCM1/High	Process/Low	DCM5/High	DCM3/High
DCM4/High	DCM5/Low	DCM3/Low	DCM3/Low
DCM5/High	DCM5/High	Process/Low	Process/High
DCM3/High	DCM3/High	Process/High	DCM5/Low
Process/High	Process/High	DCM5/Low	Process/Low

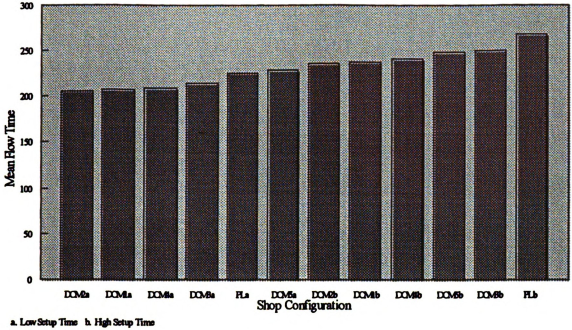
Figure 22. Tukey Multiple Comparisons for Hypothesis 3

5.3.5.4 Hypothesis 4

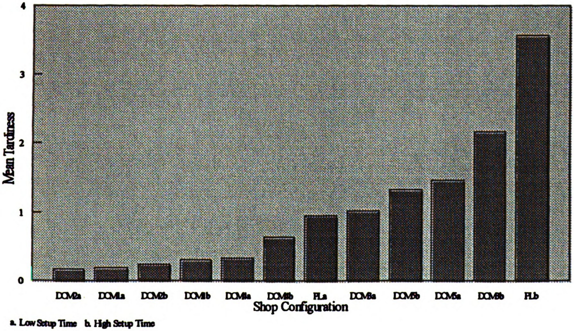
Hypothesis 4 states that when part mix is unbalanced, DCM performs better than the process layout. The results support this for DCM 1 and 2 except for their mean flow time performance, and for the work in process performance of DCM 3 and 4 (Figures 24, 25a-d). DCM 1-4 always perform better than the process layout under the same setup time conditions and DCM 5 at least well as the process layout.

5.3.5.5 Hypothesis 5

Hypothesis 5 states that when setup time is low, DCM outperforms the cellular layout. The results support this (Figures 26, 27a-d). For all measures, the cellular layout always yields the poorest performance.

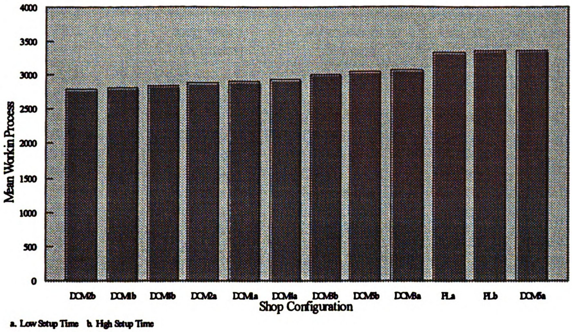


a. Mean Flow Time

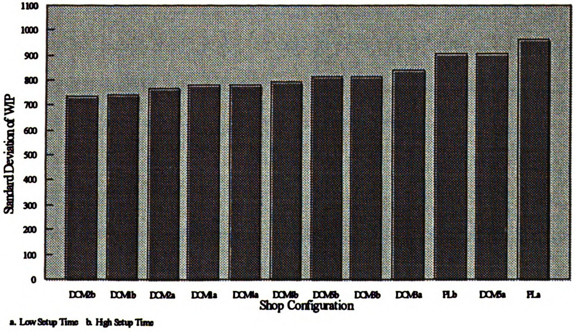


b. Mean Tardiness

Figure 23. Shop Performance for Hypothesis 3



c. Mean Work in Process



d. Standard Deviation of Work in Process

Figure 23. (cont'd)

Mean Flow Time	Log Mean Tardiness	Mean Work in Process	Log Std. Dev. of WIP
DCM2/Low	DCM2/Low	DCM2/High	DCM2/High
DCM1/Low	DCM1/Low	DCM1/High	DCM1/High
DCM4/Low	DCM4/Low	DCM4/High	DCM4/High
DCM3/Low	DCM2/High	DCM2/Low	DCM2/Low
Process/Low	DCM1/High	DCM1/Low	DCM1/Low
DCM5/Low	DCM3/Low	DCM4/Low	DCM4/Low
DCM2/High	DCM5/Low	DCM3/High	DCM3/Low
DCM1/High	Process/Low	DCM3/Low	DCM5/High
DCM4/High	DCM4/High	DCM5/High	DCM3/High
DCM3/High	DCM5/High	Process/Low	DCM5/Low
DCM5/High	DCM3/High	Process/High	Process/Low
Process/High	Process/High	DCM5/Low	Process/High

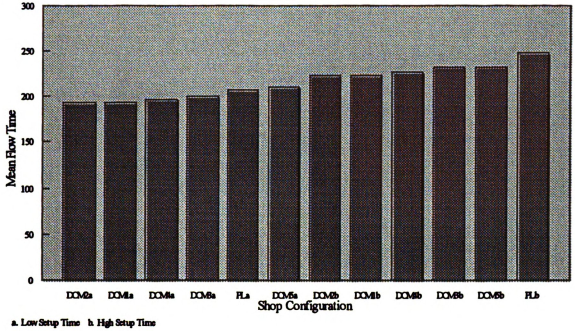
Figure 24. Tukey Multiple Comparisons for Hypothesis 4

5.3.5.6 Hypothesis 6

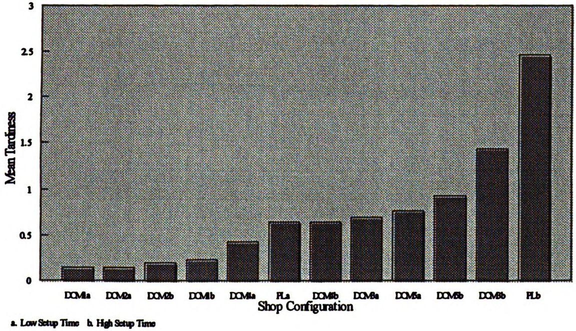
Hypothesis 6 states that when setup time is high, the cellular layout outperforms DCM. The results do not support this (Figures 28, 29a-d). DCM 1, 2 and 4 always outperform the cellular layout. DCM 3 and 5 always perform at least as well as the cellular layout. The cellular layout always yields the poorest tardiness performance.

5.3.5.7 Hypothesis 7

Hypothesis 7 states that when part mix is balanced, DCM outperforms the cellular layout. The results support this for DCM 1 and 2 except for their mean work in process performance, for DCM 4 for mean flow time and tardiness, and for DCM 3 and 5 for mean tardiness (Figures 30, 31a-d). DCM never performs poorer than the cellular layout with the exception of the mean work in process performance of DCM 5.

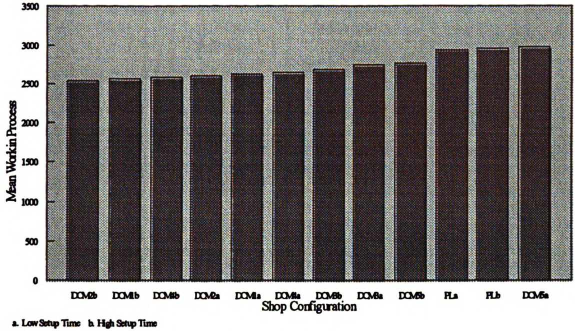


a. Mean Flow Time

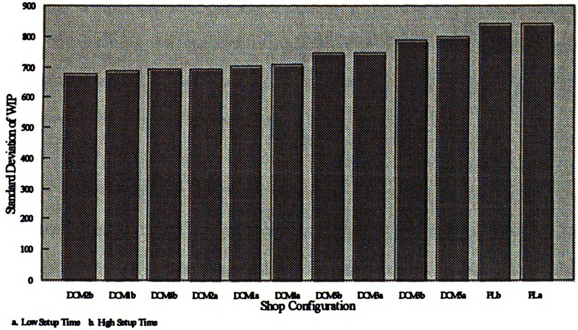


b. Mean Tardiness

Figure 25. Shop Performance for Hypothesis 4



c. Mean Work in Process



d. Standard Deviation of Work in Process

Figure 25. (cont'd)

Mean Flow Time	Log Mean Tardiness	Mean Work in Process	Log Std. Dev. of WIP
DCM2/Unbal	DCM2/Unbal	DCM2/Unbal	DCM2/Unbal
DCM1/Unbal	DCM1/Unbal	DCM1/Unbal	DCM1/Unbal
DCM4/Unbal	DCM2/Bal	DCM4/Unbal	DCM4/Unbal
DCM3/Unbal	DCM1/Bal	DCM3/Unbal	DCM3/Unbal
DCM2/Bal	DCM4/Bal	DCM2/Bal	DCM2/Bal
DCM1/Bal	DCM4/Unbal	DCM1/Bal	DCM1/Bal
DCM4/Bal	DCM3/Unbal	DCM4/Bal	DCM4/Bal
DCM5/Unbal	DCM3/Bal	DCM5/Unbal	DCM5/Unbal
DCM3/Bal	DCM5/Unbal	DCM3/Bal	DCM3/Bal
DCM5/Bal	DCM5/Bal	DCM5/Bal	DCM5/Bal
Cellular/Bal	Cellular/Bal	Cellular/Bal	Cellular/Bal
Cellular/Unbal	Cellular/Unbal	Cellular/Unbal	Cellular/Unbal

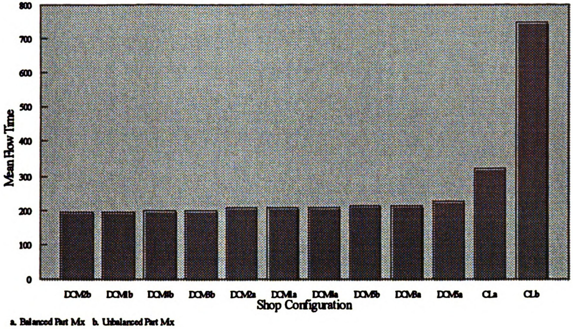
Figure 26. Tukey Multiple Comparisons for Hypothesis 5

5.3.5.8 Hypothesis 8

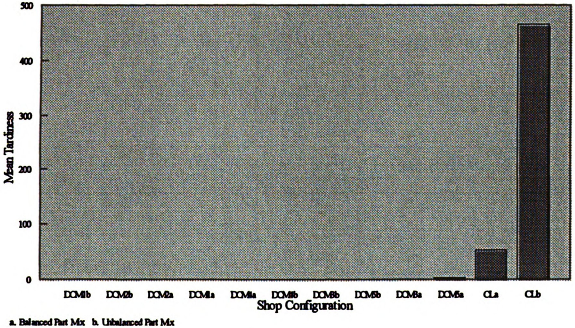
Hypothesis 8 states that when part mix is unbalanced, DCM outperforms the cellular layout. The results support this with the exception of the work in process performance of DCM 5 (Figures 32, 33a-d). With this one exception, the cellular layout always yields the poorest performance for all measures.

5.3.5.9 Hypothesis 9

Hypothesis 9 states that DCM implementations that recognize material flows in cell formation (DCM 3-5) yield better performance than those that do not (DCM 1 & 2). The results do not support this (Figures 34, 35a-d). Given the range of shop conditions examined, it is understandable that no single implementation consistently yields the best

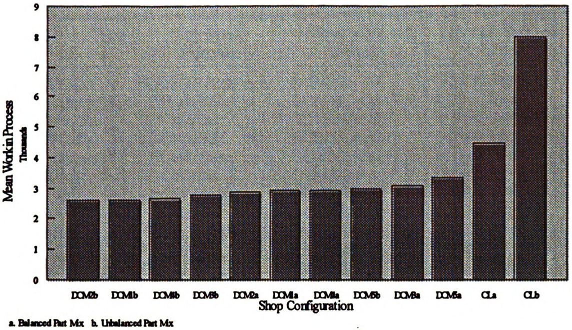


a. Mean Flow Time

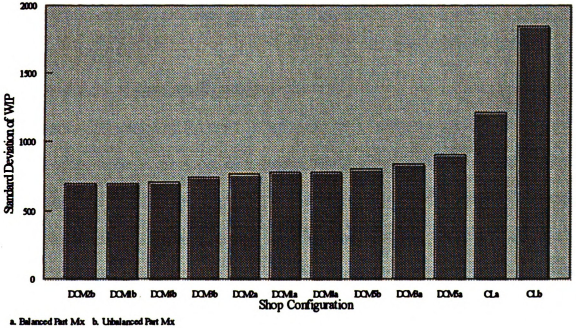


b. Mean Tardiness

Figure 27. Shop Performance for Hypothesis 5



c. Mean Work in Process



d. Standard Deviation of Work in Process

Figure 27. (cont'd)

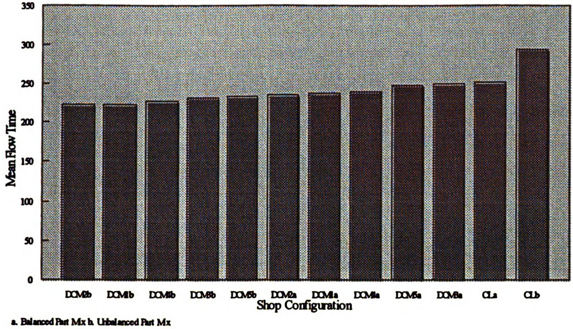
Mean Flow Time	Log Mean Tardiness	Mean Work in Process	Log Std. Dev. of WIP
DCM2/Unbal	DCM2/Unbal	DCM2/Unbal	DCM2/Unbal
DCM1/Unbal	DCM1/Unbal	DCM1/Unbal	DCM1/Unbal
DCM4/Unbal	DCM2/Bal	DCM4/Unbal	DCM4/Unbal
DCM3/Unbal	DCM1/Bal	DCM3/Unbal	DCM2/Bal
DCM5/Unbal	DCM4/Unbal	DCM5/Unbal	DCM5/Unbal
DCM2/Bal	DCM4/Bal	DCM2/Bal	DCM1/Bal
DCM1/Bal	DCM5/Unbal	DCM1/Bal	DCM3/Unbal
DCM4/Bal	DCM5/Bal	DCM4/Bal	DCM4/Bal
DCM5/Bal	DCM3/Unbal	DCM3/Bal	DCM3/Bal
DCM3/Bal	DCM3/Bal	Cellular/Bal	DCM5/Bal
Cellular/Bal	Cellular/Bal	DCM5/Bal	Cellular/Bal
Cellular/Unbal	Cellular/Unbal	Cellular/Unbal	Cellular/Unbal

Figure 28. Tukey Multiple Comparisons for Hypothesis 6

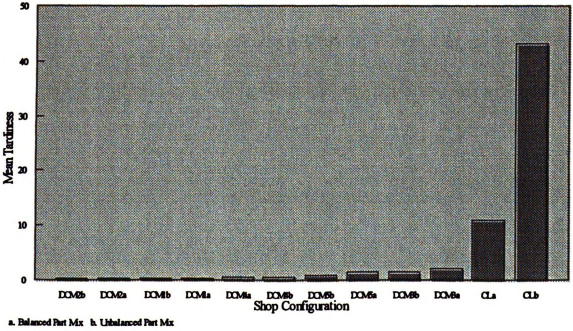
performance. However, DCM 1, 2 and 4 typically yield the best performance under a given set of conditions. Of these, only DCM 4 recognizes material flows.

5.3.6 <u>Summary of Research Hypotheses</u>

The information yielded by the multiple comparisons indicates that DCM performs well under a wider range of conditions than anticipated. In comparison to the process layout, DCM generally performs better regardless of setup time conditions. DCM performs better, as expected, when setup time is high. It also performs well when setup time is low, a scenario in which setup time was not expected to greatly compromise the performance of the process layout. With respect to part mix, the results suggest that DCM performance is in general better, but not conclusively so. Comparing DCM to the cellular layout, the results suggest that DCM performs better not only when setup time

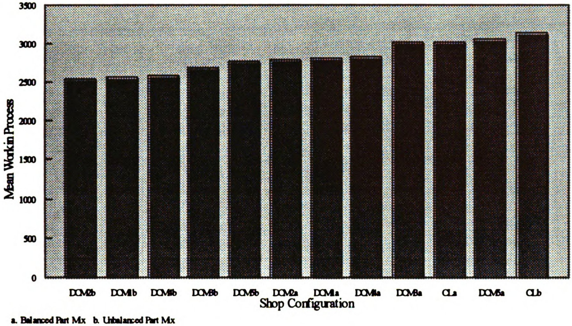


a. Mean Flow Time

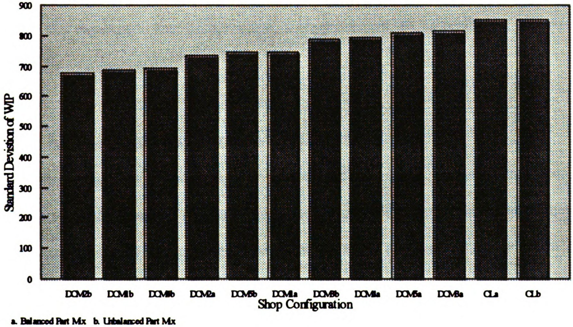


b. Mean Tardiness

Figure 29. Shop Performance for Hypothesis 6



c. Mean Work in Process



d. Standard Deviation of Work in Process

Figure 29. (cont'd)

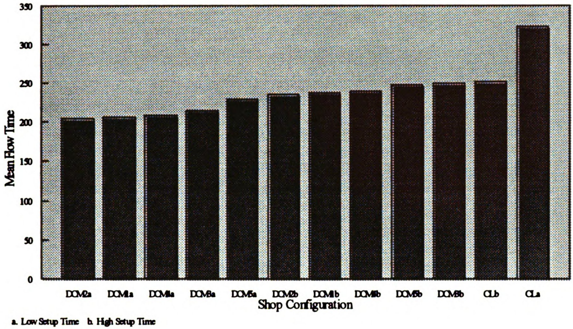
Mean Flow Time	Log Mean Tardiness	Mean Work in Process	Log Std. Dev. of WIP
DCM2/Low	DCM2/Low	DCM2/High	DCM2/High
DCM1/Low	DCM1/Low	DCM1/High	DCM1/High
DCM4/Low	DCM4/Low	DCM4/High	DCM4/High
DCM3/Low	DCM2/High	DCM2/Low	DCM2/Low
DCM5/Low	DCM1/High	DCM1/Low	DCM1/Low
DCM2/High	DCM3/Low	DCM4/Low	DCM4/Low
DCM1/High	DCM4/High	DCM3/High	DCM5/High
DCM4/High	DCM5/Low	Cellular/High	DCM3/High
DCM5/High	DCM5/High	DCM5/High	DCM3/Low
DCM3/High	DCM3/High	DCM3/Low	Cellular/High
Cellular/High	Cellular/High	DCM5/Low	DCM5/Low
Cellular/Low	Cellular/Low	Cellular/Low	Cellular/Low

Figure 30. Tukey Multiple Comparisons for Hypothesis 7

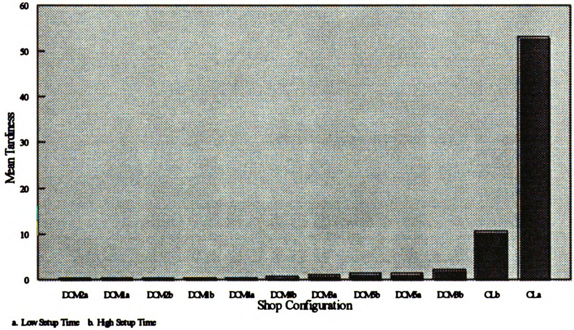
is low, as expected, but also when setup time is high. Under these conditions, the cellular layout was expected to have an advantage. As hypothesized, DCM performed better for both part mix conditions.

5.3.7 Analysis of Secondary Performance Measures

In addition to the primary performance measures discussed so far, data was also collected for secondary performance measures. DCM is able to obtain the benefits described above while simultaneously increasing effective capacity (Table 9). Mean utilization for DCM ranges from 0.4 to 5% lower than that for the process layout, depending on setup and part mix conditions. As expected, the cellular layout consistently yields low utilization, varying from 61% to 70%. The utilization of the different DCM implementations is essentially similar with the exception of DCM 5 which yields utilization that is about 2%

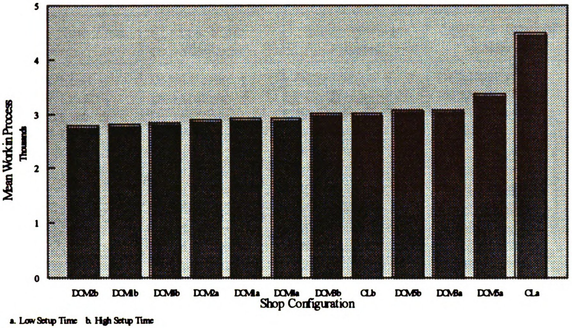


a. Mean Flow Time

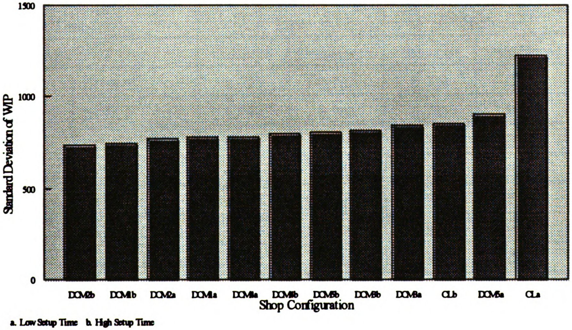


b. Mean Tardiness

Figure 31. Shop Performance for Hypothesis 7



c. Mean Work in Process



d. Standard Deviation of Work in Process

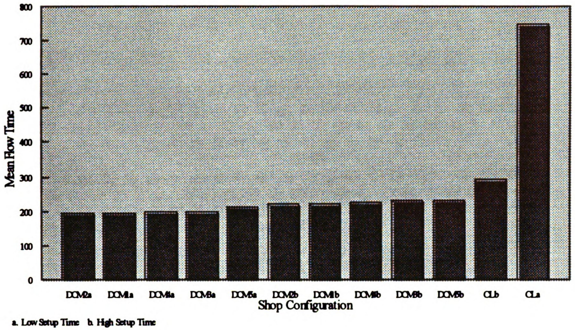
Figure 31. (cont'd)

Mean Flow Time	Log Mean Tardiness	Mean Work in Process	Log Std. Dev. of WIP
DCM2/Low	DCM2/Low	DCM2/High	DCM2/High
DCM1/Low	DCM1/Low	DCM1/High	DCM1/High
DCM4/Low	DCM4/Low	DCM4/High	DCM4/High
DCM3/Low	DCM2/High	DCM2/Low	DCM2/Low
DCM5/Low	DCM1/High	DCM1/Low	DCM1/Low
DCM2/High	DCM3/Low	DCM4/Low	DCM4/Low
DCM1/High	DCM5/Low	DCM3/High	DCM3/Low
DCM4/High	DCM4/High	DCM3/Low	DCM5/High
DCM3/High	DCM5/High	DCM5/High	DCM3/High
DCM5/High	DCM3/High	DCM5/Low	DCM5/Low
Cellular/High	Cellular/High	Cellular/High	Cellular/High
Cellular/Low	Cellular/Low	Cellular/Low	Cellular/Low

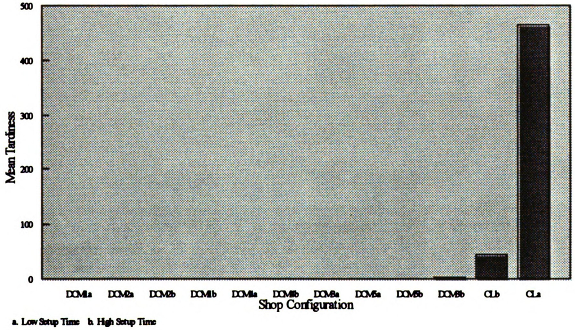
Figure 32. Tukey Multiple Comparisons for Hypothesis 8

Table 9. Treatment Means for Mean Utilization

Setup Time		Low		High	
Part Mix		Balanced	Unbalanced	Balanced	Unbalanced
Shop Config.	DCM 1	0.790	0.763	0.784	0.757
	DCM 2	0.789	0.762	0.782	0.755
	DCM 3	0.795	0.768	0.791	0.762
	DCM 4	0.791	0.765	0.786	0.759
	DCM 5	0.770	0.747	0.754	0.733
	Process Layout	0.799	0.772	0.804	0.774
	Cellular Layout	0.698	0.677	0.628	0.607

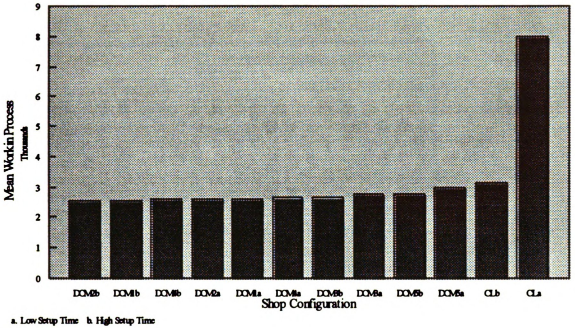


a. Mean Flow Time

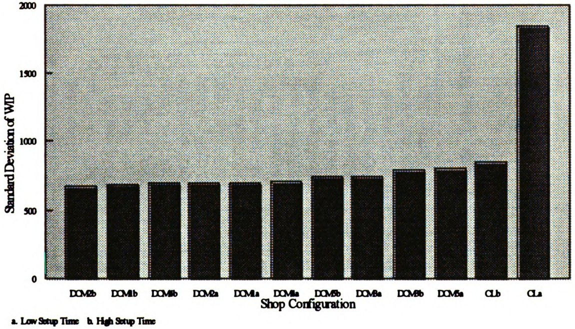


b. Mean Tardiness

Figure 33. Shop Performance for Hypothesis 8



c. Mean Work in Process

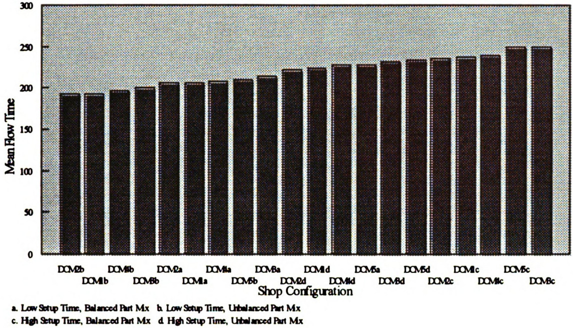


d. Standard Deviation of Work in Process

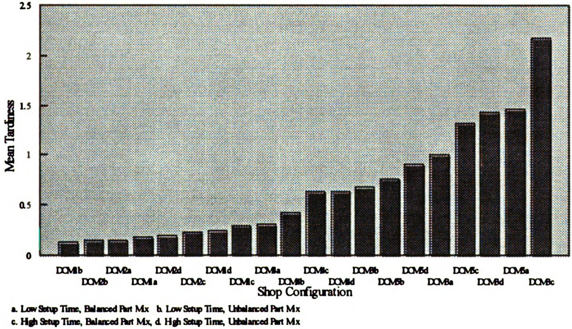
Figure 33. (cont'd)

Mean Flow Time	Log Mean Tardiness	Mean Work in Process	Log Std. Dev. of WIP
DCM2/Low/Unbal	DCM1/Low/Unbal	DCM2/High/Unbal	DCM2/High/Unbal
DCM1/Low/Unbal	DCM2/Low/Unbal	DCM1/High/Unbal	DCM1/High/Unbal
DCM4/Low/Unbal	DCM2/Low/Bal	DCM4/High/Unbal	DCM2/Low/Unbal
DCM3/Low/Unbal	DCM1/Low/Bal	DCM2/Low/Unbal	DCM4/High/Unbal
DCM2/Low/Bal	DCM4/Low/Bal	DCM1/Low/Unbal	DCM1/Low/Unbal
DCM1/Low/Bal	DCM4/Low/Unbal	DCM4/Low/Unbal	DCM4/Low/Unbal
DCM4/Low/Bal	DCM2/High/Unbal	DCM3/High/Unbal	DCM2/High/Bal
DCM5/Low/Unbal	DCM1/High/Unbal	DCM3/Low/Unbal	DCM3/Low/Unbal
DCM3/Low/Bal	DCM3/Low/Unbal	DCM5/High/Unbal	DCM5/High/Unbal
DCM2/High/Unbal	DCM2/High/Bal	DCM2/High/Bal	DCM1/High/Bal
DCM1/High/Unbal	DCM1/High/Bal	DCM1/High/Bal	DCM3/High/Unbal
DCM4/High/Unbal	DCM3/Low/Bal	DCM4/High/Bal	DCM4/High/Bal
DCM5/Low/Bal	DCM5/Low/Unbal	DCM2/Low/Bal	DCM2/Low/Bal
DCM3/High/Unbal	DCM4/High/Unbal	DCM1/Low/Bal	DCM1/Low/Bal
DCM5/High/Unbal	DCM4/High/Bal	DCM4/Low/Bal	DCM4/Low/Bal
DCM2/High/Bal	DCM5/Low/Bal	DCM5/Low/Unbal	DCM5/Low/Unbal
DCM1/High/Bal	DCM5/High/Unbal	DCM3/High/Bal	DCM5/High/Bal
DCM4/High/Bal	DCM5/High/Bal	DCM5/High/Bal	DCM3/High/Bal
DCM5/High/Bal	DCM3/High/Unbal	DCM3/Low/Bal	DCM3/Low/Bal
DCM3/High/Bal	DCM3/High/Bal	DCM5/Low/Bal	DCM5/Low/Bal

Figure 34. Tukey Multiple Comparisons for Hypothesis 9

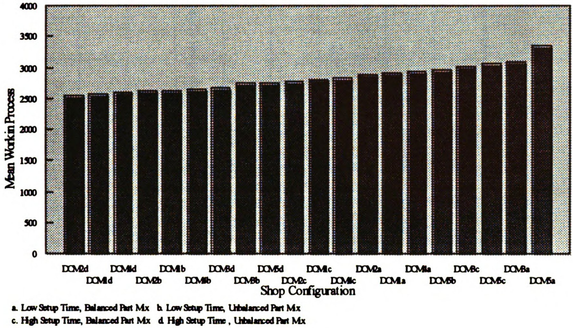


a. Mean Flow Time

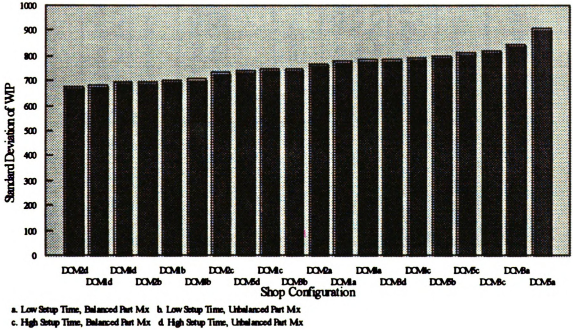


b. Mean Tardiness

Figure 35. Shop Performance for Hypothesis 9



c. Mean Work in Process



d. Standard Deviation of Work in Process

Figure 35. (cont'd)

Hypothesis	Conclusion
1. Process layout outperforms DCM when setup time is low.	Do not accept.
2. DCM outperforms process layout when setup time is high.	Accept for DCM 1, 2 & 4 for all performance measures. Accept for DCM 5 for mean tardiness.
3. Process layout outperforms DCM when part mix is balanced.	Do Not Accept.
4. DCM outperforms process layout when part mix is unbalanced.	Accept for DCM 1 & 2 for all performance measures except mean flow time. Accept for DCM 3 & 4 for mean and standard deviation of WIP.
5. DCM outperforms cellular layout when setup time is low.	Accept.
6. Cellular layout outperforms DCM when setup time is high.	Do not accept.
7. DCM outperforms cellular layout when part mix is balanced.	Accept for DCM 1 & 2 for all performance measures except mean WIP. Accept for DCM 3 & 5 for mean tardiness. Accept for DCM 4 for mean flow time and tardiness
8. DCM outperforms cellular layout when part mix is unbalanced.	Accept except for DCM 5 for mean and standard deviation of WIP.
9. DCM that recognizes material flows outperforms DCM that does not.	Do not accept.

Figure 36. Summary of Hypothesis Conclusions

lower. This is due to the enforced machine idleness that it permits. DCM 5 also yields the poorest overall utilization of the five DCM implementations. Considering only DCM 1-4, the maximum difference in utilization between DCM and the process layout is about 2.2%. The ability of DCM to increase effective capacity is as anticipated higher when setup time is high. Not only are utilization levels lower when setup time is high (with the exception of the process layout upon which the 80% utilization level was established), but they are also lower when part mix is unbalanced.

With few exceptions, DCM yields lower proportions of jobs tardy than either the process or cellular layouts (Table 10). Whereas the process layout has proportions tardy between

Table 10. Treatment Means for Mean Proportion Tardy

Setup Time		Low		High	
Part Mix		Balanced	Unbalanced	Balanced	Unbalanced
Shop Config.	DCM 1	0.003	0.003	0.009	0.007
	DCM 2	0.003	0.004	0.007	0.007
	DCM 3	0.014	0.009	0.031	0.022
	DCM 4	0.007	0.008	0.015	0.014
	DCM 5	0.026	0.015	0.029	0.022
	Process Layout	0.020	0.013	0.065	0.046
	Cellular Layout	0.237	0.549	0.103	0.253

1.3 and 6.5% and the cellular layout between 35.4 and 60%, DCM has at most 3.1% tardy, with the proportion generally much lower. When setup time is high, DCM implementations always yield lower proportions tardy than the process layout. The relative benefit of DCM is, as expected, higher when setup time is high and when part mix is unbalanced.

As anticipated, the proportion of time spent incurring setups is lowest when using the cellular layout (Table 11). Conversely, jobs in the cellular layout also spend the greatest

Table 11. Treatment Means for Mean Setup Time Proportion (Mean Setup Time)

Setup Time		Low		High	
Part Mix		Balanced	Unbalanced	Balanced	Unbalanced
Shop Config.	DCM 1	0.113 (23.35)	0.115 (22.28)	0.203 (48.23)	0.206 (46.08)
	DCM 2	0.113 (23.25)	0.114 (22.05)	0.202 (47.67)	0.206 (45.87)
	DCM 3	0.116 (24.91)	0.118 (23.61)	0.205 (51.24)	0.211 (49.03)
	DCM 4	0.114 (23.77)	0.116 (22.77)	0.203 (48.82)	0.207 (49.99)
	DCM 5	0.090 (20.58)	0.095 (20.03)	0.170 (42.33)	0.179 (41.70)
	Process Layout	0.113 (25.48)	0.117 (24.39)	0.196 (52.56)	0.204 (50.59)
	Cellular Layout	0.030 (9.66)	0.020 (14.982)	0.060 (15.12)	0.053 (15.55)

proportion of time in queue even under conditions known to be conducive to CM (high setup time, balanced part mix). There is little difference in the proportion of time spent in setups between DCM and the process layout when setup time is low, with the exception as expected of DCM 5, where jobs spend less time incurring setups. Curiously however, when setup time is high, DCM, again with the exception of DCM 5, yields marginally higher proportions. DCM 5 consistently has setup time proportions 2-3% lower than the next best configuration other than the cellular layout. This suggests the potential of DCM 5 as setup time increases further. Part mix has little effect on the proportion of time spent in setups.

DCM yields large improvements in proportion of time spent in queues (Table 12). When

Table 12. Treatment Means for Mean Queue Time Proportion

Setup Time		Low		High	
Part Mix		Balanced	Unbalanced	Balanced	Unbalanced
Shop Config.	DCM 1	0.233	0.215	0.232	0.214
	DCM 2	0.233	0.216	0.229	0.213
	DCM 3	0.242	0.221	0.244	0.220
	DCM 4	0.237	0.221	0.237	0.220
	DCM 5	0.291	0.264	0.272	0.248
	Process Layout	0.265	0.239	0.282	0.252
	Cellular Layout	0.448	0.599	0.354	0.420

part mix is balanced, the proportion for DCM is generally of the order of 23-24% with the exception of DCM 5. DCM 5 yields higher proportions due to the potential delay in re-allocating machines. For the process layout, this figure is between 26 and 28%. When part mix is unbalanced, the proportion is around 21-22% for DCM and 24-25% for the process layout. When setup time is high, even DCM 5 yields marginal improvements over the process layout.

5.3.8 Discussion of Stage 1 Results

The analysis of effects and a priori hypotheses demonstrate the benefits of DCM. When the shop configurations are compared under different operating conditions, DCM always performs as well as, if not better than, the traditional process and cellular layouts.

As expected, the cellular shop, being rigid and inflexible, consistently performs poorly. Similar to existing findings (e.g., Morris, 1988), its relative performance is good only when setup time is high and part mix is balanced. Though the cellular layout outperforms the process layout with respect to mean flow time and work in process under these conditions, it cannot outperform any of the DCM implementations, and is consistently outperformed by most of them. The impact of reduced setup frequency in the cellular layout is small compared to the considerable loss of routing flexibility, providing additional evidence of the effects of permanent machine dedication. Even under supposedly conducive conditions, the cellular layout yields the worst due date performance, likely the result of large flow time variance. When part mix is unbalanced, performance is particularly poor, the result of uneven utilization, frequent bottlenecks, and ever increasing queues.

The failure to accept hypothesis 6 shows that even under conditions that have been shown to be conducive to CM, the addition of flexibility to CM systems has a significant impact on their performance. Although the reduction of setup frequency can have a beneficial effect by reducing queue sizes, if this is done while permanently dedicating equipment, the benefits are significantly lower than when flexibility is present. If the location of a bottleneck were to remain constant and the cell configuration designed to accommodate this, the cellular layout can be expected to perform better. Typically however, bottlenecks are non-stationary. By letting cells evolve by shrinkage and growth to adjust to this, a cellular configuration can overcome this problem. Alternatively, the planning system must consider conditions within individual cells when making decisions regarding job release to those cells.

The performance of the process layout compared to DCM is more interesting since it does not have the same problem of inflexibility. However, as the results demonstrate, its lack of recognition of part families is a significant factor. Even when this might have been expected to be a relatively minor problem, i.e., when setup time is low, DCM, despite being relatively less flexible, performs better. Indeed, the relative performance of the process layout is only marginally better under low setup time conditions than under high setup time conditions. Comparing the process layout to DCM under different part mix conditions, there is again little difference in relative performance. These observations suggest that under normal and common operating environments, DCM is a better choice than a process layout.

The results demonstrate that the lower flexibility of DCM compared to the process layout does not compromise material flows through the shop. When machine dedication is permanent as in the cellular layout, forcing jobs to utilize specific machines often leads to problems of long queues. However, these problems are not encountered in DCM.

Clearly all DCM configurations do not perform the same, though in general, differences in performance between them are small. This is particularly true for flow time related performance. DCM 1-4 consistently perform better than DCM 5. This shows that increasing the degree of permanence of cells, even dynamically formed cells, has a detrimental effect on performance. This provides additional evidence to support the assertion of Flynn & Jacobs (1986) that machine dedication is a limiting factor in the performance of traditional cellular systems. It also suggests that forcing machines to remain idle may not be beneficial. However, it is also clear that the relative performance of DCM 5 improves as setup time increases, as might be expected. This suggests that under extreme setup time conditions, increasing machine dedication may be beneficial, <u>but only if this dedication is still of a temporary nature</u>. Given the simplicity of the cell formation heuristic used by DCM 5 and the fairly small decrease in performance when it is used when setup time is high (flow time is 5% higher than the best DCM implementation when part mix is balanced), a similar but more efficient heuristic that utilizes greater cell permanence, may make such cells more viable. One way to accomplish this is to consider the length of time a machine is allowed to remain idle. If this is longer than the time it takes to carry out a major setup, immediate re-allocation of the machine may be more appropriate. As it is currently implemented, DCM 5 does not consider this trade-off.

Of the remaining DCM implementations, the observation that DCM 3 yields relatively poor performance under high setup time conditions is interesting. DCM 3 explicitly attempts to promote the flow of jobs by extending cells forward to their successor departments, allowing the cell to grow. However, when setup time is high, this implementation performs poorly relative to the two more myopic implementations, DCM 1 and 2. On the other hand, DCM 4, which also considers shop-wide family processing requirements, performs relatively well. This may be due to DCM 3 being too myopic itself by not considering the extent to which the newly allocated machine can be used by a family. The potential exists for the machine to be allocated to a family with only a single job in the current queue and only the job currently being processed in the predecessor department. Under this extreme case, only two jobs take advantage of the major setup incurred. On the other hand, the current queue may contain families without jobs in process in their respective predecessor departments, but more jobs or more urgent jobs in the current queue. DCM 4 is again likely to be more effective under these conditions since it considers processing requirements of the family throughout the shop, not just at the current and predecessor departments. This suggests that DCM 3 may yield better performance if its implementation is modified to make it recognize material flows more globally. This could be done by considering the total number of jobs in both the current and predecessor departments that can use the new setup.

Comparing DCM 3 and 5 as a group to DCM 1, 2, and 4, the results show that differences in mean flow time when setup time is high, are, though statistically significant, small in magnitude. DCM 3 and 5 have flow times that are less than 4% higher than that required for them not to be statistically significantly different from the other implementations. The difference in flow times is due to increases in both setup time and time spent in queues. However, the increase in time spent in queues is relatively higher. This lends further support to the contention that DCM implementations that recognize information about material flows may indeed perform better than those that do not, if they are designed effectively. Recognizing material flows provides a mechanism to route work more efficiently. By making available all machines required by a family, the potential for delays while jobs await major setups is reduced. This enables jobs to pass through the shop with the fewest obstacles.

An observation concerning all DCM implementations is that they generally perform better when part mix is unbalanced. This suggests that under these conditions, the greater ability of parts from high demand families to share setups more than offsets the increase in setups caused when corresponding machines are re-assigned to families with low demand.

5.3.9 Summary of Stage I Results

The results of stage one demonstrate that DCM is a more effective means of production than that using a traditional process or cellular layout under certain conditions. For the conditions examined, DCM consistently outperforms these alternatives when conditions are not suited to them. Under conditions conducive to these alternatives, DCM performs at least as well as them, and often better than them. The increased setup efficiency of DCM allows the process layout to be operated more efficiently than at present, despite the loss of some degree of routing flexibility. The increased flexibility of DCM compared to traditional CM, enables family based production to be carried out so that it is more responsive to change, without being compromised by the decrease in setup efficiency. Given the tradeoff between flexibility and setup efficiency that exists in a small/medium batch production environment, DCM offers an alternative between the extremes of high flexibility/low efficiency (process layout), and high efficiency/low flexibility (cellular layout). The results suggest that some sacrifice along one dimension is justified and in fact beneficial, if it is substituted with an increase in the other. Furthermore, it appears that it is more beneficial to sacrifice setup efficiency than flexibility. DCM allows the tradeoff to be made without changing the physical nature of the shop.

5.4 ANALYSIS OF STAGE II DATA

5.4.1 Introduction

The treatments included in stage two are re-stated in Figure 37. Of the five DCM shop configurations used in stage one, DCM 4 was selected for use in stage two. DCM 4 consistently performed well in stage one and is also one of the implementations that utilizes shop information on a more global scale, actively seeking to complete the machine requirements of part families.

	Volume Mix	100			N(100,10)			50		
	Utilization (%)	70	80	90	70	80	90	70	80	90
Disp. Rule	Part Mix									
FCFS	Balanced	1	7	13	19	25	31	37	43	49
	Unbalanced	2	8	14	20	26	32	38	44	50
SPT	Balanced	3	9	15	21	27	33	39	45	51
	Unbalanced	4	10	16	22	28	34	40	46	52
Minslk	Balanced	5	11	17	23	29	35	41	47	53
	Unbalanced	6	12	18	24	30	36	42	48	54

Legend : 1 - 54 : Treatment Numbers
Dispatching Rule : FCFS - First Come First Served, SPT - Shortest Processing Time, Minslk - Minimum Job Slack
Volume Mix : 100 - Job Size = 100, N(100,10) - Job Size = N(100,10), 50 - Job Size = 50
Balanced Part Mix : Part families have equal demand probabilities
Unbalanced Part Mix : Three part families have demand probabilities of .233, two have demand probabilities of .15)

Figure 37. Stage II Treatments

5.4.2 Residual Analysis

For mean flow time, though there was a reasonable fit with the assumption of normality, this was improved considerably by the use of a log transformation. For the raw data, all but eight treatments yielded PCCT values within 5% of that required to accept the hypothesis of normality. However, three were more than 20% less than the critical value. When a log transformation was used, all but three of the treatments yielded PCCT values within 5% of that required to accept the hypothesis of normality, and all were within 7%. None of the three transformations used increased the homogeneity of residual variances.

However, examination of the residuals showed that heterogeneity increased as utilization increased and performance deteriorated.

The analysis for mean tardiness again showed that using a log transformation on the data yielded the best fit with the assumption of normality. All but ten treatments yielded PCCT values within 5% of that required to accept the hypothesis of normality. The fit with the raw data was poor. Homogeneity of variances also increased when this transformation was used. When a log transformation was used for the two measures of work in process, the fit with the assumptions was again better than that with the raw data. For mean work in process, all treatments yielded PCCT values within 2.5% of the critical value, and for the standard deviation, all but one was within 4%. However, as with the other measures, the variance of residuals increased as utilization increased, but this also led to a deterioration in shop performance.

5.4.3 Analysis of Effects

5.4.3.1 Mean Flow Time

ANOVA results for the log of mean flow time are reported in Table 13. Treatment means for mean flow time are reported in Table 14. In order to examine the impact of the significant interactions, Tukey multiple comparisons were carried out at each level of utilization for each combination of part mix and volume mix (Figures 38, 39a-c).

Table 13. Analysis of Variance for Log Mean Flow Time

SOURCE	DF	SS	MS	F	p
Random Numbers	99	4.976	0.050	7.56	0.0001
Dispatching Rule (D)	2	0.047	0.024	3.54	0.0292
Part Mix (P)	1	5.381	5.381	809.33	0.0001
Volume Mix (V)	2	61.292	30.646	4609.69	0.0001
Utilization (U)	2	101.471	50.735	7631.47	0.0001
D * P	2	0.019	0.009	1.41	0.2446
D * V	4	0.030	0.007	1.12	0.3474
D * U	4	0.063	0.016	2.38	0.0495
P * V	2	0.599	0.300	45.05	0.0001
P * U	2	15.198	7.599	1142.99	0.0001
V * U	4	0.023	0.006	0.87	0.4780
D * P * V	4	0.007	0.002	0.28	0.8922
D * P * U	4	0.039	0.010	1.48	0.2065
D * V * U	8	0.036	0.004	0.67	0.7192
P * V * U	4	0.924	0.231	34.74	0.0001
D * P * V * U	8	0.013	0.002	0.24	0.9823
Error	5247	34.883	0.007		

$R^2 = 0.84$

Table 14. Treatment Means for Mean Flow Time

	Volume Mix	100			N(100,10)			50		
	Utilization	70	80	90	70	80	90	70	80	90
Disp. Rule	Part Mix									
FCFS	Balanced	186.8	214.1	316.8	187.5	214.8	319.5	112.2	124.3	162.2
	Unbalanced	180.0	208.5	525.6	180.5	209.5	526.2	108.5	123.8	380.8
SPT	Balanced	186.9	213.6	317.7	186.9	212.7	312.3	112.1	124.0	162.3
	Unbalanced	179.9	208.4	546.8	179.9	207.3	504.1	108.5	123.6	388.5
Minslk	Balanced	186.5	213.6	312.0	187.0	213.9	315.7	112.0	123.7	160.6
	Unbalanced	179.6	208.7	491.1	180.2	208.6	489.0	108.3	123.1	347.7

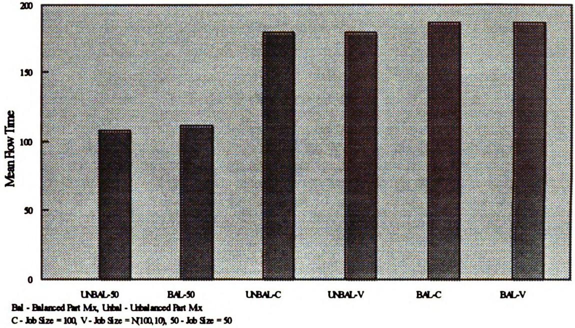
Log Mean Flow Time by Part Mix x Volume Mix		
Utilization = 70%	Utilization = 80%	Utilization = 90%
Unbal/50	Unbal/50	Bal/50
Bal/50	Bal/50	Bal/N(100,10)
Unbal/100	Unbal/100	Bal/100
Unbal/N(100,10)	Unbal/N(100,10)	Unbal/50
Bal/100	Bal/100	Unbal/100
Bal/N(100,10)	Bal/N(100,10)	Unbal/N(100,10)

Figure 38. Tukey Multiple Comparisons for Log Mean Flow Time

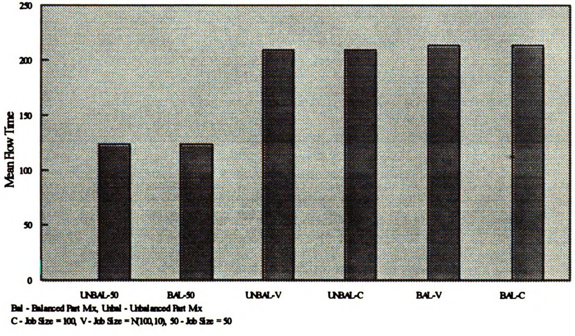
The results show that at low utilization levels (70%), flow time is as expected, lowest when jobs are of batch size 50, with flow times lowest if part mix is unbalanced. For jobs of batch size 100, performance is the same when part mix is unbalanced, regardless of whether job size is constant or variable. Performance deteriorates when part mix is balanced, though again it is not affected by variability in job size. As utilization increases to 80%, these results repeat themselves with the exception that when job size is 50, there is no difference if part mix is balanced or unbalanced. At high utilization levels (90%), the results change dramatically. Flow time is lowest when job size is 50 and part mix balanced. However, there is now no difference between jobs of size 50 when part mix is unbalanced, and jobs of size 100 when part mix is balanced. The poorest performance is obtained when jobs are of size 100 and part mix unbalanced.

5.4.3.2 <u>Mean Tardiness</u>

ANOVA results for log mean tardiness are reported in Table 15. Treatment means for mean tardiness are reported in Table 16. The significant effects were examined by

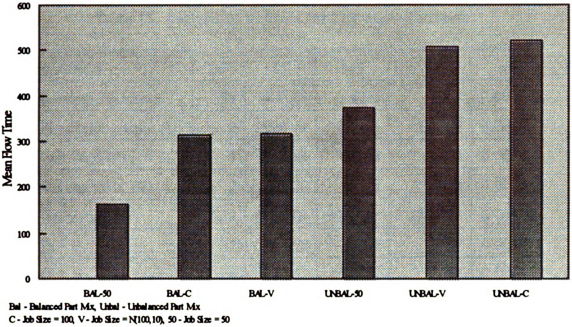


a. Utilization = 70%



b. Utilization = 80%

Figure 39. Mean Flow Time by Part Mix x Volume Mix



c. Utilization = 90%

Figure 39. (cont'd)

Table 15. Analysis of Variance for Log Mean Tardiness

SOURCE	DF	SS	MS	F	p
Random Numbers	99	490.68	4.96	5.38	0.0001
Dispatching Rule (D)	2	924.11	462.05	501.99	0.0001
Part Mix (P)	1	53.84	53.84	58.50	0.0001
Volume Mix (V)	2	99.30	49.65	53.94	0.0001
Utilization (U)	2	4031.04	2015.52	2189.73	0.0001
D * P	2	9.70	4.85	5.27	0.0052
D * V	4	114.57	28.64	31.12	0.0001
D * U	4	1423.32	355.83	386.59	0.0001
P * V	2	0.11	0.05	0.06	0.9435
P * U	2	5.72	2.86	3.11	0.0447
V * U	4	492.89	123.22	133.87	0.0001
D * P * V	4	1.16	0.29	0.32	0.8674
D * P * U	4	7.42	1.86	2.02	0.0895
D * V * U	8	171.29	21.41	23.26	0.0001
P * V * U	4	3.60	0.90	0.98	0.4187
D * P * V * U	8	13.36	1.67	1.81	0.0695
Error	5247	4829.56	0.92		

$R^2 = 0.62$

Table 16. Treatment Means for Mean Tardiness

	Volume Mix	100			N(100,10)			50		
	Utilization	70	80	90	70	80	90	70	80	90
Disp. Rule	Part Mix									
FCFS	Balanced	0.02	0.79	35.80	0.03	0.80	37.24	0.06	0.60	11.38
	Unbalanced	0.03	1.47	249.87	0.05	1.58	247.88	0.11	1.46	225.51
SPT	Balanced	0.37	4.42	64.70	0.28	3.73	58.98	0.40	2.20	21.10
	Unbalanced	0.48	6.13	302.40	0.43	5.14	260.17	0.57	3.94	247.39
Minslk	Balanced	0.01	0.56	31.16	0.01	0.51	32.94	0.03	0.38	9.91
	Unbalanced	0.01	1.53	216.40	0.02	1.11	211.83	0.06	1.11	193.05

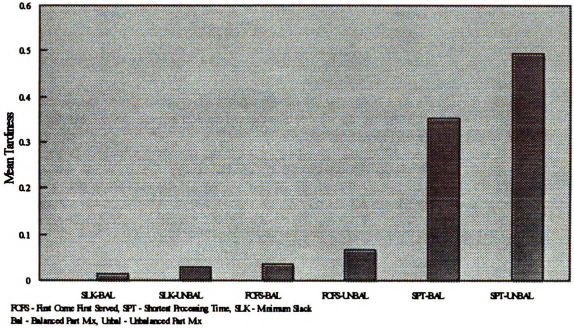
carrying out Tukey multiple comparisons by utilization for each combination of dispatching rule and part mix, and dispatching rule and volume mix (Figures 40, 41a-c, 42a-c).

Log Mean Tardiness by Dispatching Rule x Volume Mix		
Utilization = 70%	Utilization = 80%	Utilization = 90%
MINSLK/100	MINSLK/N(100,10)	MINSLK/50
MINSLK/N(100,10)	MINSLK/100	FCFS/50
FCFS/100	MINSLK/50	MINSLK/100
FCFS/N(100,10)	FCFS/100	MINSLK/N(100,10)
MINSLK/50	FCFS/N(100,10)	SPT/50
FCFS/50	FCFS/50	FCFS/100
SPT/N(100,10)	SPT/50	FCFS/N(100,10)
SPT/100	SPT/N(100,10)	SPT/N(100,10)
SPT/50	SPT/100	SPT/100

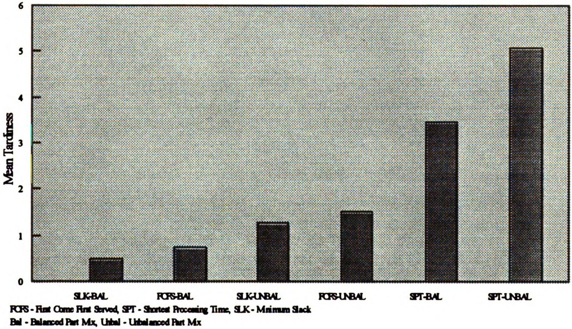
Log Mean Tardiness by Dispatching Rule x Part Mix		
Utilization = 70%	Utilization = 80%	Utilization = 90%
MINSLK/Bal	MINSLK/Bal	MINSLK/Bal
MINSLK/Unbal	FCFS/Bal	FCFS/Bal
FCFS/Bal	MINSLK/Unbal	SPT/Bal
FCFS/Unbal	FCFS/Unbal	MINSLK/Unbal
SPT/Bal	SPT/Bal	SPT/Unbal
SPT/Unbal	SPT/Unbal	FCFS/Unbal

Figure 40. Tukey Multiple Comparisons for Log Mean Tardiness

At low utilization levels, tardiness is as expected lowest whenever the minimum slack dispatching rule is used. The FCFS rule outperforms the SPT rule. For both of these rules, tardiness is lower when part mix is balanced. Slack based dispatching generally yields lower tardiness when job size is large, regardless of whether it is constant or variable. At 80% utilization, tardiness is lowest when slack based dispatching is used and

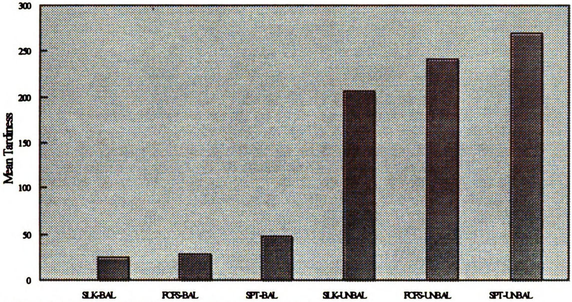


a. Utilization = 70%



b. Utilization = 80%

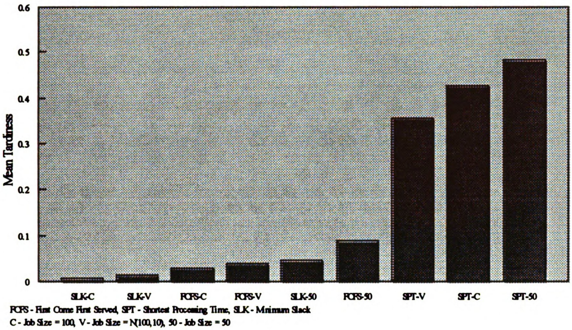
Figure 41. Mean Tardiness by Dispatching Rule x Part Mix



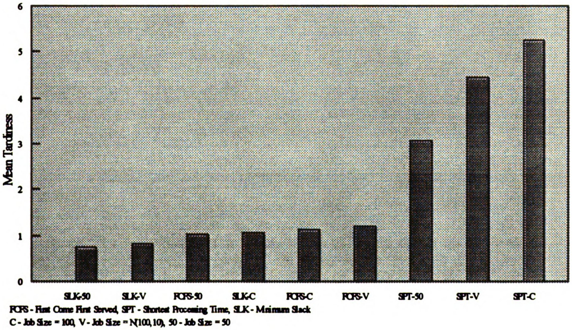
FCFS - First Come First Served, SPT - Shortest Processing Time, SLK - Minimum Slack
Bal - Balanced Part Mix, Unbal - Unbalanced Part Mix

c. Utilization = 90%

Figure 41. (cont'd)

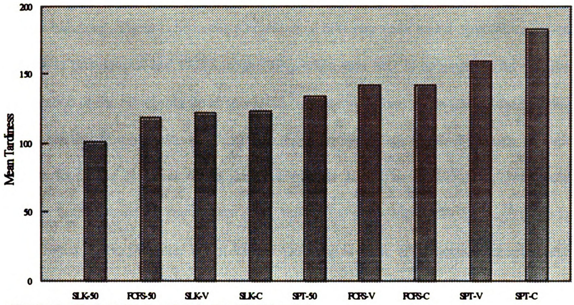


a. Utilization = 70%



b. Utilization = 80%

Figure 42. Mean Tardiness by Dispatching Rule x Volume Mix



FCFS - First Come First Served, SPT - Shortest Processing Time, SLK - Minimum Slack
C - Job Size = 100, V - Job Size = N(100,10), 50 - Job Size = 50

c. Utilization = 90%

Figure 42. (cont'd)

part mix balanced. There is however no difference between slack based dispatching when part mix is unbalanced and FCFS dispatching when part mix is balanced. The relative performance of the remaining three scenarios is the same as that when utilization is 70%. Slack based dispatching always yields the best performance regardless of job size, though again performance is better when jobs are of size 100. The FCFS dispatching rule performs better than SPT for all job sizes, but unlike slack based dispatching, there is no difference due to job size. When SPT dispatching is used, small jobs yield relatively better due date performance than large jobs. At high utilization levels, there is no difference between minimum slack and FCFS dispatching when part mix is balanced. Tardiness is always lower when part mix is balanced. Only at 90% utilization do small jobs yield relatively lower tardiness, and this only if minimum slack or FCFS dispatching are used. Overall, slack based dispatching as expected yields better performance, and SPT dispatching performs poorly.

5.4.3.3 Mean Work in Process

ANOVA results for log mean work in process are reported in Table 17. Treatment means for mean work in process are reported in Table 18. Tukey multiple comparisons were carried out for each utilization level, for each combination of dispatching rule and part mix, and part mix and volume mix (Figures 43, 44a-c, 45a-c). When utilization is 70 or 80%, there is no difference in work in process based on particular dispatching rule and part mix combinations. However, at 90% utilization, a balanced part mix always yields lower work in process. For each part mix, there is no difference due to dispatching rule.

Table 17. Analysis of Variance for Log Mean Work in Process

SOURCE	DF	SS	MS	F	p
Random Numbers	99	9.818	0.099	28.40	0.0001
Dispatching Rule (D)	2	0.002	0.001	0.34	0.7113
Part Mix (P)	1	2.414	2.414	691.19	0.0001
Volume Mix (V)	2	101.203	50.601	14488.80	0.0001
Utilization (U)	2	164.557	82.278	23558.92	0.0001
D * P	2	0.028	0.014	4.06	0.0173
D * V	4	0.010	0.002	0.71	0.5832
D * U	4	0.032	0.008	2.31	0.0552
P * V	2	0.876	0.438	125.36	0.0001
P * U	2	7.939	3.970	1136.60	0.0001
V * U	4	0.067	0.017	4.83	0.0007
D * P * V	4	0.004	0.001	0.26	0.9023
D * P * U	4	0.058	0.014	4.13	0.0024
D * V * U	8	0.011	0.001	0.40	0.9189
P * V * U	4	0.969	0.242	69.37	0.0001
D * P * V * U	8	0.007	0.001	0.24	0.9831
Error	5247	18.325	0.003		

$R^2 = 0.94$

Table 18. Treatment Means for Mean Work in Process

	Volume Mix	100			N(100,10)			50		
	Utilization	70	80	90	70	80	90	70	80	90
Disp. Rule	Part Mix									
FCFS	Balanced	2259	3007	5135	2271	3016	5172	1159	1471	2277
	Unbalanced	2168	2897	6857	2179	2916	6845	1128	1491	4311
SPT	Balanced	2260	3006	5142	2268	3003	5144	1159	1469	2282
	Unbalanced	2168	2896	7222	2177	2902	6952	1129	1493	4405
Minslk	Balanced	2268	3044	5211	2281	3052	5274	1164	1481	2314
	Unbalanced	2176	2940	6683	2189	2945	6628	1133	1504	4100

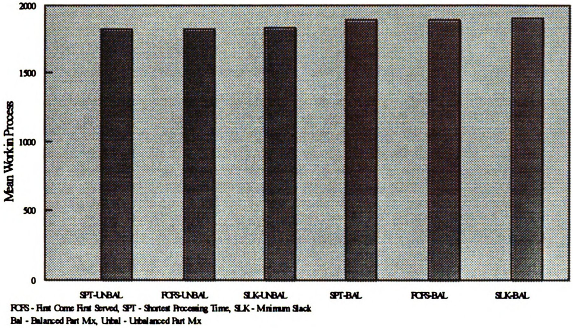
Log Mean Work in Process by Part Mix x Volume Mix		
Utilization = 70%	Utilization = 80%	Utilization = 90%
Unbal/50	Bal/50	Bal/50
Bal/50	Unbal/50	Unbal/50
Unbal/100	Unbal/100	Bal/100
Unbal/N(100,10)	Unbal/N(100,10)	Bal/N(100,10)
Bal/100	Bal/100	Unbal/100
Bal/N(100,10)	Bal/N(100,10)	Unbal/N(100,10)

Log Mean Work in Process by Dispatching Rule x Part Mix		
Utilization = 70%	Utilization = 80%	Utilization = 90%
SPT/Unbal	FCFS/Unbal	SPT/Bal
FCFS/Unbal	SPT/Unbal	FCFS/Bal
MINSLK/Unbal	MINSLK/Unbal	MINSLK/Bal
FCFS/Bal	SPT/Bal	MINSLK/Unbal
SPT/Bal	FCFS/Bal	FCFS/Unbal
MINSLK/Bal	MINSLK/Bal	SPT/Unbal

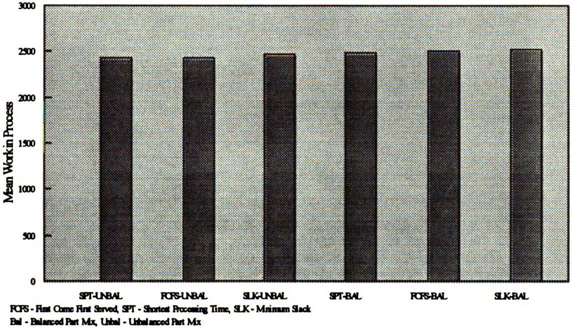
Figure 43. Tukey Multiple Comparisons for Log Mean Work in Process

Work in process is as expected, always lowest when job size is small. At 70% utilization, an unbalanced part mix yields lower work in process than a balanced part mix when jobs are of size 50. For jobs of size 100, work in process is lower whenever part mix is unbalanced, though for a particular mix, variability in job size is not significant.

These observations repeat themselves at higher utilization levels with few exceptions. At 80% utilization, there is no difference between a balanced and an unbalanced part mix when job size is 50, but for jobs of size 100 under balanced part mix conditions, constant job size yields lower work in process. At 90% utilization, jobs of size 50 yield the lowest

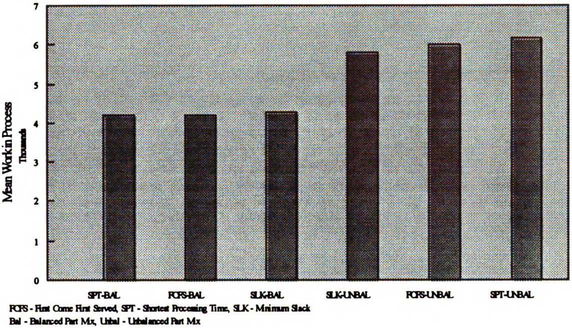


a. Utilization = 70%



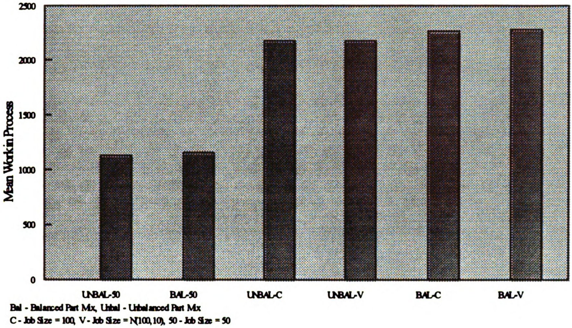
b. Utilization = 80%

Figure 44. Mean Work in Process by Dispatching Rule x Part Mix

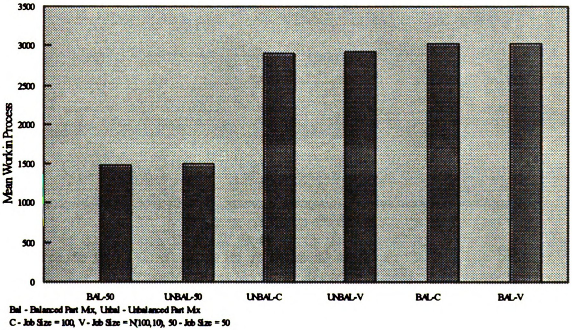


c. Utilization = 90%

Figure 44. (cont'd)

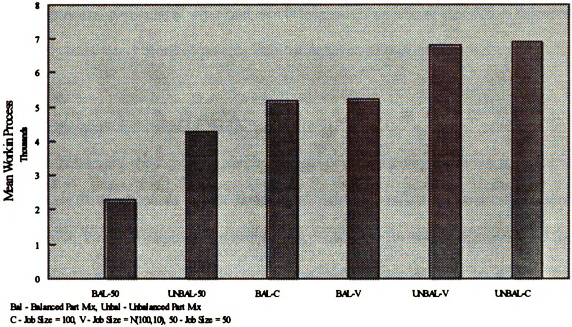


a. Utilization = 70%



b. Utilization = 80%

Figure 45. Mean Work in Process by Part Mix x Volume Mix



c. Utilization = 90%

Figure 45. (cont'd)

work in process, particularly when part mix is balanced. For jobs of size 100, a balanced part mix yields lower work in process than an unbalanced part mix.

5.4.3.4 Standard Deviation of Work in Process

ANOVA results for the log of the standard deviation of work in process are reported in Table 19. Treatment means for the standard deviation of work in process are reported in Table 20. Tukey multiple comparisons were carried out for each utilization level for all combinations of dispatching rule, part mix and volume mix (Figures 46, 47a-c). The comparisons show that the standard deviation of work in process is always lower when job size is 50. For this job size, no differences exist based on part mix or dispatching rule. When utilization is 70 or 80%, there is no difference in work in process based on particular dispatching rule and part mix combinations. However, at 90% utilization, such differences do exist. Performance is generally lower when part mix is unbalanced.

5.4.4 Analysis of Secondary Performance Measures

The proportion of time spent in setups decreases as utilization increases, falling from 12.6% to between 6 and 8% for jobs of size 100, and from 21.6% to between 10 and 14% for jobs of size 50 (Table 21). Most of this decrease occurs when utilization goes from 80 to 90%. The proportion is also higher for jobs of size 50, typically of the order of 9% higher than for jobs of size 100. This falls to only 6% as utilization increases. For jobs of size 50, setup time proportion at high utilization levels is also around 2-3% higher when part mix is balanced. The SPT dispatching rule yields poorer performance

Table 19. Analysis of Variance for Log Standard Deviation of Work in Process

SOURCE	DF	SS	MS	F	p
Random Numbers	99	23.383	0.236	69.13	0.0001
Dispatching Rule (D)	2	0.062	0.031	9.14	0.0001
Part Mix (P)	1	0.764	0.764	223.51	0.0001
Volume Mix (V)	2	121.311	60.655	17752.16	0.0001
Utilization (U)	2	75.250	37.625	11011.79	0.0001
D * P	2	0.001	0.001	0.20	0.8208
D * V	4	0.014	0.004	1.04	0.3828
D * U	4	0.035	0.009	2.60	0.0345
P * V	2	0.350	0.175	51.26	0.0001
P * U	2	0.157	0.079	23.03	0.0001
V * U	4	0.454	0.114	33.25	0.0001
D * P * V	4	0.074	0.019	5.42	0.0002
D * P * U	4	0.001	0.000	0.10	0.9840
D * V * U	8	0.035	0.004	1.28	0.2467
P * V * U	4	0.315	0.079	23.06	0.0001
D * P * V * U	8	0.150	0.019	5.48	0.0001
Error	5247	17.928	0.003		

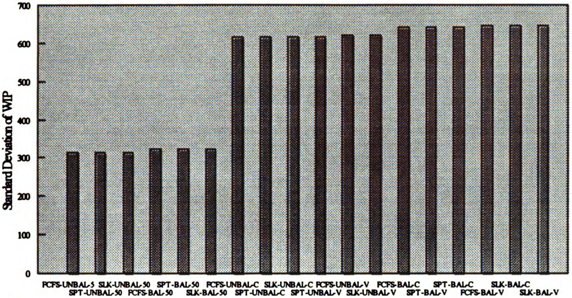
$R^2 = 0.93$

Table 20. Treatment Means for Standard Deviation of Work in Process

	Volume Mix	100			N(100,10)			50		
	Utilization	70	80	90	70	80	90	70	80	90
Disp. Rule	Part Mix									
FCFS	Balanced	641	825	1406	644	815	1421	322	386	578
	Unbalanced	615	773	1235	619	781	1115	312	383	619
SPT	Balanced	642	824	1404	641	813	1340	322	383	581
	Unbalanced	615	773	1226	617	774	1216	314	385	557
Minslk	Balanced	644	836	1429	646	831	1456	323	387	584
	Unbalanced	616	795	1325	621	786	1127	314	387	625

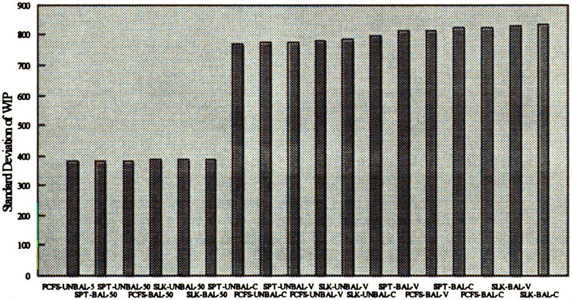
Log Std. Dev. of WIP by Dispatching Rule x Part Mix x Volume Mix		
Utilization = 70%	Utilization = 80%	Utilization = 90%
FCFS/Unbal/50	FCFS/Unbal/50	SPT/Unbal/50
SPT/Unbal/50	SPT/Bal/50	FCFS/Bal/50
MINSLK/Unbal/50	SPT/Unbal/50	SPT/Bal/50
FCFS/Bal/50	FCFS/Bal/50	MINSLK/Bal/50
SPT/Bal/50	MINSLK/Bal/50	FCFS/Unbal/50
MINSLK/Bal/50	MINSLK/Unbal/50	MINSLK/Unbal/50
FCFS/Unbal/100	FCFS/Unbal/100	FCFS/Unbal/N(100,10)
SPT/Unbal/100	SPT/Unbal/100	MINSLK/Unbal/N(100,10)
SPT/Unbal/N(100,10)	SPT/Unbal/N(100,10)	SPT/Unbal/N(100,10)
MINSLK/Unbal/100	FCFS/Unbal/N(100,10)	SPT/Unbal/100
FCFS/Unbal/N(100,10)	MINSLK/Unbal/N(100,10)	FCFS/Unbal/100
MINSLK/Unbal/N(100,10)	MINSLK/Unbal/100	MINSLK/Unbal/100
FCFS/Bal/100	SPT/Bal/N(100,10)	SPT/Bal/N(100,10)
SPT/Bal/100	FCFS/Bal/N(100,10)	SPT/Bal/100
SPT/Bal/N(100,10)	SPT/Bal/100	FCFS/Bal/100
FCFS/Bal/N(100,10)	FCFS/Bal/100	FCFS/Bal/N(100,10)
MINSLK/Bal/100	MINSLK/Bal/N(100,10)	MINSLK/Bal/100
MINSLK/Bal/N(100,10)	MINSLK/Bal/100	MINSLK/Bal/N(100,10)

Figure 46. Tukey Multiple Comparisons for Log Standard Deviation of Work in Process



FCFS - First Come First served, SPT - Shortest Processing Time, SLK - Minimum Slack,
Bal - Balanced Part Mix, Unbal - Unbalanced Part Mix, C - Job Size = 100, V - Job Size = N(100,10), 50 - Job Size = 50

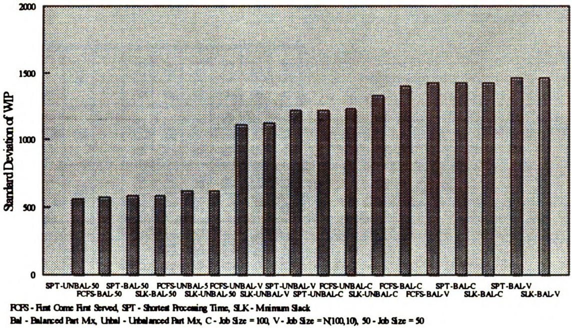
a. Utilization = 70%



FCFS - First Come First Served, SPT - Shortest Processing Time, SLK - Minimum Slack
Bal - Balanced Part Mix, Unbal - Unbalanced Part Mix, C - Job Size = 100, V - Job Size = N(100,10), 50 - Job Size = 50

b. Utilization = 80%

Figure 47. Standard Deviation of Work in Process by Dispatching Rule x Part Mix x Volume Mix



c. Utilization = 90%

Figure 47. (cont'd)

Table 21. Treatment Means for Mean Setup Time Proportion

	Volume Mix	100			N(100,10)			50		
	Utilization	70	80	90	70	80	90	70	80	90
Disp. Rule	Part Mix									
FCFS	Balanced	0.126	0.110	0.071	0.126	0.110	0.071	0.216	0.195	0.136
	Unbalanced	0.124	0.108	0.066	0.124	0.107	0.065	0.214	0.187	0.104
SPT	Balanced	0.126	0.112	0.079	0.125	0.112	0.079	0.216	0.197	0.143
	Unbalanced	0.124	0.110	0.077	0.124	0.110	0.079	0.214	0.190	0.125
Minslk	Balanced	0.126	0.111	0.072	0.127	0.111	0.072	0.217	0.196	0.137
	Unbalanced	0.124	0.108	0.067	0.124	0.109	0.066	0.213	0.187	0.106

when part mix is unbalanced, increasing the proportion by 1% when job size is 100, and 2% when it is 50.

Results for queue time proportion mirror those for setup time proportion (Table 22). The proportion increases as utilization increases, going from 17-19% to as high as 53%. Jobs of size 50 are in queues proportionately longer when utilization is low. At 70% utilization, they consistently spend about 2% longer in queues than jobs of size 100. However, at medium and high utilization levels, the proportion is higher only when part mix is unbalanced. At 80% utilization this is only about 1% higher, but at 90% utilization it is 4-5% higher. Queue time proportion is consistently higher for an unbalanced part mix particularly when utilization is high, except when SPT dispatching is used. For jobs of size 100, this proportion is 4-5% higher. For jobs of size 50, an unbalanced part mix yields an 11% increase when FCFS or minimum slack dispatching is used, and 4% when SPT dispatching is used. This increase is only 2% when utilization is 80%.

The choice of dispatching rule yields differences, again primarily at high utilization, with SPT dispatching yielding lower proportions. When job size is a constant 100, SPT dispatching yields 6% lower queue time proportions when part mix is balanced, and 10% lower when part mix is unbalanced, compared to the FCFS rule. Compared to slack based dispatching, these differences are 5 and 8%. Compared to jobs of size N(100,10), the differences are 7 and 11% and 6 and 9% respectively. For jobs of size 50 they are

Table 22. Treatment Means for Mean Queue Time Proportion

	Volume Mix	100			N(100,10)			50		
	Utilization	70	80	90	70	80	90	70	80	90
Disp. Rule	Part Mix									
FCFS	Balanced	0.169	0.258	0.448	0.171	0.260	0.451	0.193	0.266	0.428
	Unbalanced	0.169	0.263	0.491	0.172	0.267	0.501	0.196	0.285	0.538
SPT	Balanced	0.166	0.244	0.387	0.166	0.243	0.386	0.190	0.255	0.390
	Unbalanced	0.165	0.247	0.394	0.166	0.247	0.390	0.192	0.272	0.439
Minslk	Balanced	0.165	0.251	0.438	0.166	0.253	0.444	0.190	0.260	0.421
	Unbalanced	0.165	0.257	0.478	0.167	0.257	0.488	0.193	0.279	0.525

4 and 10%, and 3 and 9% respectively. At 80% utilization, SPT dispatching typically yields only a 1-1.5% improvement over other rules.

As expected, proportion tardy increases significantly as utilization increases (Table 23). For jobs of size 100, it goes from near zero at 70% utilization, to 1-4% at 80% utilization, to 14-30% at 90% utilization. For jobs of size 50, it rises from near zero to 2-6% to 17-40% at utilization levels of 70, 80 and 90% respectively. Again, smaller jobs consistently fare poorly, particularly when part mix is unbalanced. At 90% utilization, when part mix is unbalanced, proportion tardy is typically 9% higher for jobs of size 50. Proportion tardy is slightly higher when job size is N(100,10) compared to a constant 100. Again, small increases in proportion tardy are caused by an unbalanced part mix. These rise as utilization increases. At 80% utilization, an unbalanced part mix yields increases in proportion of about 1% when job size is 100, and 2% when job size is 50. However at 90% utilization, these rise to 10 and 20% respectively, except when SPT dispatching is used. In this case the increases are of the order of 2 and 7% respectively. At 70 and 80% utilization levels, the FCFS and minimum slack dispatching rules yield similar proportions tardy. SPT dispatching yields 1-2% poorer performance at 80% utilization, but at 90% utilization, it is more effective. For jobs of size 100, it yields 5-6% lower proportions tardy when part mix is balanced, and 13-14% lower when unbalanced. For jobs of size N(100,10), these are about 2% higher in each case, and for jobs of size 50, about 2% lower.

Table 23. Treatment Means for Mean Proportion Tardy

	Volume Mix	100			N(100,10)			50		
	Utilization	70	80	90	70	80	90	70	80	90
Disp. Rule	Part Mix									
FCFS	Balanced	0.000	0.015	0.209	0.000	0.016	0.215	0.003	0.026	0.209
	Unbalanced	0.000	0.024	0.302	0.001	0.026	0.321	0.006	0.050	0.406
SPT	Balanced	0.004	0.032	0.145	0.003	0.027	0.134	0.013	0.044	0.171
	Unbalanced	0.005	0.039	0.165	0.005	0.034	0.153	0.016	0.061	0.240
Minslk	Balanced	0.000	0.010	0.199	0.000	0.010	0.206	0.002	0.019	0.200
	Unbalanced	0.000	0.021	0.291	0.001	0.019	0.309	0.003	0.040	0.395

5.4.5 Discussion of Stage II Results

The results demonstrate a number of characteristics of DCM, some of which are similar to those of traditional process and cellular shops, and some which appear to be specific to DCM. Utilization, as expected, has a considerable effect on performance. Whereas an increase in utilization from 70 to 80% does not significantly affect flow times, an increase to 90% has a dramatic effect, particularly when part mix is unbalanced. Mean flow time increases by about 10-15% when utilization is increased to 80%. When utilization is 90%, flow times (compared to those at 70% utilization), are typically 70 or 44% higher when part mix is balanced, for jobs of size 100 and 50 respectively. When part mix is unbalanced, these are 190 or 250% respectively.

Similar increases in work in process are found. Mean work in process increases by 25-30% when utilization increases to 80%. At 90% utilization, work in process is 127 or 216% higher (compared to work in process at 70% utilization) when part mix is balanced, for jobs of size 100 and 50 respectively. When part mix is unbalanced, these are 216 and 282% respectively. The corresponding figures for the standard deviation of work in process are a 20-30% increase at 80% utilization regardless of part mix, and increases of 120 or 80% at 90% utilization.

This in turn explains the large increases in tardiness that occur at higher utilization levels. At 80% utilization, the percentage increases are large due to the negligible tardiness at 70% utilization, though actual tardiness is low, of the order of less than seven minutes. However, at 90% utilization, tardiness is of the order of 10-60 minutes for a balanced part mix, and over 200 for an unbalanced part mix. This behavior is to be expected since it is well known that shop performance deteriorates under high utilization levels (Baker, 1984).

The result of increased utilization and the cause of the decreased performance is as expected a dramatic increase in time spent in queues. At 80% utilization, the impact of queues is relatively small since there is sufficient capacity to absorb the extra workload. At 90% utilization, this is no longer true. The benefits of setup efficiencies are eroded by the volume of work. However, this does not detract from the increase in effective capacity yielded by reducing major setups. As was seen in stage one, even at 80% utilization, DCM outperforms a traditional process layout. One can surmise that at higher utilization levels, the greater setup efficiency of DCM will yield relatively larger improvements over the traditional process layout. Indeed, DCM performance at 90% utilization is not considerably poorer than comparable process layout performance at 80% utilization (see stage one results). Even at 90% utilization, flow time performance with a balanced part mix does not increase in an explosive manner. Given that existing CM systems are more conducive to an environment characterized by a balanced part mix, the results show that the incorporation of flexibility increases the potential of manufacturing based on the cellular concept. The traditional cellular layout, as stage one demonstrates, performs poorly even when it is operated at utilization levels of 60-70%.

An important point to recognize is the impact of minor setups on DCM performance. DCM attempts to schedule jobs within a cell based on a single stage dispatching rule and treats minor setups as relatively insignificant. As utilization increases, though the frequency of major setups may decrease due to an increase in number of jobs in a queue from the same family, the frequency of minor setups necessarily increases. By reducing this frequency, for example by using sequence-dependent scheduling within a cell, or by reducing minor setup times, potential exists to reduce the negative impact of higher utilization further. A possible drawback with sequence-dependent scheduling however, is that it discriminates against jobs requiring a change in minor setup. A large number of identical jobs in the queue could thus lead to an increase in flow time variance and thus tardiness, by making jobs that require a setup endure long waits. This problem will be exacerbated if the number of machines in each process department is small in relation to the number of part families.

The response of DCM to part mix and volume mix variability is an important characteristic of it. At high utilization levels, unbalanced part mix leads to a degradation in flow time related performance, not unlike traditional CM. Though the setup time proportion does not change significantly except when job size is 50, queue time proportion does. Two explanations are plausible. First, the permanence of cells corresponding to high demand families may be resulting in low demand families competing for few remaining machines. In addition, when high demand families gain access to multiples of the same machine, these machines must be relinquished when required by cells lacking that machine type. The result is that more frequent setups occur on these two groups of machines, i.e., those used by low demand families and 'shared' machines. This may be resulting in longer waits for jobs competing for these machines. No adverse impact on average setup time proportion is seen since cells corresponding to high demand families incur few major setups. An alternative explanation is that since multiple machines must be relinquished by more permanent cells as demand elsewhere dictates, these cells, though able to increase their capacity when machines are available, generally have fewer machines than necessary to efficiently reduce the queues in front of them. More likely, the cause of poor performance under unbalanced part mix conditions is a combination of these two explanations. DCM therefore exhibits behavior similar to a traditional cellular layout with respect to part mix, but only at much higher levels of utilization. At lower utilization levels, DCM is unlike traditional CM, performing better when part mix is unbalanced. It appears that not only is there a greater ability of high demand families to retain multiple machines of the same type, but competition among low demand families for machines not already allocated, is lower. This reduces the impact of setups and queues. These observations further substantiate the claims of Flynn & Jacobs (1986) regarding the effects of permanent machine dedication. Reducing machine dedication and allowing machines to supplement cells or be re-assigned between them, makes CM more responsive to changes in production needs.

The impact of small jobs is also evident. Although as expected flow times are lower at low and medium utilization levels when jobs are small, these flow times are greater in proportion to job size than for large jobs. At low and medium utilization levels, flow times of jobs of size 50 are 60% or more of those of jobs of size 100, indicating the absence of returns to scale. Consistent with the findings for part mix, this becomes worse at higher utilization levels when part mix is unbalanced. Flow times grow to as much as 70% of that for jobs of size 100. The only instance when flow times of jobs of size 50 are in proportion to their size is when utilization is high and part mix balanced.

Less pronounced effects exist for work in process. At 70 and 80% utilization levels, mean work in process is as expected, half that for jobs of size 100. At 90% utilization however, this is only 44% when part mix is balanced, but 62% when unbalanced. The standard deviation of work in process is in all cases close to the one half expected. The poor performance when jobs are small can be attributed to the increased impact of setups. Setup time is larger in proportion to processing time when batch size is small. This can be seen by the higher setup time proportions when jobs are of size 50. This also translates into longer times spent in queues by jobs awaiting setups, increasing the queue time proportion further. In order for small jobs to be processed efficiently, further setup time reduction is required. It should however be pointed out that since for each utilization level the arrival rate was established based on processing and setup times, this has an important effect on small jobs. Due to more frequent setups, the productive capacity of the shop is lower when batch size is small. The arrival rate for jobs of size 50 is consistently about 58% of that for jobs of size 100, not one half. This implies that if the impact of setups on small jobs is held constant, the arrival rate will decrease, and work in process will increase. What remains to be seen is whether the increase in arrival rate will further degrade performance, or whether the reverse will happen. Increased arrival rate increases the potential number of jobs that can share a setup, and may thus reduce setup frequency.

The absence of differences in performance due to introducing variability in job size when job size is 100 does suggest DCM to be robust with respect to uncertainty in volume mix. One would expect a reduction in variance to yield better results, yet the results consistently show this not to be so. Given this and the observations regarding part mix variability, DCM appears to be an effective method of production even in an environment characterized by the kind of uncertainty modelled here, except when utilization is high.

As expected, DCM exhibits similar behavior to process and cellular layouts with respect to job dispatching. Minimum slack dispatching yields better due date performance when this is measured by mean tardiness. In addition, it performs well at high utilization levels when part mix is unbalanced. However, SPT performs relatively better with respect to proportion tardy. This is no surprise based on evidence from past job shop research. For other performance measures, dispatching rule has little effect on shop performance. This can be attributed to the fact that dispatching rules are often used in job shops in situations where more effective planning would have been more appropriate. Since DCM explicitly considers family production characteristics prior to scheduling jobs, it compensates for poor planning to a greater extent than traditional job shops do. This reduces the impact of dispatching rules.

5.5 SUMMARY OF STAGE II RESULTS

The results suggest that DCM performs well under a wide range of shop conditions and is fairly robust against usual forms of variability found to adversely affect other shop configurations. Performance is good at both low and medium utilization levels, and shows substantial deterioration only when utilization is at a high level. Even then DCM appears to provide improved performance compared to traditional methods of small batch production. DCM is robust to part and volume mix variability except when the shop is subject to heavy loads. However, DCM does not perform well when batch size is small. DCM is in general not overly sensitive to different dispatching rules, but when it is, it exhibits behavior similar to that found in traditional process and cellular layout production.

5.6 SUMMARY OF EXPERIMENTAL RESULTS

The results indicate that DCM is an effective configuration for small/medium batch size production under the conditions investigated. Not only does it outperform traditional process and cellular layout production under conditions when it was expected to, but also when conditions were thought to be more conducive to these alternative configurations. Further, while these other configurations have in the past been shown to be sensitive to variability in the shop environment, DCM is not affected in the same way.

Though one of the objectives of DCM is to make small batch production more efficient, DCM does not perform well when batch sizes are decreased. DCM resolves some of the difficulties inherent in existing production methods, particularly with respect to scheduling issues, but it does not address others such as setup time. DCM focusses on operating the shop more effectively, not changing the physical characteristics of the shop. Only by simultaneously addressing both can additional improvements in performance be obtained. Despite this, DCM appears to be more effective than existing small/medium batch production methods for the same batch size, setup time environment.

5.7 CONCLUSIONS AND FUTURE DIRECTIONS

A preponderance of evidence suggests that manufacturing systems that physically embody the principles of CM perform poorly in an environment characterized by small batch sizes, changing demand patterns, and an emphasis on short lead times. This is true regardless of whether the system is composed either fully or partially of manufacturing cells, or if it is designed to compensate for the limitations of cellular production methods. This research shows that the principles of CM can be utilized effectively if two of its main properties, layout and similarity in part design/processing needs, are separated. The study shows that if the production system embraces CM's philosophy with regard to part design/similarity in isolation from CM's layout requirements, it has the potential to perform well under a variety of conditions that can be found in contemporary batch production environments.

The research carried out in this study has examined relatively simple implementations of DCM under a limited set of conditions. However, this does not undermine the value of DCM. To the contrary, by keeping the design of DCM simple and not introducing potentially confounding factors, it emphasizes how important the separation of the layout and design/processing aspects of CM is. In addition, it demonstrates that reaping the benefits of DCM is a realistic objective for manufacturing organizations, since DCM does not add significant constraints, either operational or financial, to existing job shop production environments.

The results suggest a number of areas where additional investigation may add to the benefits and understanding of DCM. As discussed earlier, one of the reasons why DCM implementations that recognize material flows do not perform as well as anticipated is that their design is possibly overly simplistic and myopic. Similar but more far-sighted cell formation methods may more clearly demonstrate the benefits of recognizing material flows. In addition to using heuristics to form dynamic cells, the formation of dynamic cells using optimization methods may further improve the performance of DCM. This might be accomplished by using optimization models similar to those used for traditional CM cell formation.

Given that DCM cells are not fixed entities, part families do not have to be pre-determined as they must be in traditional CM. This suggests that 'families' or groups of parts that will be processed together, can be created in real time based on parts currently awaiting processing. This also eliminates the problem of parts that do not naturally fit into existing families. Instead of identifying families based on setup requirements, they might be distinguished based on the machines individual parts use, and/or the sequence in which they are used. This is similar in principle to how similarity coefficients have been used in traditional cell formation models. This also allows the potential for DCM to be evaluated in an environment characterized by less repetitive production.

The study indicates that DCM becomes less effective as batches become smaller. This is due to the relatively greater impact of setup time. One can surmise that as setup time is reduced, this will be less of a problem. Closer examination of the impact of setup time may make it possible to determine whether smaller batches can be produced as effectively as larger batches, or whether lower setup time still yields relatively better performance with larger batches. Another way to evaluate the effect of setup time and batch size is to consider the use of lot splitting. One would expect that some reduction in batch size may improve throughput by making processing more continuous. Since DCM recognizes family processing requirements, problems of increased setup frequency found in other studies on lot splitting should be reduced. This can be extended to incorporate transfer batch scheduling based on the repetitive lots logic.

Additional factors that define the physical characteristics of the shop can also be expected to affect DCM performance. The impact of these factors needs to be investigated. These factors include shop size, family size, and the number of families. Any negative effects of dedicating a particular machine to a family are likely to be reduced if the number of machines of that type is increased. More machines of the same type should result in less competition for remaining machines of this type. Similarly, fewer families should reduce the competition for available machines. The size of a family may be important since the larger a family is, the larger is the number of its parts that may require the use of a machine at any instant. This may increase the extent to which the family retains use of machines, thus increasing the life of the cell.

The research also provides insight into how traditional CM implementations might perform more effectively. DCM's separation of the processing and layout properties of CM shows that CM is effective if the shop is not viewed as individual cells that do not interact. Part of the reason for this layout effect may be due to the planning system releasing jobs to the shop, not to individual cells. The cells however are independent and have their own processing, capacity and workload constraints that change over time. Releasing work to the shop without regard to the status of individual cells may place demands on cells that are inconsistent with their current capabilities. In contrast, DCM and job shops consist of process departments that are linked by the routings of individual jobs, and by prevailing processing requirements. Since there are no permanent layout restrictions, the shop as a whole assumes the demands placed by prevailing work patterns. Whereas a planning system that releases jobs to the shop as a whole is consistent with this environment, this may not be so for a shop that consists of independent elements. Consistent with the concepts of focus and plants within plants

(Skinner, 1974), the infrastructure of a manufacturing facility needs to be consistent with the demands placed by its individual components. In traditional CM, this appears not to be the case. One way to resolve this issue is to release work to cells in a traditional cellular layout based on their individual workload or utilization, not on the behavior of the shop as a whole.

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