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Manufacturing Processes with Nearly Sequential Routings: A Comparative Analysis

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Abstract

The manner in which jobs move through a manufacturing process is a critical ingredient in determining how effectively that process performs. Processing systems that are characterized by a large number of jobs, each with potentially different routings, behave differently than systems wherein all jobs follow the same processing pattern. We use the term *flow dominance* to describe at an aggregate level the manner in which jobs move through the manufacturing process. High flow dominance is exhibited by pure flow shops, wherein all products have the same routings. At the other extreme, low flow dominance is a characteristic of random job shops, wherein routings may vary from job to job.

Recent advances in automated technology have made it possible to incorporate many of the benefits of flow lines in the production of low-to-medium volume products found in a batch manufacturing environment. The resulting flows from the use of automated technology and cellular manufacturing are somewhere in between the extremes, but typically are nearer the high flow dominance end. In this paper, we study the effect on manufacturing performance of slight departures from purely sequential flows. To do so, we examine the interactions of various product and process characteristics. Using a full factorial simulation experiment, we examine both the main and interaction effects of product attributes, such as the number of products and job size, and of process attributes, such as operation-time variance, setup time, and flow dominance. Our results illustrate that movement to nearly sequential routings from pure sequential ones can sometimes cause substantial degradation in system performance, as measured by average flow times and flow-time variance.

1 Introduction

The manner in which jobs move through a manufacturing process is a critical ingredient in determining how effectively that process performs. Processing systems that are characterized by a large number of jobs, each with potentially different routings, behave differently than systems wherein all jobs follow the same or similar processing patterns. We use the term *flow dominance* to describe at an aggregate level the manner in which jobs move through the manufacturing process. High flow dominance is exhibited by pure flow shops, wherein all products have the same routings. At the other extreme, low flow dominance is a characteristic of random job shops, wherein routings may vary from job to job.

To date, the influence of flow dominance on the performance of manufacturing systems has been confined mainly to flow shops and job shops. (See Conway, et al. (1988), Hillier and Boling (1979), and Baker (1975) for examples of recent studies that examine the manufacturing performance of flow shops. Studies by Jacobs and Bragg (1988) and Ragatz and Mabert (1984) are examples of the performance of job shops.) A good deal of work in the facility layout literature has studied the consequences of intermediate levels of flow dominance. (See Vollman and Buffa (1966) and Ritzman (1972) for comprehensive reviews of the layout literature and expositions of the structure of the general problem.) These studies, however, typically specify the minimization of material movement costs as their objective. The performance of systems with intermediate levels of flow dominance, measured in other terms such as job flow times and work-in-process (WIP) inventory levels, has only been investigated for special cases in the cellular manufacturing area. For example, Garza and Smunt (1991) and Morris and Tersine (1990) have addressed the issue of intermediate flow dominance and its effect on flow times and WIP by focusing on intercell flow in cellular manufacturing environments. While these studies provide a foundation for understanding some effects of intermediate flow dominance, they were designed to test a specific set of conditions that occur in some cellular manufacturing settings.

Recent advances in automated technology and cellular manufacturing now make it possible to realize many of the efficiencies of flow lines in the production of low-to-medium volume products. Within the context of the Hayes and Wheelwright (1979) paradigm, advances in manufacturing technology may be shifting the set of ideal product-process pairs to the left (Figure 1). Such production environments will likely result in process configurations that have characteristics of both flow shops and job shops. In these systems, the flow of the products become more sequential. Given the wider range of products produced in these systems, some non-sequential routings – either within a cell or between cells – are still required, however. We refer to this hybrid process, characterized by the preponderance of jobs having similar routings with a relative small number of jobs with non-sequential routings, as a *nearly-sequential shop.* The main objective of this paper is to study the effects that a slight departure from purely sequential flows have on the performance of batch manufacturing systems in a wide variety of settings. We demonstrate that only a small departure from the pure sequential environment can greatly degrade system performance. The severity of the performance reduction depends on the relationship between manufacturing attributes and product demand characteristics. We specify a wide range of production environments and product demand conditions in order to identify the circumstances that require close control of routing dominance.

Our first task is to identify important characteristics of both product demand and manufacturing processes. To do this, we focus on the low-to-medium product volume quadrant of the Hayes and Wheelwright product-process matrix We then use a simulation model to examine how these characteristics influence system performance. We examine not only the direct effects but interaction effects as well. The results from the simulation experiments show that processes that more closely job shops (processes with multiple machines per department configured in a traditional process layout) is also appropriate for many high variance, high product variety settings. Our results also indicate that when operation-time variance, setup times, and production volumes are low, processes that more closely resemble flow lines can perform better than traditional job shops. Most importantly, we find that only slight departures from perfectly sequential routings, i.e., from the flow shop to the nearly-sequential shop, can cause substantial changes in system performance.

In the Sections 2.1 and 2.2, we discuss the product and process characteristics we use in our study. A description of a full-factorial simulation experiment is given in Section 3. The results from the experiment are then discussed in Sections 4. We begin the discussion of the results by describing both first-and second-order interaction effects of individual factors on system performance. We then define a number of system configurations in terms of combinations of product and process factors and certain levels of these factors that were used in the full factorial experiment. These configurations represent systems that span the continuum of process designs, ranging from a pure flow shop to a pure job shop. We use this range of configurations to illustrate how process designs can be effectively matched to product attributes. In Section 5 we investigate the sensitivity of our results to alternative simulation models. We summarize our results in 6. Section 7 contains implications that this study has for future research.

**** Insert Figure 1 about here ****

2 Product-Process Characteristics

Several process and product attributes and their interactions are important determinants of system performance as measured, for example, by mean flow time (MFT), flow time standard deviation (FTSD), or WIP.

2.1 Manufacturing Process Characteristics

We identify four characteristics of a manufacturing process that may greatly influence its performance in a batch processing environment. These characteristics are: flow dominance (FD), number of machines in each department (M), setup time (SU), and operation-time variance (CV).

We implicitly specify flow dominance in terms of the proportion of jobs going from one "department" to another, where "department" may contain one or more machines that are similar. (An explicit measure of flow dominance that reduces routing information for a variety of products to a single number is a challenging problem and is the subject of our ongoing research. In this study, we do not require such an explicit measure.) A high level of flow dominance characterizes flow lines – all jobs follow the same routing through the process. At the other extreme, job shops typically have low flow dominance, since jobs may have many different routings. When flow dominance is low, it is more likely that short-term bottlenecks will occur due to jumbled flows. Furthermore, the location of bottlenecks tends to shift from department to department in low flow dominance environments. The number of machines in each department determines the extent to which parallel processing is possible. Some of the negative effects of low flow dominance can be mitigated by the presence of multiple machines in each department.

It is well-known that setup time influences system performance. High machine setup times tend to increase the severity of bottlenecks. Low setup times, resulting from faster changeovers, worker method improvements, or dedicated equipment to produce families with similar processing requirement (cellular manufacturing), results in the ability to economically produce a larger variety of parts without the need for larger finished- goods inventory.

Finally, we use operation-time variance to measure the degree of disruption that occurs in the manufacturing process and, as such, serves as a surrogate for the many types of variation that can occur in a batch production environment. For example, machine breakdowns, defective component parts, and worker interference resulting from an insufficient number of machine operators all represent factors that lead to higher levels of operation-time variance. High levels of variance further contribute to the shifting bottleneck problem since following jobs will temporarily be delayed due to a longer than normal operation time of a preceding job or jobs.

2.2 Product Demand Characteristics

Characteristics of product demand that can be effectively produced in a batch production environment differ from those products that are more suitably produced in assembly-line environments. In order to determine the type of production process most appropriate for a particular type of demand environment, we examine two product characteristics that may influence system performance: number of products (N) and job size (JS).

For a given overall demand volume, a system with a larger product mix experiences an increase in the number of setups. The result is diminished effective capacity. On the other hand, larger job sizes reduce the number of setups required and increase effective capacity. Therefore, the negative influence of increasing the product mix can be countered by stipulating that order sizes be relatively large.

3 Full Factorial Simulation Experiment

In order to test the effects of intermediate flow dominance in a variety of stochastic environments, we designed a fairly general simulation model. There are several ways in which to study effects of departures from sequential routings. Various forms of processing configurations, such as a flow shop, a flexible manufacturing process, or a job shop, can be specifically modelled by fixing the values of certain variables in the model, including routings, number of machines, and setup times. Given the large number of variables in the model and the somewhat arbitrary definition of what constitutes a "job shop" or other processing configuration, we have elected to design a more generalizable study. In pilot experiments, we originally modelled three particular process configurations similar to those reported in Monahan and Smunt (1987). However, we found that cogent analysis of system performance of only a few configurations was difficult, at best. Therefore, we designed a full factorial experiment to study the performance model.

3.1 Simulation Design

The major simulation design assumptions are listed in Table 1. Detailed discussion of some of these factors follows.

We define utilization from three perspectives: 1) *operation utilization* – the percent of machine time spent producing units, 2) *setup utilization* – the percent of machine time that is nonproductive due to required changeovers between production of different product types, and 3) *total utilization* – operation utilization plus setup utilization. We set average operation utilization at 60%. Total utilization varied with job size and the setup time. (We verified that operation utilization of 60% was a steady-state condition after 5,000 simulated hours.) At 60% operation utilization, the manufacturing process' total utilization ranged from 70% to 90%, which are typical values in practice and in prior research studies of job shops.

An order is released immediately upon its arrival to the shop. Therefore, orders are not batched. We do this for two reasons. It is difficult to determine optimal batch sizes a priori considering the complex multi-product, multi-machine environment of our model. Furthermore, batching on a periodic basis is quite arbitrary. Delaying the release of an order might increase MFT unless complex order release and due date assignment mechanisms are used to keep track of the system's state. Although these mechanisms can be used to improve MFT performance in some situations (see Ragatz and Mabert (1984)), the influence of these rules on system performance is beyond the scope of this study. We assume that task operation times are Gamma distributed. The Gamma distribution has several desirable properties: 1) operation times are strictly positive and are not truncated, 2) it can represent the exponential distribution, and 3) it is skewed for coefficients of variation less than 1.0, which is supported by empirical evidence on work-time distributions (Dudley (1963)).

Setup times are specified in terms of the *setup ratio*, which we define as the ratio of the desired setup time to a base setup time. Pilot experiments revealed that a base setup time of 3.0 hours yields our targeted range of approximately 70% to 90% of total utilization. A setup occurs whenever a different product type is to be produced next on a machine. If multiple machines are available, the system looks for a machine that is already setup for the product type that is to be run. The average total operation time to complete a 150 unit job that has a setup ratio of 0.50 and requires a setup is $0.048 \times 150 + 0.5 \times 3.0 = 8.7$ hours, on average.

3.2 Simulation Factors

A comprehensive factory simulation model was developed and coded in SIMSCRIPT. Using this model, we conducted an extensive full factorial experiment. Based upon pilot runs, we established initial values of the variables in the model that were both reasonable and generated interesting and sometimes unexpected phenomenon. The experimental product-process factors and their levels are shown in Table 1. These values are consistent with prior simulation studies for both flow and job shops. A total of 2,700 ($= 3 \times 3 \times 5 \times \times 5 \times 3$) combinations of parameter values were run. In order to eliminate transient-state effects, the simulation for each combination was initialized for 5,000 hours of simulated factory time. Then, performance statistics (batch means) for ten intervals of 5,000 hours each were collected to reduce sample variance. Each interval was separated by a 1,000 hour interval to further reduce autocorrelation between the batch means. Therefore, a total of 27,000 runs were made. Since it took a long time for the simulation to reach steady state and since the standard deviation of results across batches was high for the high levels of setup ratio and CV, run lengths were appropriately long.

A significant factor in the experiment is the specification of flow dominance, which we now discuss in more detail.

3.3 Operationalizing Flow Dominance

The production process consists of a number of different workcenters. Flow dominance is specified by the routings that jobs take through these workcenters. Table 2 specifies three levels of the flow dominance factor: FD=SR (sequential routings), NSR (nearly sequential routings), and RR (random routings). Table 3 contains the routings for the 12 product base case that are associated with these three factor levels. For the 24 and 36 product scenarios, the routing matrices are doubled and tripled, respectively.

In the high flow dominance case (FD=SR), the routings for each of the twelve jobs are sequential and identical. The production facility is a flow shop. The nearly sequential routings case (FD=NSR) represents a slight departure from the flow shop–ten of the jobs have identical routings. The routings of Jobs K and L are significantly different, however.

In the low flow dominance case (FD=RR), our objective is to specify random routings that are congruent with those found in industrial settings that are typically classified as "job shops". Jobs that consist of the same product type tend to follow the same route through the facility, but these routes vary across product types. In practice, shops confronted with jumbled flows tend to have a larger number of machines per department. Multiple copies of relatively inexpensive equipment are used to counter the high setup times and low processing times. With this objective in mind, we expand the number of workcenters from six to twelve. As before, each product type still requires processing at exactly six workcenters, but these centers are now distributed among twelve possibilities. The use of a twelve workcenter job shop with a predetermined set of task routings is an appropriate way to test the conversion from a process layout to a flow shop layout. It is conceivable, however, that after the conversion occurs, the same number of machines are used in the two settings. In the twelve workcenter job shop, only 50% of the job types visit any one workcenter. Therefore, since the job shop contains twice as many workcenters, it is likely to incur fewer machine changeovers and experience lower MFT's than the flow shop, wherein a workcenter is visited by twice as many job types. For completeness, we report in Section 5 on results for the additional case where FD=RR, but processing is restricted to only the six workcenters used in the experiment for the other levels of FD.

3.4 Controlling the Operation Utilization Level

For every combination of factor levels, we maintained the operation utilization level at 60% by adjusting the arrival rate of jobs entering the system. At this level, the system is neither excessively over- or under-utilized. For example, when the number of product types doubles from twelve to 24, the arrival rate of every product type is halved. Similarly, when the number of machines is increased from one to two per workcenter, the arrival rate is doubled. When FD changes from either SR or NSR to RR, the number of workcenters increases from six to twelve, so that the arrival rate is doubled in order to maintain the 60% utilization rate.

3.5 Performance Measures

The performance measures (dependent variables) we use are MFT, FTSD, and WIP. MFT is calculated as the average flow time for all jobs that are completed during the run, where flow time for a job is the difference between the time the job completes processing the last task in its assigned task sequence and the time it arrives at the factory. Flow-time variance is measured as the standard deviation of flow times within the run. WIP is measured as the number of units waiting to use any machine plus the number of units being processed by all machines. Little's Law suggests that MFT and WIP are proportional, a relationship we did indeed observe. To be concise, we do not report the WIP values.

4 Simulation Results

Analysis of Variance (ANOVA) indicates that all main and first-order interaction effects are significant at the 0.0001 level or better. The ANOVA table is shown in the Appendix.

Our discussion of the results focuses on the interactions between flow dominance and the other factors. Our objective is to draw conclusions regarding the effect that slight departures from sequential routings have on system performance. To do this, we examine the performance of the system at several orders of factor interaction.

4.1 First-Order Interactions

The most aggregate level of analysis examines first-order interactions between flow dominance and each of the other factors. In this and the following section, we compare the performance of the system when FD=NSR to the performance when FD is either SR or RR. Table 4 shows MFT values for each of these first-order effects.

An examination of Table 4 indicates several conditions where slight departures from sequential routings (i.e., when the process moves from SR to NSR) results in substantial degradation of system performance: SU=0.75 or 1.0, operation time CV=0.01 or 0.50, and M=1. Note that the MFT mean values when CV=0.01 and 0.50 and M=1 are significantly different at the 95% level and, for SU=0.75 and 1.0, are significant at the 90% level. When FD=RR, MFT values are generally higher than when FD=NSR for all factors except when CV=1.50. These increases are statistically significant at the 95% level.

We also note that there are no instances in which a slight departure from sequential routings resulted in better system performance then the pure sequential routings case. Furthermore, the degradation in MFT increases as the setup ratio increases. For example, the percent increase in MFT when SU=0.1 as FD moves from SR to NSR is 2.0% $(1 - \frac{71.7}{70.3})$. For SU=0.5 and SU=1.0, the values are 3.7% and 7.4%, respectively. As the system moves from SR to NSR, there is an increase in the number of setups that are required due to the two product types that now have conflicting routes through the facility. When the setup ratio is low, these added setups do not significantly increase the amount of time devoted to setups. As the setup ratio increases, however, the added setup time results in severe congestion.

Note that as the system moves from SR to NSR, the added congestion that results is mitigated by increasing the level of parallel processing. When N=1, the relative increases in MFT is 6.1% $(1 - \frac{142.8}{134.6})$. When N=2, the increase is only 3.7%.

Finally, note that the effects of changes in flow dominance diminish as operation time CV increases. When CV=.01, the relative increase in MFT is 10.1% $(1 - \frac{64.1}{58.2})$. For CV=.50 and CV=1.00, these values are 9.1% and 5.6%, respectively. The high CV's result in blocking and starving that overshadows the effect of changes in flow dominance.

4.2 Second-Order Interactions

Setup, Flow Dominance, and Number of Machines

Tables 5 and 6 give average MFT and FTSD performance measures, respectively, for SU by FD by M. This second order interaction was significant at the 0.0001 level. In Table 5, we see that MFT's for FD=SR are uniformly lower than they are for the other flow dominance levels. Note that when M=1 (i.e., one machine per department and, therefore, no parallel processing capabilities), MFT for FD=NSR falls midway between the MFT's for SR and RR. The relative differences in MFT between NSR and SR increases as the setup ratio increases. However, as the number of machines per department increases (more parallel processing is available), the effect of flow dominance becomes insignificant, especially when the setup ratio is small.

These observations have significant implications regarding the conversion of a job shop to a set of manufacturing cells. In a job shop, there are typically multiple machines per department. As cells are formed, these machines are distributed across cells, thus reducing the parallel processing capability *within* each cell. In Table 5, note that the MFT associated with a facility with random routings and three machines per department is larger than the MFT of a system with nearly sequential routings and one machine per department. This is true for all levels of the setup ratio. Therefore, the performance of a manufacturing facility that is moving from a job shop to cellular manufacturing can actual improve as the number of machines per department decrease.

Consistency of the output rate can also be an important measure of a manufacturing system's performance. We use Table 6 to ascertain how variation in flow times is influenced by flow dominance. When M=1, we see that SR has the lowest FTSD. The relative performance of the system with sequential routings improves as SU increases. However, as the number of machines per department increases to two or three, these differences diminish.

These observations have implications for the prediction of job due dates to the extent that these predictions are more accurate when standard deviations of flow times are lower. In particular, we see that both flow dominance and the number of machines per department may be important determinants of flow time variation and, therefore, the ability to accurately predict due dates.

Operation Time Variance, Flow Dominance, and Number of Machines

In Tables 7 and 8, we examine the interactions of CV, FD, and M for MFT and FTSD performance measures, respectively. While our ANOVA shows this interaction is significant at only the .16 level, overall, it is interesting to see which specific factor level combinations are significant at the 0.05 level. In Table 7, note that MFT's are lowest when FD=SR. Slight departures from sequential routing result in the greatest increase in MFT when the operation time variance is low and there is only one machine per department. We also observe that when CV is high, neither the flow dominance level nor the number of machines per department are important determinants of system performance.

In Table 8 we again see that variation in flow time is influenced by flow dominance. The differences in FTSD diminish as both CV and M increase. Note that FTSD is minimized when FD=SR, M=1, and CV=0.01. When M increases, however, FTSD also increases when FD=SR and CV=0.01 and is significantly greater than the case where FD=RR and M=3. This suggests job completion dates are easier to predict in facilities that have sequential routings, low operation-time variance, and few machines per department than those with random routings and many machines per department.

4.3 Comparative Analysis of Processing Configurations

In the previous sections, we examined the influence of flow dominance on system performance at a fairly aggregate level: MFT's are averaged across a wide range of factors and factor levels. In this section, we examine the system at a more detailed level. We do this for two reasons. While insights are not as generalizable at the detailed level, they do confirm observations made at the more aggregate level. Furthermore, the analysis at the most basic level allows us to contrast and compare our processing configurations with two configurations widely discussed in the operations management literature: job shops and flow shops. Using the factors in our experiment, a job shop is typically characterized as a system wherein routings are random, setups are high, there are multiple machines per department, and processing times are moderately variable. Flow shops on the other hand, are systems wherein routings are sequential, setups are low, there are few (identical) machines per department, and processing times exhibit low variability.

To be concise, we specify ten of the 180 possible combinations of processing configurations from our full factorial experiment that consist of factors SU, CV, M, and FD. The set of factor levels, given in Figure 2, describe systems that span those described as flow shops and job shops. At one extreme, Configuration A describes what might typically be called a pure flow shop in the literature–setup time, CV, and M are at their lowest levels, and routings are sequential. Configuration J, at the other extreme, represents a random job shop. The eight intermediate configurations represent a fairly uniform progression from one extreme to the other. The analysis in this section also enables us to examine the consequences of product mix on system performance across a wide range of processing configurations.

In Figure 2, note that for Configurations A–G, MFT's are uniformly lower (with respect to the number of products) when JS=100 than when JS=200. Furthermore, the differences in MFT's attributable to differences in job size are nearly constant across these seven process designs. We also see that increases in the product mix is not detrimental to system performance in any of these configurations. These observations are somewhat unexpected in light of the wide range of factor levels that make up Configurations A–G.

As the process design moves from Configurations H (where FD=NSR) to I and J (where FD=RR), MFT's when JS=100 become larger than when JS=200. Also, an increase in the product mix when JS=100 results in a substantial increase in MFT. These configurations are characterized by high levels of congestion—SU and CV are at there highest levels. The added congestion occurs in spite of the added parallel processing capabilities afforded by the three machines per department.

Configurations I and J represent manufacturing processes that are often referred to as job shops. Folklore suggests that a job shop is the appropriate process design for producing small batches of a wide variety of products. Our observations indicate that this characterization may be too simplistic. Suppose the firm's objective is to produce a wide variety of products in small batches. With this objective in mind, the firm seeks to identify the processing configuration that results in the lowest

MFT. The results in Figure 2 suggest that processes more closely resembling flow shops may be more appropriate.

Our results provide support for process simplification that is currently an important goal of many batch manufacturing firms. As Schonberger (1982) points out, process simplification, exemplified by the move toward more repetitive processes and JIT, occurs over a number of stages. This section illustrates a procedure for evaluating the performance of a system that is progressing though these stages. Candidate configurations being considered at a given stage can be represented by combinations of processing factor levels. The significance of this type of approach is illustrated by examining the consequences of intermediate levels of flow dominance discussed in this section. During the intermediate stages of simplification, flow dominance is neither purely random nor purely sequential. The specification of intermediate levels of flow dominance can have significant implications on the performance of the system.

5 Sensitivity to Alternate Simulation Models

In all modelling research, certain assumptions must be made to control the size of the experiment. The number of workcenters, for example, is an important choice variable. There are also different procedures that could be used to generate task routings and hence FD levels. We examined some alternate schemes in a partial experiment to test for bias in our results.

5.1 Number of Workcenters

In Section 4.3, we discussed the operationalization of flow dominance in the random routing case and explained why we specified twelve workcenters instead of six. In this section we describe a small experiment designed to see how sensitive our performance measures are to this particular assumption.

The auxiliary simulation experiment utilizes a process that consists of six workcenters with three machines each. The flow patterns are similar to the twelve workcenter experiment. Similarly, each of the twelve job types has a different routing. Note that it is more difficult to design truly random flows when there are only six workcenters since two job types must start and end at the same workcenter. Even though we attempted to "jumble" the flow as much as possible, the flow dominance may be higher in this setting. (See Buss, et al. (1992) for a discussion of the difficulties in determining a good flow dominance measure, especially when the shops are not comparable in size.)

We set operation-time CV at 0.50, the setup ratio at 0.75, and FD=RR. For the twelve workcenter shop, the MFT's for 12, 24, and 36 products are 72.96, 76.46, and 77.48, respectively. For the six workcenter process, we found that the average MFT's for the 12, 24, and 36 products settings were 72.97, 74.97, and 75.05, respectively. Note that there is little change in the results. If anything, there is a slight improvement in system performance for the six workcenter case with 36 products. We conclude that performance of the system appears to be influenced more by the flow pattern than by the ratio of job types to workcenters.

5.2 Routing Generation

In our full factorial experiment, we developed deterministic routings for each of the three levels of FD. Although the routings for a particular job type are deterministic, the arrival of job types into the system is stochastic. We felt that orders within a job-type family should have similar task sequences and modelled the routings accordingly. In much of the research in facility layout, however, flow dominance is modelled by assigning a probability for the next task in the processing sequence. A transition matrix that defines the probability of the next task as a function of the current task can then be used to dynamically generate routings within the simulation. A matrix with 1's in the entries immediately above the diagonal corresponds to the specification of FD=RR. A matrix with conditional probabilities equal to $1/(n-1)$, where n is the number of workcenters, in the non- diagonal corresponds to FD=SR.

We reran the part of the experiment with CV=0.01 and N=12 for both extreme FD values and six intermediate transition matrices. As expected, the results for FD=RR were exactly the same as those from our original experiment. The MFT results for FD=SR using the transition matrix approach were 3.6% higher for SU=0.10, 5.1% higher for SU=0.25, 7.8% higher for SU=0.50, 12.8% higher for SU=0.75, and 27.4% higher for SU=1.00. When flow dominance is specified by the intermediate transition matrices, a similar linear relationship between FD=SR and FD=RR occurs. We conclude from this auxiliary experiment that when routings are more stochastic, increases in SU causes MFT to increase at an increasing rate. MFT increases since the likelihood of "implicit" shocks is greater in this scenario. We could conclude, therefore, that the use of deterministic versus stochastic routings introduces a bias in the performance measure. However, the form in which this bias enters does not qualitatively change any of our results.

6 Summary

We conducted a comprehensive full factorial simulation experiment to investigate relationships between process designs and product characteristics in a batch manufacturing setting. Of particular interest to us is the comparison the impact of an intermediate flow dominance level to the extreme flow dominance conditions of sequential and random routings. We chose to test an intermediate flow dominance level that was "nearly" sequential for two reasons. First, we recognize that the current practices of converting traditional job shop manufacturing to cellular manufacturing, to flexible manufacturing systems, or to repetitive manufacturing all seek to reduce randomness of routings. In essence, one of the major objectives of these conversions is to obtain routings that are as sequential as possible. We also recognize that the resulting flow dominance may be close to sequential, but not *purely* sequential due to a variety of practical considerations. Second, we hypothesized that relatively small departures from purely sequential routings would have substantial impact on system performance in some situations.

In the remainder of this section, we summarize our major findings. Some of our observations confirm traditional views of process design, while others illustrate the need to more closely analyze the effects of nearly sequential routings.

- Our results confirm previous research on processes that are tightly linked. (See Smunt and Perkins (1985) for a comprehensive review of the stochastic assembly line design literature.) The process designs represented by one machine per workcenter in our simulation behave much like assembly-line systems and only work well when the variance of operation times is low. When operation time variance is high, the performance of the system is significantly improved by increasing the number of machines at each workcenter. Furthermore, large reductions in setup times can improve the performance of a tightly-linked systems.

- When flow dominance is low (FD=RR), we found that bottlenecks may shift from department to department, resulting in relatively poor system performance. The degradation in performance occurs for all levels of setup time and can occur when there is only a small number of different routings.

- When parallel processing capability decreases (M decreases), perhaps due to the assignment of machines to cells as part of the movement from a job shop (organized as a process layout), to cellular or automated manufacturing, system performance degrades if significant improvements are not made in other factors of the process design. However, adding even a small amount of parallel processing capability to a system can dramatically improve its performance. Further, we found that relative decreases in system performance resulting from a reduction in parallel processing capability are the greatest when there is low flow dominance.

- Our results also show that improved system performance resulting from high flow dominance is dampened by high operation-time variance. Operation-time variance has the greatest negative effect on systems with few machines per department.

- One of the most interesting findings from this study is that shops that necessarily process jobs with random routings work best when setups are *low* and not *high*. The jumbled flow results in shifting bottlenecks. Low setups are needed to offset the effects of "implicit shocks" at the workcenters caused by the bottlenecks.

- As the product mix increases (holding total demand volume steady), our results suggest that systems with low flow dominance or high setup times will incur substantial degradations in performance. However, small amounts of parallel processing capability, such as a two-machine configuration, counteract performance degradation as the number of job types increases.

- Finally, through our additional studies of modelling alternatives, we found that system performance is influenced more by flow dominance than by either the ratio of job types to workcenters or the particular method used to generate task sequences.

7 Conclusions and Future Research

In this paper, we used a comprehensive simulation model to examine many of the complex interactions between process and product characteristics in batch production environments. Our primary objective was to determine the consequences of slight departures from purely sequential flows. For illustrative purposes, we also compare systems with nearly sequential flows to those with random routings. The insights from this analysis are useful, for example, to firms who are undertaking "simplification" measures that will eventually result in processes that resemble flow lines but can efficiently produce a moderate range of products at low to medium volumes.

Many questions related to flow dominance remain unanswered, however. For example, under what conditions do flow dominance levels other than nearly sequential routings significantly influence system performance? What are the interaction effects of flow dominance and the total number of workcenters in the system? In this study, we assumed that the system included either 6 or 12 workcenters with one, two, or three machines each. While our assumptions are consistent with previous analyses of flow shops and job shops, we believe that larger systems may react to changes in flow dominance levels in a different manner than do smaller systems. Another unanswered question is whether system performance can be accurately predicted through formulae that include a number of operating characteristic levels. For example, given a firm's current or projected levels of factors such as setup times, flow dominance, operation time variance, and product mix, can MFT, WIP, and FTSD be predicted with some level of confidence? Unfortunately, there is no robust measure of flow dominance in the literature. The coefficient of variance (CV) measure used in the layout literature is well-known to be size dependent. That is, when the number of departments increases but routings remain similar, the CV measure varies. In this regard, we have developed a new measure for flow dominance (see Buss, Monahan, and Smunt (1992)) and are currently testing its efficacy in predicting system performance.

There are a number of other interesting unanswered questions. Is there an interaction between flow dominance levels and the ability to predict due dates of new jobs? Are order release mechanisms more useful for low flow dominance systems? Is lot splitting effective for intermediate flow dominance systems? These particular questions highlight some of the limitations of previous studies that focus entirely on the performance of job shops with purely random routings or flow shops with purely sequential routings. As real systems move away from these extreme cases, we need to better understand the consequences of intermediate levels of flow dominance on a wide range of operational issues.

The interaction between process design and additional product and market attributes should also be examined. In this study, we assumed that product demand was uniform across all products and was stable over time. However, depending upon the dynamics of a particular firm, some products may have low demand (perhaps because they are in the introduction or decline stages of their life cycle) and some may have high demand (perhaps because they are well into the growth or mature stages). The effect of unstable demand (resulting from a sales promotion, for example) and intermediate flow dominance levels may be significant and important.

The manner in which we examine operating systems in this research is unusual in that we do not explicitly define a job shop or a flow shop in terms of processing factor levels. Rather, we separate the flow dominance and parallel processing factors. In the preponderance of the operations management literature, job shops are assumed to be systems with high levels of both parallel processing and routing variability — flow shops are at the other extreme. However, since modern manufacturing practice allows any mixture of these two factors, we believe that these operating characteristics should be viewed as separate contributors to system performance. The separation of flow dominance and parallel processing capabilities enables us to understand the effects of changes in operating system design. Arbitrary choices of what constitutes a "cellular," "flow," or "job" shop are no longer necessary nor are they desired.

References

Baker, K. R., "A Comparative Study of Flow Shop Algorithms," *Operations Research*, Vol. 23, No. 1 (1975), 62-73.

Buss, A. H, Monahan, G. E. and T. L. Smunt, "A Measure of Flow Dominance in Job Shops," University of Illinois, Department of Business Administration, working paper (August 1992).

Conway, R. , Maxwell, W., McClain, J. O., and Thomas, L. J., "The Role of Work-in-Process Inventory in Serial Production Lines," *Operations Research*, Vol. 36 (March-April 1988), 229-241.

Dudley, N. A., "Work-Time Distributions," *International Journal of Production Research*, Vol. 2, No. 2 (1963), 137-144.

Garza, O. and Smunt, T. L., "Countering the Negative Impact of Intercell Flow in Cellular Manufacturing," *Journal of Operations Management*, Vol. 10 (January 1991), 92-??.

Hayes, R. H. and S. C. Wheelwright, "Link Manufacturing Process and Product Life Cycles," *Harvard Business Review*, 57, 1 (Jan-Feb 1979), 133-140.

Hillier, F. S. and R. W. Boling, "On the Optimal Allocation of Work in Symmetrically Unbalanced Production Line Systems with Variable Operation Times," *Management Science*, 25, 8 (August 1979), 721-728.

Jacobs, F. R. and D. J. Bragg, "Repetitive Lots: Flow-Time Reductions through Sequencing and Dynamic Batch Sizing," *Decision Sciences*, 19, 2 (Spring 1988), 281-294.

Monahan, G. E. and T. L. Smunt, "A Multilevel Decision Support System for the Financial Justification of Automated Flexible Manufacturing Systems," *Interfaces*, 17, 6, (November- December 1987), 29-40.

Ragatz, G. L. and V. A. Mabert, "A Simulation Analysis of Due Date Assignment Rules," *Journal of Operations Management*, 5, 1, (November 1984) 27-40.

Ritzman, L. P., "The Efficiency of Computer Algorithms for Plant Layout," *Management Science*, Vol. 18 (1972), 240-248.

Schonberger, R., *Manufacturing Techniques: Nine Hidden Lessons in Simplicity*, The Free Press, New York, 1982.

Smunt, T. L. and W. C. Perkins, "Stochastic Unpaced Line Design: Review and Further Experimental Results," *Journal of Operations Management*, 5, 3 (May 1985) 351-373.

Vollman, T. E. and Buffa, E. S., "The Facilities Layout Problem in Perspective," *Management Science*, Vol. 12B (1966), 450-468.

Appendix A – ANOVA

Class Level Information		
Class	Levels	Values
FD (flow dominance–routings)	3	SR (sequential), NSR (nearly seq.), RR (random)
L (no. of machines)	3	1 machine, 2 machine, 3 machine
M (no. of products)	3	12, 24, 36
SU (setup ratio)	5	0.1, 0.25, 0.5, 0.75, 1.0
CV (operation variation)	4	0.01, 0.5, 1.0, 1.5
JS (job size)	5	100, 125, 150, 175, 200
Number of Observations in Data Set=27000 (2700 observations × 10 repetitions)		

Dependent Variable: MFT			
Source	DF	Sum of Squares	Mean Square
F Value			
Model	563	155923662.039	276951.443
Error	26436	10511413.820	397.617
Pr > F			
Corrected Total	26999	166435075.858	
0.0			
R-Square	C.V.	Root MSE	MFT Mean
0.937	18.824	19.940	105.931

F-test Assumptions

We tested the assumptions of normality of residuals and homogeneity of variance in order to determine the validity of the ANOVA results. While the Kolmogorov-Smirnov and Bartlett tests did not confirm the normality and homogeneity assumptions, respectively, further analysis showed that our ANOVA results were valid. Log transformations of the data resulted in imperceptible changes in the probability values and in nearly perfect normal distribution of the residuals. Further, plots of the residuals showed that the variances tend to be equal except for the few conditions where the estimate of MFT is large. In a full factorial experiment such as ours, combinations of certain factors, e.g. high levels of SU and CV, lead to a small set of outlier data points. These outliers will cause the standard tests to indicate that the F-test assumptions were not met even though the vast majority of the data fit the assumed distributions.

Source	DF	ANOVA SS	F Value	Pr > F
FD	2	1285858.872	1616.95	0.0
L	2	24423497.625	30712.31	0.0
M	2	309992.651	389.81	0.0
SU	4	31871878.694	20039.29	0.0
CV	3	37902634.911	31774.79	0.0
JS	4	1822941.701	1146.17	0.0
FD*L	4	472782.525	297.26	0.0
FD*M	4	39921.473	25.10	0.0001
FD*SU	8	606010.108	190.51	0.0
FD*CV	6	708894.985	297.14	0.0
FD*JS	8	53269.930	16.75	0.0001
L*M	4	36615.319	23.02	0.0001
L*SU	8	4463821.715	1403.30	0.0
L*CV	6	12409070.483	5201.43	0.0
L*JS	8	282854.645	88.92	0.0
M*SU	8	567152.394	178.30	0.0
M*CV	6	144016.723	60.37	0.0
M*JS	8	319334.206	100.39	0.0
SU*CV	12	10120925.060	2121.16	0.0
SU*JS	16	13141081.472	2065.60	0.0
CV*JS	12	1065229.996	223.25	0.0
FD*L*M	8	8647.920	2.72	0.0054
FD*L*SU	16	264974.940	41.65	0.0
FD*L*CV	12	334202.452	70.04	0.0
FD*L*JS	16	47236.317	7.42	0.0001
FD*M*SU	16	57664.512	9.06	0.0001
FD*M*CV	12	6679.872	1.40	0.1574
FD*M*JS	16	21072.817	3.31	0.0001
FD*SU*CV	24	460832.966	48.29	0.0
FD*SU*JS	32	163172.575	12.82	0.0
FD*CV*JS	24	117447.645	12.31	0.0
L*M*SU	16	76629.827	12.05	0.0001
L*M*CV	12	25155.149	5.27	0.0001
L*M*JS	16	49908.134	7.84	0.0001
L*SU*CV	24	1720430.226	180.29	0.0
L*SU*JS	32	2345232.176	184.32	0.0
L*CV*JS	24	144347.198	15.13	0.0
M*SU*CV	24	291001.940	30.49	0.0
M*SU*JS	32	1029499.284	80.91	0.0
M*CV*JS	24	192355.794	20.16	0.0
SU*CV*JS	48	6519384.804	341.59	0.0

Item	Assumption
Average Operation Utilization	60%
Job arrivals	Deterministic
Job type distribution	Uniform – plus or minus 50% of average job size
Processing batch size	Equal to job size
Operation time distribution	Gamma
Mean operation time	.048 hours per operation
Number of operations	6 per job
Setup times	Deterministic; base setup time = 3.0 hours
Dispatching rule	Shortest operation time first
Buffer capacity	Unlimited

Table 1: Simulation Design Assumptions

Factor	Level 1	Level 2	Level 3	Level 4	Level 5
FD (Flow Dominance)	SR	NSR	RR	—	—
SU (Setup Time)	0.10	0.25	0.50	0.75	1.00
CV (Oper.-Time Var.)	0.01	0.50	1.00	1.50	—
M (# of Machines)	1	2	3	—	—
JS (Job Size)	100	125	150	175	200
N (# of Products)	12(Base)	24	36	—	—

Table 2: Simulation Factors

FD	Product	Task 1	Task 2	Task 3	Task 4	Task 5	Task 6
SR	A–L	1	2	3	4	5	6
NSR	A–J	1	2	3	4	5	6
	K	6	5	4	3	2	1
	L	2	4	6	1	3	5
RR	A	1	2	4	10	6	8
	B	2	11	3	4	8	7
	C	3	10	5	6	7	12
	D	4	8	2	7	1	11
	E	9	7	1	12	4	5
	F	6	12	10	11	9	3
	G	7	6	8	3	5	2
	H	8	1	9	2	3	10
	I	10	5	12	1	2	4
	J	5	3	11	9	10	6
	K	11	4	6	8	12	9
	L	12	9	7	5	11	1

Table 3: Routings through Workcenters by Flow Dominance.

SU Ratio	Flow Dominance (FD) SR	NSR	RR
.1	70.3	71.7	75.9
.25	76.4	78.5	84.0
.50	88.7	92.0	100.8
.75	106.9	112.7*	126.8
1.00	152.0	163.3*	188.9

Operation CV	SR	NSR	RR
.01	58.2	64.1	84.9
.50	67.9	74.1	93.1
1.00	104.0	109.9	120.6
1.50	165.3	166.5	162.2

Number of Machines	SR	NSR	RR
1	134.6	142.8	164.6
2	88.6	91.9	100.6
3	73.4	76.3	80.6

Product Mix	SR	NSR	RR
12	95.4	100.2	108.5
24	99.7	104.6	116.6
36	101.4	106.2	120.8

Job Size	SR	NSR	RR
100	99.6	107.0	122.4
125	87.0	91.6	103.9
150	93.3	97.6	108.2
175	102.7	105.9	116.2
200	111.7	116.1	125.7

Table 4: MFT Results–First-Order Interactions by Flow Dominance. All values covered by a horizontal bar are not significantly different from one another. * denotes significant difference at the 90% level.

SU Ratio	FD	Number of Machines (M) 1	2	3
.10	SR	51.5	48.6	46.8
	NSR	56.2	50.1	47.6
	RR	69.3	54.4	49.9
.25	SR	54.5	51.5	49.5
	NSR	60.2	53.6	50.7
	RR	77.1	59.0	53.4
.50	SR	59.7	56.7	54.3
	NSR	67.9	59.8	56.2
	RR	93.6	68.4	60.5
.75	SR	65.2	62.2	59.6
	NSR	77.2	67.3	62.9
	RR	119.7	81.4	69.9
1.00	SR	71.6	68.7	65.9
	NSR	92.1	78.0	71.6
	RR	173.1	104.6	85.8

Table 5: MFT Results–Setup by Flow Dominance by Number of Machines (CV = .01, N = 12). All values covered by the same vertical bar are not significantly different from one another.

SU Ratio	FD	Number of Machines (M) 1	2	3
.10	SR	8.48	10.66	11.63
	NSR	11.16	11.74	12.10
	RR	14.85	9.13	7.66
.25	SR	8.31	10.46	11.50
	NSR	11.38	11.73	12.08
	RR	16.81	10.05	8.16
.50	SR	8.00	10.13	11.31
	NSR	11.91	11.79	12.11
	RR	21.21	12.18	9.47
.75	SR	7.68	9.77	11.08
	NSR	13.01	12.03	12.28
	RR	29.21	15.34	11.50
1.00	SR	7.43	9.52	10.81
	NSR	15.26	13.02	12.28
	RR	42.19	21.79	15.63

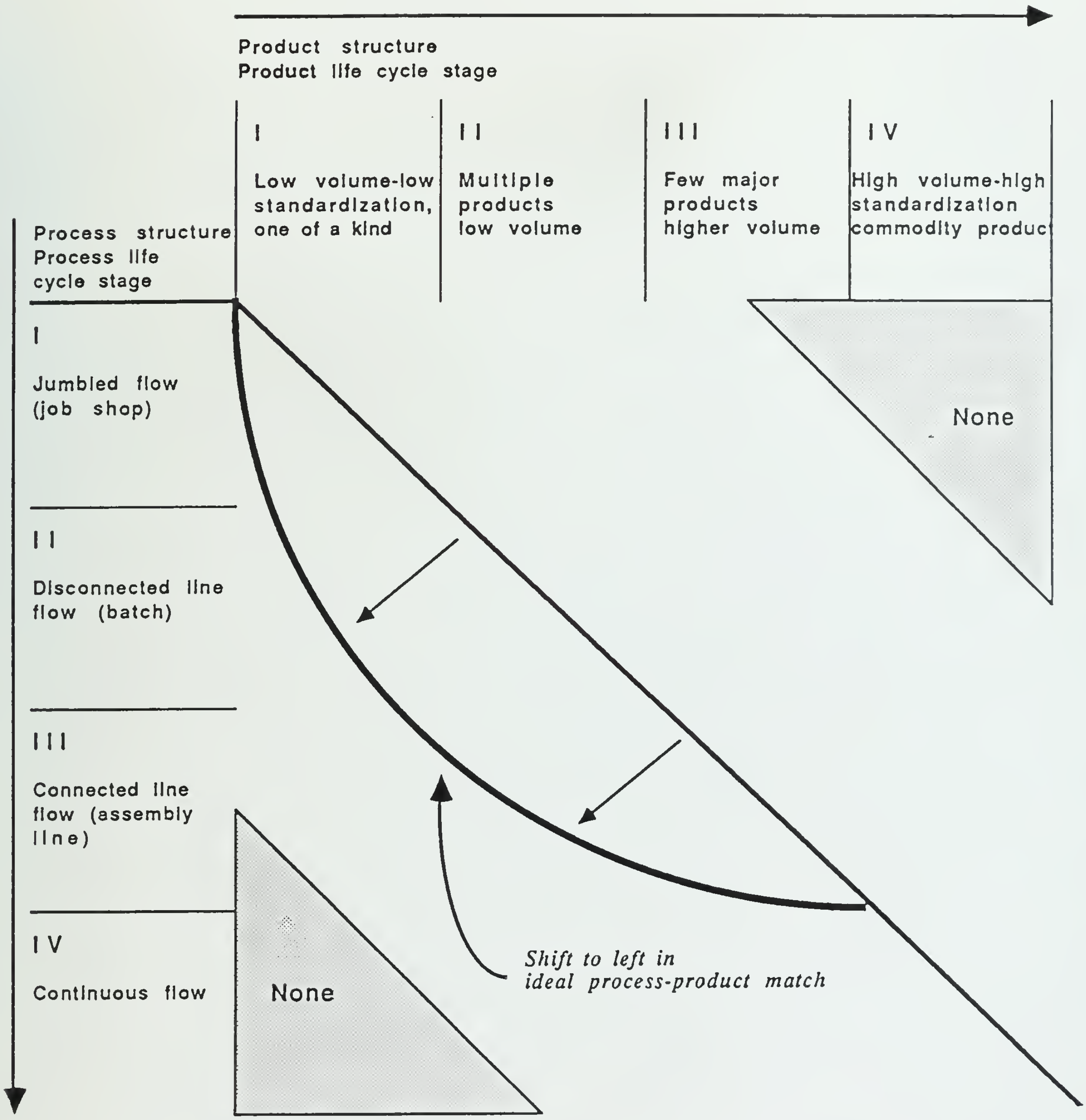
Table 6: Standard Deviation Results–Setup by Flow Dominance by Number of Machines (CV = .01, N = 12). Vertical bars on the right cover values that are not significantly different from one another. Vertical bars on the left indicate that the values at the beginning and end of that bar are not significantly different.

Oper. CV	FD	Number of Machines (M) 1	2	3
0.01	SR	77.15	64.11	58.97
	NSR	87.81	68.62	61.76
	RR	120.08	79.59	67.46
0.50	SR	77.15	64.11	58.97
	NSR	87.81	68.62	61.76
	RR	120.08	79.59	67.46
1.00	SR	139.26	89.37	73.01
	NSR	146.36	93.30	75.73
	RR	163.46	98.45	78.24
1.50	SR	241.97	129.97	98.13
	NSR	246.79	131.79	99.58
	RR	227.39	128.02	95.29

Table 7: MFT Results–Operation Time CV by Flow Dominance by Number of Machines (CV = .01, N = 12). All values covered by a vertical bar on the right are not significantly different from one another.

Oper. CV	FD	Number of Machines (M) 1	2	3
0.01	SR	7.98	10.11	11.26
	NSR	12.55	12.06	12.26
	RR	24.85	13.70	10.48
0.50	SR	15.24	15.25	15.24
	NSR	19.18	16.62	16.01
	RR	31.88	18.94	15.22
1.00	SR	36.62	26.78	24.20
	NSR	39.48	28.07	25.03
	RR	53.04	31.58	25.31
1.50	SR	66.04	41.95	36.15
	NSR	70.69	43.61	36.93
	RR	81.02	48.62	37.91

Table 8: Standard Deviation Results–Operation Time CV and Flow Dominance Effect. Vertical bars on the right cover values that are not significantly different from one another. Vertical bars on the left indicate that the values at the beginning and end of that bar are not significantly different.



Shift in Ideal Product-Process Match

Figure 1

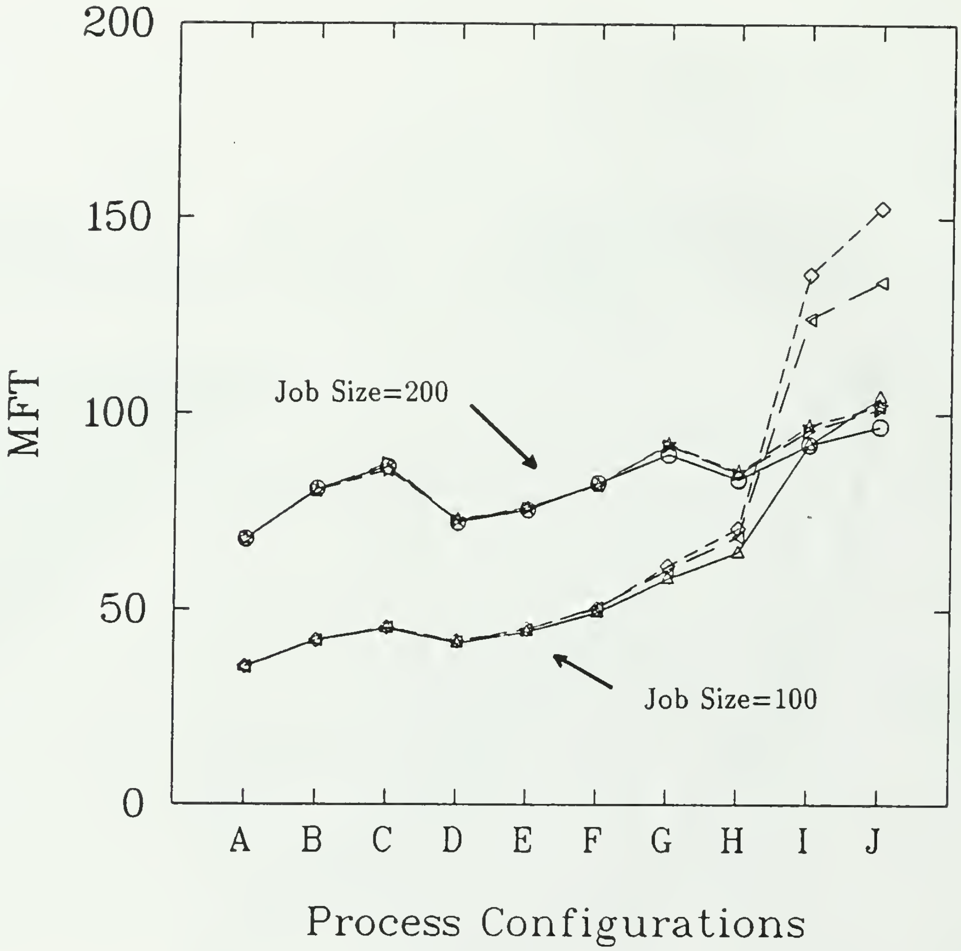


Figure 2: MFT Results by Processing Configuration and Job Size.

Legend				
Config-uration	SU	CV	M	FD
A	.1	.01	1	SR
B	.1	.5	1	NSR
C	.1	.5	1	SR
D	.5	.01	2	SR
E	.5.	.01	2	NSR
F	.5	.5	1	NSR
G	.5	.5	1	RR
H	1.0	.01	3	NSR
I	1.0	.01	3	RR
J	1.0	.5	3	RR
	- - - - - - -		36 Products	
	– – – – – –		24 Products	
	————		12 Products	