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Product-Process Relations in Batch Manufacturing

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Product-Process Relations in Batch Manufacturing

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Abstract

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. In this paper, we examine the interactions between product and process characteristics in such an environment in order to better understand the conditions under which one type of processing configuration performs better than another. Using a simulation model, we examine both the main effects and the interaction effects of product attributes, such as the number of products and job size, and process attributes, such as operation-time variance, setup time, and flow dominance. The results of two experiments are discussed. In the first experiment, demand on the system is stable. The second experiment allows demand on the system to experience periodic "shocks" – the demand rate is temporarily increased for a number of periods and is then returned to normal. The objective of the second experiment is to determine how a system described by various combinations of product and process characteristics responds to explicit demand shocks. One of the ways in which we use the results from these experiments is to quantify a portion of the Hayes-Wheelwright product-process matrix.

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Product-Process Relations in Batch Manufacturing

1. Introduction

Hayes and Wheelwright (1979) discuss the interdependencies between manufacturing processes and products as they both evolve over their life cycles. In their product-process matrix, the set of ideal production-process pairs appears along the main diagonal, reflecting the notion, for example, that the most efficient method of producing a high-volume product is through the use of dedicated flow lines utilizing specialized machines. For lower-volume products, however, the ideal relationship between product and process is less obvious. The product-process matrix would suggest that a job shop with jumbled flows would be the best process for low volumes of high product variety. However, recent advances in automated technology and cellular manufacturing have made it possible to realize many of the efficiencies of flow lines for the production of low-to-medium volume products. The development of flexible, programmable manufacturing technology has made it possible to quickly change over the production process from one product to another. The result is the potential for low-to-medium volume product demand to be efficiently produced in a flow-line manner. Within the context of the Hayes and Wheelwright paradigm, advances in manufacturing technology may be shifting the set of ideal product-process pairs to the left.

The ability to efficiently product low volumes of products with flow-line processes has important strategic implications. Shorter product life cycles and the apparent change in consumer demand toward customized manufactured products are increasing the pressure for firms to enhance their "manufacturing flexibility" without losing production efficiency.

(The notion of flexibility in manufacturing is multi-faceted. See, for example, Swamidass and Newell (1987) and Jaikumar (1984) for a discussion of the numerous ways in which flexibility has been discussed in the operations management literature.) The use of automated, flexible manufacturing systems is one way to accomplish this dual objective. Another way is to group similar parts into families and dedicate machines to process only parts within the families, thereby reducing setups and increasing flexibility.

The objective of this paper is to better understand the relationship between manufacturing attributes and product demand characteristics in a batch manufacturing environment. We specify several types of production environments and product demand conditions so that we can identify the circumstances under which a job shop, a flow shop, or an intermediate type of shop works best. We focus on the low-to-medium product volume quadrant of the Hayes and Wheelwright product-process matrix to determine what might cause the ideal product-process pairs to shift toward flow-line production. To do this, we identify important characteristics of both product demand and manufacturing processes. Using a simulation model, we then examine the effects and interactions of these characteristics on system performance. The results from the simulation experiments indicate that the use of job shops with multiple machines per department (the traditional process layout) is still appropriate for many high variance, high product variety settings. However, our results also indicate that when operation-time variance and setup times are both low enough and production volume is low, flow lines can perform better than traditional job shops.

The insights we gain here are useful in other contexts as well. In previous research related to the acquisition of automated technology in batch manufacturing (Monahan and Smunt, 1987 and 1989), we make the assumption that the product mix is stable over a period of time but manufacturing technology is advancing. Clearly, if a firm modifies a process design so as to increase (or decrease) its flexibility, the optimal product mix might also increase (or decrease). In principle, we would like to identify the "ideal" product-process pair by *simultaneously* determining both the optimal product mix and the optimal process design. The results of this simulation study will be useful in this regard.

2. Product-Process Characteristics

Several process and product attributes and their interactions are an important determinant of system performance as measured, for example, by mean flow time (MFT) or flow time standard deviation. We typically discuss the simulation results in terms of MFT, since MFT is highly correlated to other important performance measures, such as work-in-process (WIP) inventory and customer service levels. In several instances, we also present flow-time standard deviation and WIP results.

2.1 Manufacturing Process Characteristics

Watts, et al.(1989) discuss the relationships between attributes, such as process type, setup times, capacity, routing, scheduling, and product design, that they term *secondary flexibilities*, with characteristics of the firm's competitive position that they term *primary flexibilities*, which include product volume, mix, variety, and delivery. We prefer to distinguish between various types of flexibilities by classifying important characteristics into two categories – those that deal with the manufacturing process and those that deal with product demand.

We hypothesize that four characteristics of a manufacturing process greatly influence its performance in a batch processing environment. These characteristics are:

- flow dominance
- number of machines in each department
- setup time
- operation-time variance.

Flow dominance measures the proportion of jobs going from one machine to another. Flow lines, for example, are characterized by a high degree of flow dominance – 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. Because of this low flow dominance, bottlenecks may shift from department to department, resulting in a possible degradation of system performance. At any point in time, jobs in the system compete for manufacturing resources.

We use the number of machines in each department as a measure of the ability of the system to respond to simultaneous demand on a resource. Setup times certainly influence system performance. High setup times, for example, tend to create bottlenecks that can again degrade system performance. An example of primary flexibility, defined by Watts, et al., is the use of general-purpose equipment that allows a wider product line to be produced. Primary flexibility might also stem from faster changeovers of the equipment, so that the existing product line can be economically produced in relatively small batches. Faster changeovers can come from better tooling, worker method improvements, or dedicated equipment to product families with similar processing requirement (cellular manufacturing). The result is a shortening of lead times. Variations in demand can be handled without the need for larger finished-goods inventory.

Finally, operation-time variance measures the extent to which disruptions occur in the manufacturing process. Operation-time variance serves as a surrogate for the many types of variation that can occur in a batch production environment, caused, for example, by machine breakdowns, defective component parts, and worker interference (an insufficient number of machine operators). Kochman (1989) categorizes disruptions and explicitly models the effect of disruptions on system performance in an assembly line setting. He models several forms of process variation and finds that increases in variance rapidly increase flow times. He does not, however, consider the batch production environment or the interaction of setups with operation-time variance.

2.2 Product Demand Characteristics

The nature of product demand in a batch production environment is different from the demands patterns in assembly-line or continuous-flow environments since jobs are typically starting and stopping at various workcenters as they progress through their task sequence. As a result, machine setups increase and queues of jobs tend to form sporadically in the system. The flow shop we consider in this study is actually a batch flow process, since setups may be required at each workcenter in the flow line. These setup times, however, will be at least as low as the setup times in a job-shop process. Assembly lines that are designed for high volume production generally require extensive effort for changeover to a new model line or product and are not considered in this study.

The characteristics of product demand that we hypothesize have a significant influence on the system performance are:

- number of products
- job size
- demand stability.

System performance depends on the variety of products being produced by the production process. As the number of products increases, setup times increase resulting in diminished effective capacity. On the other hand, larger job sizes reduce the number of setups required and increase effective capacity.

We call product demand *stable* when the load on the manufacturing system remains constant. Unstable product demand is characterized by a temporary increase in the load on the system. For example, such an increase may be the result of a recent advertising campaign or a price discount. In our study, we assume that the temporary increase in the load on the shop does not decrease its load before or after the temporary increase. Although that situation is certainly possible, we are most interested in the system's ability to return to its steady-state condition following a period of time in which severe bottlenecks have occurred.

3. Simulation Experiment – Design

We use a factory simulation written in SIMSCRIPT to examine a number of product and process characteristics. The manufacturing process characteristics we test are flow dominance, number of machines in each department, setup time, and operation-time variance. The three product characteristics included in the simulation experiment are job size, number of products, and demand shocks.

Typically, manufacturing process factors are controlled (to a varying extent) by the operations management function, whereas product factors either are determined by an external market (and are therefore uncontrollable) or are dictated by the marketing function. Since the product factors tend to be uncontrollable from an operations management point-of-view, we test various levels of these factors so as to make our results generalizable.

The manufacturing factors, as a whole, represent different levels of manufacturing process flexibility or varying levels of process structure.

Two major experiments were conducted. The first experiment examines the product and process factors under the assumption that demand is steady. The second experiment tests the influence of demand shocks in various product-process settings. (We create a demand shock by doubling the demand for two periods, beginning in period five. After the two-period shock, demand returned to normal levels.)

For these experiments, we develop a factory simulation model that ranges from a flow line (complete flow dominance) to a random job shop (no flow dominance). Jobs arrive deterministically into the factory, although the type of product that the job represents is random and varies uniformly across 12, 24, or 36 product types. Job size is also random and varies uniformly by plus or minus 50% of the average job size. The job size is also the processing batch size. We do not batch orders in this study for two reasons. First, it is difficult to determine optimal batch sizes a priori considering the complex multi-product, multi-machine environment of our model. Second, 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 (see Ragatz and Mabert (1984)), it would add a confounding variable to the study.

Operation time for the job at each step in the task sequence is random with an Erlang distribution. We used the Erlang distribution since it has the following properties; 1) operations are strictly positive and are not truncated, 2) it can represent the exponential distribution, and 3) it is skewed for coefficients of variation (CV) less than 1.0, which correlates to empirical evidence on work-time distributions (Dudley (1963)).

Setup times are deterministic and can be varied by multiplying them by a constant that we call the *setup ratio*. We define the setup ratio as the ratio of setup time to operation task time. Several setup ratio values are included in each experiment. The base case for the setup ratio is 1.0, with each machine requiring 3.0 hours of setup whenever a different product type is to be produced next. Operation task times are set to 0.048 hours each on average. Each job requires six separate tasks for completion. The total operation time on a machine, on the average, for a 150 unit job will be 7.2 hours (.048 hours $\times$ 150). A setup ratio of 0.50 results in machine setup times of 1.5 hours each, although the total average operation time for a 150 unit job remains at 7.2 hours. Jobs are processed in shortest operation time priority, with no capacity limit on the WIP inventory that may develop ahead of each workcenter.

The experimental product-process factors and their levels are shown in Table 1. The first experiment uses a full factorial design that includes the first six factors for a total of $3 \times 3 \times 5 \times 4 \times 5 \times 3 = 2,700$ combinations. In order to eliminate transient-state effects, each combination was initialized for 5,000 hours of simulated factory time. Then, performance statistics for ten intervals of 5,000 hours each were collected (batch means) to reduce sample variance. Each of these intervals was separated by 1,000 hour intervals to further reduce autocorrelation between the batch means. Therefore, a total of 27,000 runs were made in the first experiment.

The second experiment also uses a full factorial design, but tests only the 12 product case, which we refer to as our *base case*. Here, $3 \times 3 \times 5 \times 4 \times 5 = 900$ combinations with 10 repetitions each were tested for a total of 9,000 runs. These runs were also initialized for 5,000 hours. Following initialization, performance statistics were gathered for forty periods of 320 hours each, so that a time series of performance measures could be observed. Additional intervals between the batches were not utilized in this experiment because serial correlation is of interest in this setting. Since we want to test the ability of the system to return to steady-state conditions after the shock, it is important to track performance criteria as they first increase and then decrease. Period-to-period correlation shows the rate at which the system is responding.

In both of these experiments, we define utilization from three perspectives: 1) *operation utilization* is the proportion of machine time spent producing units, 2) *setup utilization* is the proportion of machine time that is nonproductive due to required changeovers between production of different product types, and 3) *total utilization* is operation utilization plus setup utilization. Average operation utilization was set to 60%. Total utilization varied with job size and the setup-time ratio. (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% – typical values in practice and in prior research studies of job shops. Note that for every combination of factor levels tested, the operation utilization remains at 60% for each workcenter.

Table 2 contains the routings for the 12 product case. In the flow shop (FLOW), each product type starts at workcenter 1 and ends at workcenter 6, after sequentially using each workcenter in between. At the other extreme, the job shop (JSHP) has twelve workcenters. We originally set the routings so that each product type uses six of these workcenters in random order. Each workcenter is used as the first, second, etc. task in the sequence. A workcenter is used only once for each product type. We modelled the job shop using double the number of workcenters as the flow shop to illustrate the typical conversion scenario as one goes from a general purpose process layout to cellular manufacturing or flexible automation. Although the process layout is general purpose, the tooling on such machines requires substantial changeover time with a resultant tendency towards dedicating a portion of the equipment for certain classes of jobs. Therefore, any particular job will require, for example, the use only 50% of the workcenters for processing in the job shop. As firms move toward multi-function machines, made possible, for example, by flexible automation or quick-change tooling that might be used in cellular manufacturing, the number of different resources in the shop may decrease. We model this effect by a requiring each job to use each of the six workcenters available. The intermediate shop (INT) is a variation of the flow shop, with two job types whose routings are in different directions. Intermediate conditions may occur as firms move from a process layout to more automated manufacturing. It is unlikely that a firm will completely change its flows from a jumbled order to a pure flow shop in one step.

We hypothesized that even small additions of non-sequential routings would have a significant impact on system performance. For the 24 and 36 product scenarios, these routing matrices are doubled and tripled, respectively.

We use twelve workcenters for the job shop case since, in practice, items produced in this setting would typically require the use of only a portion of the resources. As a job shop is converted to cellular manufacturing or to another form of flow-line process, the specific machines needed to complete the processing of various types of jobs are allocated to specific cells or lines. In our simulation experiment, we did not test parallel lines since the results of multiple lines in steady state would be redundant and just increase computation time.

FACTOR	Level 1	Level 2	Level 3	Level 4	Level 5
Flow Dominance	FLOW	INT	JSHP	—	—
Number of Machines	1	2	3	—	—
Setup Ratio	0.10	0.25	0.50	0.75	1.00
Operation Time CV	0.01	0.50	1.00	1.50	—
Job Size	100	125	150	175	200
Number of Products	12(Base)	24	36	—	—
Demand Stability	Steady	Shock	—	—	—

Table 1: Simulation Factors

Intermediate Shop Routings through Workcenters

PRODUCT	Task 1	Task 2	Task 3	Task 4	Task 5	Task 6
A–J	1	2	3	4	5	6
K	6	5	4	3	2	1
L	2	4	6	1	3	5

Flow-Shop Routings through Workcenters

PRODUCT	Task 1	Task 2	Task 3	Task 4	Task 5	Task 6
A–L	1	2	3	4	5	6

Job Shop Routings through Workcenters

PRODUCT	Task 1	Task 2	Task 3	Task 4	Task 5	Task 6
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 2: Flow Dominance Matrices for 12 Products

In the flow shop and intermediate shop (the six workcenter scenarios) and in the job shop (the twelve workcenter scenario), the number of jobs competing for any workcenter is the same. Thus, both shops are balanced and comparable.

The performance measures (dependent variables) we use are MFT, flow-time variance, WIP, amplitude of response to demand shocks, and response time to demand shocks. 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 it 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, but are not being processed by the machine. The amplitude of response to demand shocks is measured as the difference between the steady-state and the maximum level of the performance measure. Response time is measured as the interval from the shock inception to the time when the performance measure drops back to its steady-state condition.

In running these experiments, we found that it took a long time for the system to reach steady-state, necessitating the use of long startup periods and large batches. In total, the simulation experiments used over 10 CPU days on a VAX 8810.

4. Simulation Results – Stable Demand

In the stable demand experiments, average operation-time utilization was 60% for each scenario. While the mix of products varied over time, the aggregate demand arriving to the system was held steady by keeping the average interarrival time constant. The results that follow are first illustrated and discussed for the 12 product case, which is our *base case* scenario. Then, comparisons of system performance are made when the product mix increases to 24 and 36 products. In these experiments, Analysis of Variance (ANOVA) indicates that all main and first-order interaction effects are significant at the 0.01 level or better. The ANOVA table is shown in the Appendix to this paper.

We show the main effects across each flow dominance level in Table 3 for MFT and WIP. One interesting main effect concerns the setup ratio. Note that the job shop is the poorest performer for all setup ratio levels. This is due to jumbled flows causing resource competition problems. We will elaborate on this in a later section. The job shop does perform better, however, when operation-time variance is high, albeit only slightly. Obviously, increasing the number of machines improves performance of all systems, but it has the greatest *relative* effect for the job shop. Increasing the number of machines per department from one to three, decreases MFT by 51% for the job shop, whereas the MFT of the flow shop only decreases by 46% with the same addition of machines. The availability of alternate resources is particularly important in a jumbled flow environment. It is also interesting to see that increasing the product-mix from 12 to 36 products (with operation utilization held constant), increases the job shop MFT by 11% and the flow shop MFT by only 6%. Based upon the job shop's performance to increased product-mix, we might conclude that it is a poor process design. Later we will show, however, that when interaction affects are also considered, the job shop is superior in certain settings.

As the size of each job increases, setup times decrease but the time required to process a batch increases. As the job size decreases, more setups occur and again flow times increase. When setup time is relatively high (i.e. the setup ratio is 1.0), we found that for the job sizes of about 125 units, the marginal increase in MFT due to an increase in batch processing time is equal to the marginal decrease in MFT due to fewer setups. See, for example, the graphs of MFT versus job size for the JSHP3MC process in Figure 1 (for SU=1.0) and Figure 2. In this sense, the "economic" job size is about 125 units.

In Table 3, notice that WIP is highly correlated with MFT most of the designs. There is an interesting exception, however. When the job size increases from 100 to 125 units, WIP inventory decreases dramatically for all three processing configurations. As expected, MFT also decreases. But notice what happens as the job size increases to 150. WIP inventory continues to decrease but MFT *increases*. Here is an example where a change in one factor (in this case job size) causes opposite reactions in two factors that are typically highly correlated. Interactions such as these may be important and should be explicitly considered by managers when determining the optimal process choice.

4.1 Interactions of Product-Process Characteristics: The Base Case

Although the main effects can *sometimes* be predicted without complex analysis, the interaction effects are less obvious. For example, an increase in operation-time variance, *ceteris paribus*, increases mean flow time. Suppose that a firm is considering the use of Group Technology that entails the reorganization of its existing job shop into a number of manufacturing cells. The conversion to cells increases flow dominance. If operation-time variance was high in the job shop and remains so in the cells, system performance in the new configuration is likely to degrade since resources are dedicated, which increases the level of variance on any individual cell. Suppose, on the other hand, that the application of Group Technology, which groups parts into common families, reduces operation-time variance. To what extent must operation-time variance be reduced before system performance of the cells exceeds that of the job shop? Additionally, the reorganization into cells may reduce setup time, which also contributes to an improvement in system performance. This

Setup Ratio	Flow Shop MFT	Flow Shop WIP	Intermediate MFT	Intermediate WIP	Job Shop MFT	Job Shop WIP
.1	70.3	75.6	71.7	80.6	75.9	97.1
.25	76.4	87.4	78.5	94.9	84.0	116.1
.50	88.7	114.3	92.0	126.6	100.8	159.3
.75	106.9	163.0	112.7	182.6	126.8	234.4
1.00	152.0	304.3	163.3	345.5	188.9	431.4

Operation CV	Flow Shop MFT	Flow Shop WIP	Intermediate MFT	Intermediate WIP	Job Shop MFT	Job Shop WIP
.01	58.2	17.8	64.1	38.3	84.9	108.0
.50	67.9	50.2	74.1	71.1	93.1	135.5
1.00	104.0	165.3	109.9	184.0	120.6	225.3
1.50	165.3	362.4	166.5	369.9	162.6	362.8

Number of Machines	Flow Shop MFT	Flow Shop WIP	Intermediate MFT	Intermediate WIP	Job Shop MFT	Job Shop WIP
1	134.6	167.3	142.8	185.2	164.6	236.0
2	88.6	148.7	91.9	163.3	100.6	204.5
3	73.4	130.7	76.3	149.7	80.6	182.4

Product Mix	Flow Shop MFT	Flow Shop WIP	Intermediate MFT	Intermediate WIP	Job Shop MFT	Job Shop WIP
12	95.4	138.2	100.2	154.7	108.5	186.3
24	99.7	152.0	104.6	168.8	116.6	211.5
36	101.4	156.5	106.2	174.7	120.8	225.2

Job Size	Flow Shop MFT	Flow Shop WIP	Intermediate MFT	Intermediate WIP	Job Shop MFT	Job Shop WIP
100	99.6	206.6	107.0	233.9	122.4	283.0
125	87.0	135.6	91.6	151.8	103.9	195.1
150	93.3	129.2	97.6	144.5	108.2	183.5
175	102.7	134.2	105.9	146.2	116.2	184.9
200	111.7	138.9	116.1	153.9	125.7	191.7

Table 3: Summary of Simulation Results - Stable Demand

is a situation where there is an interaction of flow dominance, operation-time variance, and setup time. It is, therefore, difficult to predict the performance of the newly formed cells. In the following sections, we discuss several interesting interaction effects identified in our experiments.

Many of the results from our simulation are illustrated with three flow dominance and number of machines combinations. We chose to plot the flow dominance/number of machines combinations of flow shop/one machine (FLOW1MC), the intermediate shop/two machine (INT2MC), and the job shop/three machine (JSHP3MC) combinations in order to represent the major differences in process designs. In a job shop, process layouts are typically used, i.e., similar machines are grouped together by department or workcenter. Since jobs require various routings in this setting, the availability of parallel processing reduces (but does not negate) the probability of shifting bottlenecks in the shop. As the process design moves towards a flow shop, the machines become linked together in a sequential processing mode. Take, for example, the conversion of a process layout to cellular manufacturing. A cell would typically consist of one of each machine-type required to complete most (or all) of the steps in the task sequence for those parts assigned to the cell. Parallel processing is not possible, then, unless intercell flow is allowed. We model the intermediate shop with two machines in order to capture a case between the two extremes.

Setup and Flow Dominance Interaction Effect

The mean flow time (MFT) and flow-time standard deviation performance measures are shown in Table 4 for the case where operation times are nearly deterministic. When setup times are low (SU=0.1), the performance of JSHP3MC, as measured by MFT, is slightly better than INT2MC or FLOW1MC. As the setup times increase, however, the

FLOW1MC design performs the best, both in MFT and flow-time standard deviation. At first glance, this result may seem counter-intuitive since job shops with parallel processing are designed to handle high setup-time conditions. The job shop has routings that allow for shifting bottlenecks, however, and many different products at various stages in the task sequence can arrive at a particular workcenter in a short period of time. This "implicit shock" on one workcenter causes blocking and starving of other workcenters. These workcenters become under-utilized. The net result of the bottleneck is an increase in MFT. The flow shop has a sequential routing, so it behaves in a stable manner as long as operation and setup times exhibit little variance. Figure 1 depicts MFT for the two extreme setup ratio values for all job sizes. Note that the job shop performs noticeably worse when the setups are high and the job sizes are small.

Setup Ratio	Design	MFT	Flow-Time SD
0.10	FLOW1MC	51.51	8.48
	INT2MC	50.13	11.74
	JSHP3MC	49.98	7.66
0.25	FLOW1MC	54.49	8.31
	INT2MC	53.56	11.73
	JSHP3MC	53.45	8.16
0.50	FLOW1MC	59.70	8.00
	INT2MC	59.75	11.79
	JSHP3MC	60.51	9.47
0.75	FLOW1MC	65.24	7.68
	INT2MC	67.34	12.03
	JSHP3MC	69.91	11.50
1.00	FLOW1MC	71.57	7.43
	INT2MC	77.96	13.02
	JSHP3MC	85.81	15.63

Table 4: Setup and Flow Dominance Effect when $CV = 0.01$.

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

Operation-Time Variance and Flow Dominance Effect

Table 5 indicates that as the CV increases, the job shop performs better on MFT than the flow shop. This result is similar to previous studies dealing with stochastic assembly line design. (See, for example, Hillier and Boling (1979) and Smunt and Perkins (1985).) As the process becomes more linked, as in the case of the flow shop, large operation-time variance could cause the system to become blocked or starved. In our simulation design, we did not constrain the amount of buffer storage between machines, so the relative increase in MFT is due only to starving (input to a machine is not available). Because of this condition, capacity is not utilized smoothly and bottlenecks will form more readily throughout the flow shop process. The availability of parallel processing in the job shop reduces the problems caused by operation-time variance.

Operation CV	Design	MFT	WIP
0.01	FLOW1MC	60.50	14.10
	INT2MC	61.74	38.36
	JSHP3MC	63.93	83.46
0.50	FLOW1MC	77.14	48.55
	INT2MC	68.62	68.03
	JSHP3MC	67.45	105.82
1.00	FLOW1MC	139.26	177.10
	INT2MC	93.30	170.84
	JSHP3MC	78.23	172.06
1.50	FLOW1MC	241.93	391.34
	INT2MC	131.79	331.57
	JSHP3MC	95.29	277.70

Table 5: Operation-Time Variance and Flow Dominance Effect.

Work-in-process inventory levels for the three designs are quite similar when the operation-time CV is high, although the flow shop design has considerably less WIP when the CV=0.01. The relatively high WIP level for the job shop in the low CV case is caused by the shifting bottleneck problem. The WIP level for the flow shop increases to that of the job shop when the CV is high. Queues can easily build up in the flow shop when the one available machine is utilized longer than the average.

The two graphs in Figure 2 further illustrate the possible inverse relationship between MFT and flow-time variation. This inverse relationship occurs for the middle operation-time variance condition (CV=0.5). Although the MFT of the job shop is lower than that of the flow shop for all job sizes, its standard deviation is higher. The intermediate shop has the lowest standard deviation for small job sizes, but the highest for large job sizes. When job sizes are small, the two job types that have non-sequential routings do not cause problems in this "linked" system of six workcenters. However, as the job sizes become large, these two job types cause shifting bottlenecks as they are introduced into the process. The bottlenecks come and go often as these two jobs arrive randomly, causing the flow-time standard deviation to rise.

The interaction of flow dominance, number of machines, and operation-time variance is clearly complex. We know of no other studies that have investigated flow dominance at intermediate levels, although our results suggest that it has a major influence on system performance.

**** Insert Figure 2 about here ****

We also categorized our results for particular process design scenarios, defined by the flow dominance, number of machines, and the setup ratio. In Table 6, we show results for five combinations across the continuum of a flow line with little setup to a job shop with large setup. We assume that the type of flow lines that we are testing represent the ideal case of cellular manufacturing - setup times are reduced on dedicated general-purpose equipment by the use of special tooling for each product family. These combinations are:

- FLOW1MC/setup ratio=0.1
- INT2/setup ratio=0.1
- INT2/setup ratio=0.25
- INT2/setup ratio=0.5
- JSHP3/setup ratio=0.75

Oper. CV	Design	SU Ratio	MFT	Flow-Time SD	WIP
0.01	FLOW1	.10	51.54	8.51	10.44
	INT2	.10	50.06	11.73	19.21
	INT2	.25	53.40	11.67	22.64
	INT2	.50	59.54	11.78	30.61
	JSHP3	.75	68.93	11.25	94.25
0.50	FLOW1	.10	61.58	14.36	30.87
	INT2	.10	53.52	15.62	34.25
	INT2	.25	57.60	15.94	41.00
	INT2	.50	65.16	16.19	55.02
	JSHP3	.75	72.96	15.78	119.78
1.00	FLOW1	.10	100.16	33.61	110.18
	INT2	.10	65.46	24.70	83.82
	INT2	.25	71.92	25.35	100.76
	INT2	.50	82.34	25.49	126.28
	JSHP3	.75	84.75	25.99	192.04
1.50	FLOW1	.10	155.82	56.41	227.27
	INT2	.10	86.69	39.57	172.72
	INT2	.25	99.23	40.62	213.10
	INT2	.50	116.38	42.70	268.45
	JSHP3	.75	105.90	40.39	323.81

Table 6: Process Design and Operation-Time Variance Interaction Effect

The MFT, flow-time standard deviation, and WIP levels are displayed for the four levels of operation-time variance when the job size is 150 units. The process design that consistently performs the best in terms of all three measures is the intermediate shop with setup ratio of 0.10. With low setup times and high operation-time variance (CV=1.00 and CV=1.50), it is not surprising to see that with its tightly linked workcenters, the relative performance of the flow shop is poor. What is interesting, however, is how dramatic the performance of the system improves when parallel processing is possible. Even with the addition of a single machine per workcenter, as in the INT2 setting, MFT is nearly cut in half. Notice also that when operation-time CV is 1.00, the MFT for both the INT2 process with a setup ratio of 0.50 is nearly the same as the JSHP3 process with a setup ratio of 0.75. Again the increase in the ability to perform a number of tasks simultaneously resulting from the addition of a third machine per workcenter compensates for the increase in setup time.

There are conditions, of course, where the other process designs excel; but these data reinforce the need to carefully test intermediate process designs. As firms move from job shops to cellular manufacturing and flexible automation, the intermediate settings will become more prevalent.

4.2 Increased Product Mix

Using the same the base values of the factory simulation, we tested the effect of increasing the number of products produced by any one process design from 12 to 24 and 36 products. We kept the total demand on the system (in number of units) the same. Therefore, fewer orders for any one job type arrive into the system when the product mix increases.

Operation-Time Variance

In Table 7, we show the MFT for the three process design scenarios for each of the three product mixes and operation-time variance and for the setup ratio of 0.75. We chose the setup ratio of 0.75 since this setting is where interesting interactions with product mix occur. For each product mix, the flow shop has the lowest MFT when the operation-time variance is low. This is similar to the base case results for low operation-time variance. What is interesting here is the increasing degradation of the job shop performance, and to a lesser extent, the performance of the intermediate shop as more products are produced on the system. The "implicit shock" discussed in the previous section becomes a larger problem as more products are placed on the system. The interaction of low flow dominance and a large product mix causes MFT to increase.

As the operation-time variance increases, however, the parallel processing capability of the job shop overcomes the problems associated with low flow dominance. The results for the high CV levels in Table 7 indicate that a job shop performs well for all product mixes when operation-time variance is high.

When setup times are high and operation-time variance is moderate, a significant interaction of flow dominance, number of machines, and product mix occurs. From Table 7, we see that the flow shop is the worst performer for the SU=0.75 and CV=0.5 settings, but that the job shop is the best for 12 products and the intermediate shop is best for 24 and 36 products. Review of the detailed experimental data reveals that the largest impact occurs for small job sizes, since the "implicit shock" effect is most pronounced here. Again, we see that interactions of important process design and product characteristics are subtle and are difficult to predict a priori.

In our opinion, the use of a twelve workcenter job shop is the most 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 both settings. If the only condition that changes is the flow dominance, the positive effect of a decrease in the ratio of job types per workcenter becomes more pronounced as the product mix increases. In the twelve workcenter job shop, only 50% of the job types visit any one workcenter. Therefore, the job shop is likely to incur less machine changeovers than the flow shop, since in the flow shop a workcenter is visited by twice as many job types. Machine changeovers do not occur when the same job type is processed next on the same machine. As the number of products (job types) in the system increase, the job shop with twelve workcenters should do increasingly better than the flow or intermediate shop. To test the robustness of our results, we performed a simulation experiment for a six workcenter job shop where operation-time CV is 0.50 and the setup ratio is 0.75.

With these factor levels, JSHP3MC performs slightly better than INT2MC for 12 products, but degrades as the number of products increases to 24 and 36. Table 7 contains the MFT values for the twelve workcenter setting. The MFT's for 12, 24, and 36 products are 72.96, 76.46, and 77.48, respectively. For the six workcenter job shop (JS6-3MC), we found that the average MFTs 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 improvement in the performance of the job shop.† Apparently, the flow pattern by itself is the most influential cause of a job shop's performance. In our experiment, the performance of the job shop appears to be influenced more by the flow pattern than by the ratio of job types to workcenters.

Operation CV	Design	MFT - 12	MFT - 24	MFT - 36
0.01	FLOW1MC	65.16	65.59	65.72
	INT2MC	66.78	67.61	68.43
	JSHP3MC	68.93	71.74	73.20
0.50	FLOW1MC	82.49	83.28	84.92
	INT2MC	73.92	75.97	75.41
	JSHP3MC	72.96	76.46	77.48
1.00	FLOW1MC	151.55	146.00	155.49
	INT2MC	99.74	103.09	105.86
	JSHP3MC	84.75	89.04	90.86
1.50	FLOW1MC	245.08	264.54	276.64
	INT2MC	143.35	146.50	149.77
	JSHP3MC	105.90	112.19	112.38

Table 7: Operation-Time Variance and Product-Mix Effect when the Setup Ratio is 0.75.

Figure 3 further illustrates the interaction between flow dominance, number of machines, and product mix for the smallest job size of 100 units. The top graph is based

† The flow patterns used in the six workcenter job shop experiment are similar to those used in the twelve workcenter job shop. Each of the twelve job types have different flows. It is more difficult to design truly random flows in the smaller job shop since two job types must start and end at any workcenter. Even though we balance the job sequences in this way to "jumble" the flow as much as possible, the flow dominance may be higher in this setting. See Buss and Smunt (1989) for a discussion of the difficulties in determining a good flow dominance measure, especially when the size of the shops are not comparable.

on the original assumption of one machine per workcenter for the flow shop, two for the intermediate shop, and three for the job shop. The counter-example of one machine per workcenter for any flow dominance condition is shown in the bottom graph. By reviewing the counter-example, it is clear that the number of machines is the cause of the subtle interaction. Even jumbled flow systems can work well when parallel processing is possible; however, when only one machine is available, the processes with high flow dominance perform the best for all product-mix levels. In practice, however, the relative number of machines working in parallel depends to a large degree on the flow dominance. Again, such interactions need to be carefully analyzed.

*** *Insert Figure 3 about here* ***

5. Simulation Results - Demand Shocks

A firm may occasionally see a temporary rise in demand for their products, due perhaps to a sales promotion or to seasonality factors. One facet of manufacturing flexibility is the ability of the manufacturing process to respond to such shocks. In this section, we discuss results when demand is increased to two times the steady-state demand for two periods of 320 hours each.

Low Setup

Figure 4 compares the three shop scenarios for each level of operation-time variance. It is interesting to see that the job shop has the highest peak (i.e., has the greatest amplitude) of MFT when operation-time variance is low; but when operation-time variance is high, the flow shop has both the greatest amplitude and the longest response time, i.e., the time it takes to return to steady-state performance levels. Figure 5 comprises companion graphs of department utilization (the average utilization for all departments), including operation time and setup time. Although the utilization percentages start out approximately equal at low CV levels, the job shop peaks at the highest percent utilization when there is high operation-time variance. Even though it experiences the highest maximum utilization, the response of the job shop to the shock is better, in terms of MFT, than is the flow shop or intermediate shop. In this regard, the job shop is more flexible. When there is high operation-time variance, the flow shop rapidly loses its ability to respond to a demand pulse. In essence, the surge in demand is another type of variance added to the original variance.

**** Insert Figures 4 and 5 about here ****

<u>High Setup</u>

When setup times are high, the effect of increases operation-time variance becomes more pronounced. Figure 6 shows that the performance of all of the processes, especially in terms of response time, degrades rapidly with increased variance. Figure 7 is analogous to Figure 5 except that now setups are high rather than low. Comparing the utilization response in Figures 5 and 7, a noticeable increase is apparent in the time it takes for all the processes to return their steady-state condition. As the steady-state utilization levels of the manufacturing processes increase (due to increased setup utilization here), the recovery time from a shock to the system becomes longer.

**** Insert Figures 6 and 7 about here ****

Specific Process Designs

In the previous discussion of shock effects, we focused on aggregate results for JSHP3MC, INT2MC, and FLOW1MC scenarios. In practice, the process designs of interest could be defined more specifically, especially in terms of flow dominance, number of machines per workcenter, and setup times. The effect of a demand shock for these specific designs is illustrated in Figure 8. Note that setup reduction makes the flow shop and intermediate shop the best performers. Even when operation-time variance is high, the process designs that exhibit high flow dominance have MFT's with lowest amplitude. All-in-all, flow shops will perform well if either variance or setup is low. In the job shop scenario, the system is setup-constrained. A demand shock has a greater influence on the amplitude and response time of the MFT when capacity is constrained.

*** *Insert Figure 8 about here* ***

6. Quantifying the Product-Process Matrix

The main objective of this research is to better understand the relationships between manufacturing attributes and product demand characteristics. Toward this end, we can use the results of the simulation to establish a quantitative relationship between manufacturing processes and product attributes. In essence, we can quantify at least a portion of the Hayes-Wheelwright product-process matrix.

In Table 8, we show the MFT performance for various product-process pairs. Using the data from the base case, the MFT averages for cells that represent typical product-process pairs were calculated. We choose to represent the low volume/high product variety category by letting the job size be 100 units and the number of products be 36. In the low volume category, one would expect a high degree of variance in the system, arising not only from operation times, but also from the arrival patterns of the orders, machine changeovers, etc. We show MFT results for operation-time CV's of 1.5 and 1.0 as surrogates for these sources of variation. At the other extreme, we represent the high volume/low variety category by letting the job size be 200 units and the number of products be 12. Here, variance levels are likely to be lower since production levels are typically smooth. On the process axis, we chose JSHP3MC, INT2MC, and FLOW1MC as the three main process types.

For each product category, the minimum of the column denotes the best product-process pair. The best product-process pairs derived from our experiment follow the main diagonal, especially for the low variance conditions of each product volume category.

Our results are most appropriate for the upper quadrant of the product-process matrix, since we only test fairly low levels of product volume. Job sizes are purposely kept low since our experiments are designed to analyze issues in a batch manufacturing environment. It is difficult to determine if the ideal product-process pairs would shift to the left when attributes of flexible automation are considered.

Although such an analysis is possible, it would require a greatly expanded study of product volumes, product mixes, flow dominance level, setup times, and operation-time CV's.

Process Type	Low Volume 36 Products		Medium Volume 24 Products		High Volume 12 Products	
	CV=1.5	CV=1.0	CV=1.0	CV=0.5	CV=0.5	CV=0.01
JSHP3MC	126.7*	91.5*	79.3*	68.7	80.4*	77.2
INT2MC	180.2	109.4	91.6	68.6*	83.0	76.5*
FLOW1MC	328.2	162.2	135.7	76.5	92.8	76.5*

* denotes the minimum MFT in the column

Table 8: Experiment Results in Product-Process Matrix Form

7. Summary and Conclusions

Two comprehensive simulation experiments were conducted to investigate relationships between process designs and product characteristics in a batch manufacturing setting. The large number of important factors that were included in the experiments necessarily generated a great deal of data. We now summarize the major insights established in each of the experiments.

Findings from the Stable Demand Experiment

- Job shops work best when setups are *low* and not *high*. The jumbled flow of the job shop results in shifting bottlenecks. Low setups are needed to offset the affects of "implicit shocks" at the workcenters caused by the bottlenecks.
- Tightly-linked processes, represented by the flow shop with 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 the variation of operation time 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.

- As expected, job shops perform better as the number of job types increases.
- WIP inventory and MFT are generally highly correlated, but can respond differently to changes in job size.

Findings From the Demand Shock Experiment

- Job shops continue to respond better to explicit demand shocks when operation times are highly variable.

The relationship between process and product characteristics for batch production was shown to be complex, yet explainable if sufficient analysis is undertaken. Firms that are considering the move to more flow-line production, while staying in the low-to-medium volume production mode, need to first define the type of demand conditions under which they will be operating in the future. Then, based on practical process alternatives available to them, they need to analyze the performance of such processes under typical operating conditions. Simulation analysis, such as we illustrated in this study, is an appropriate tool for better understanding the product/process relations.

REFERENCES

Buss, A.H, and T.L. Smunt, "A Measure of Flow Dominance in Job Shops," John M. Olin School of Business, Washington University, working paper (August 1989).

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

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.

Jaikumar, "Flexible Manufacturing Systems: A Managerial Perspective,", Harvard Business School Discussion Paper # 1-784-078 (January 1984).

Kochman, G.A., "The Performance of Manufacturing Systems in a Disruptive Environment," Presentation given at 1989 TIMS meeting in Osaka, Japan.

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

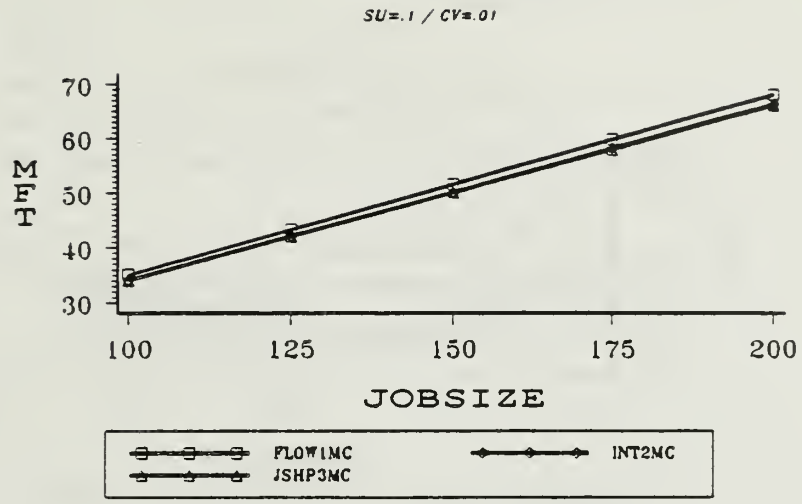
Monahan, G.E. and T.L. Smunt, "Optimal Acquisition of Automated Flexible Manufacturing," *Operations Research*, 37, 2 (March-April 1989) 288-300.

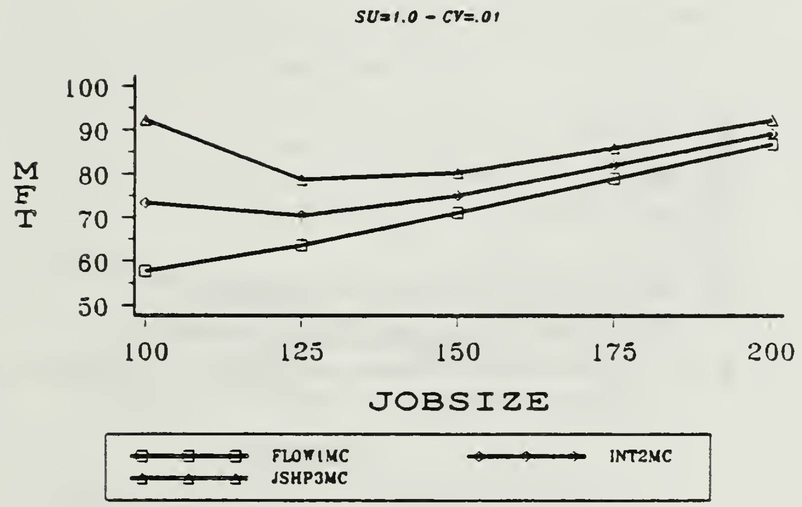
Ragatz, G.L. and V.A. Mabert, "A Simulation Analysis of Due Date Assignment Rules," *Journal of Operations Management*, 5, 1, (November 1984) 27-40.

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.

Swamidass, P.M. and W.T. Newell, "Manufacturing Strategy, Environmental Uncertainty and Performance: A Path Analytic Model," *Management Science*, 33, 4, (April 1987) 509-524.

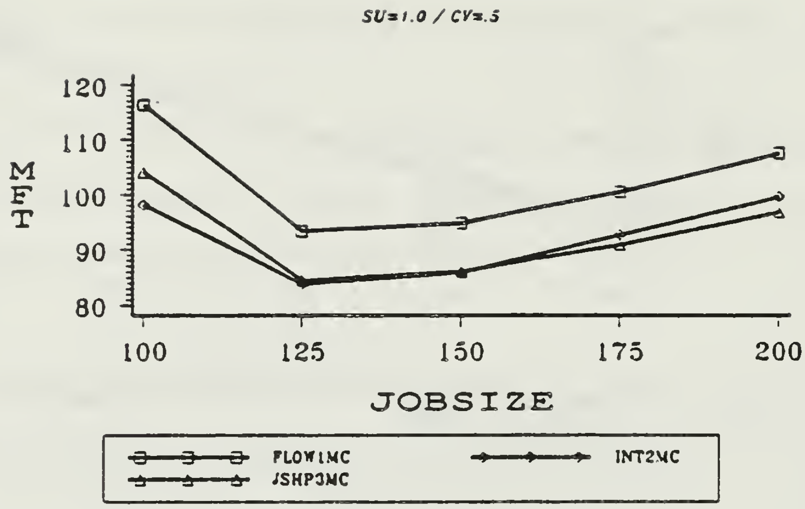
Watts, C.A., B.K. Sohn, and C.K. Hahn, "Manufacturing Flexibility and Competitive Strategy," 1989 Midwest Decision Sciences Institute Proceedings.

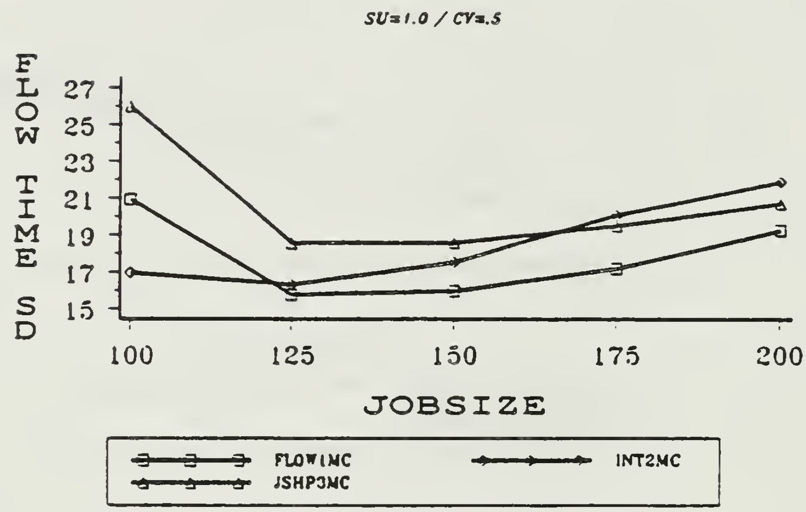




Setup Time and Flow Dominance
Interaction Effect

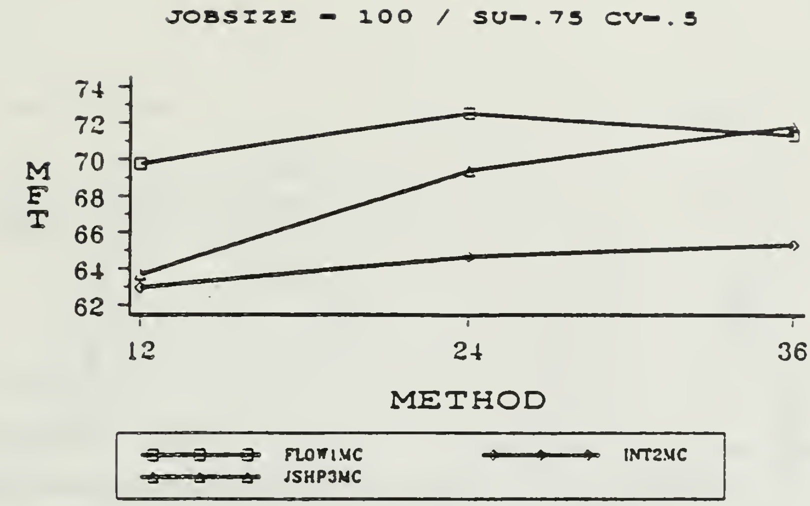
Figure 1

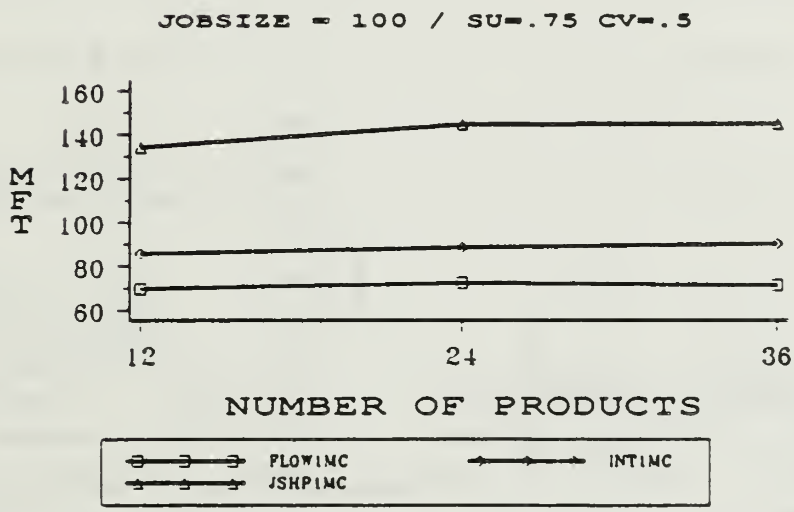




Flow-Time Mean and
Standard Deviation

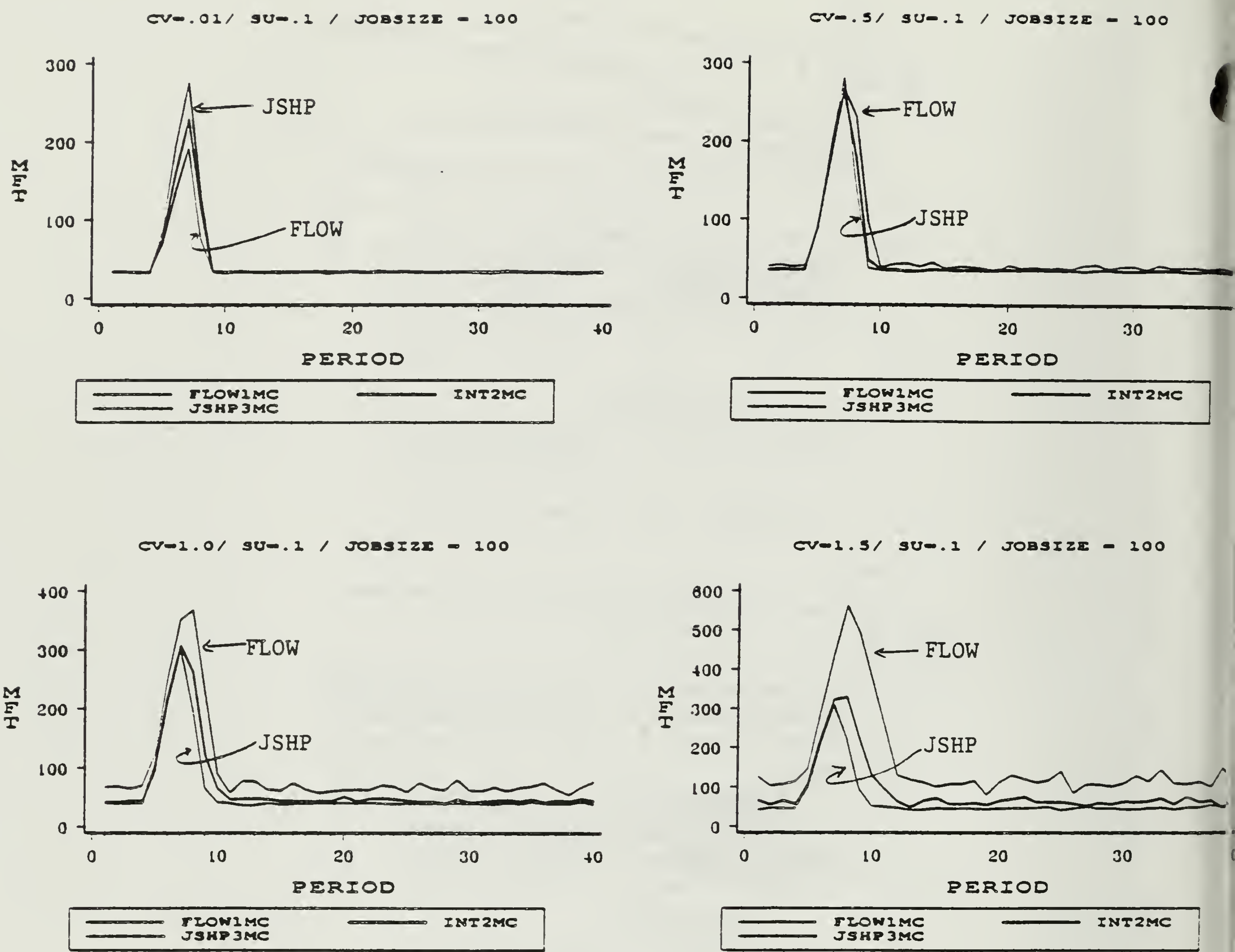
Figure 2





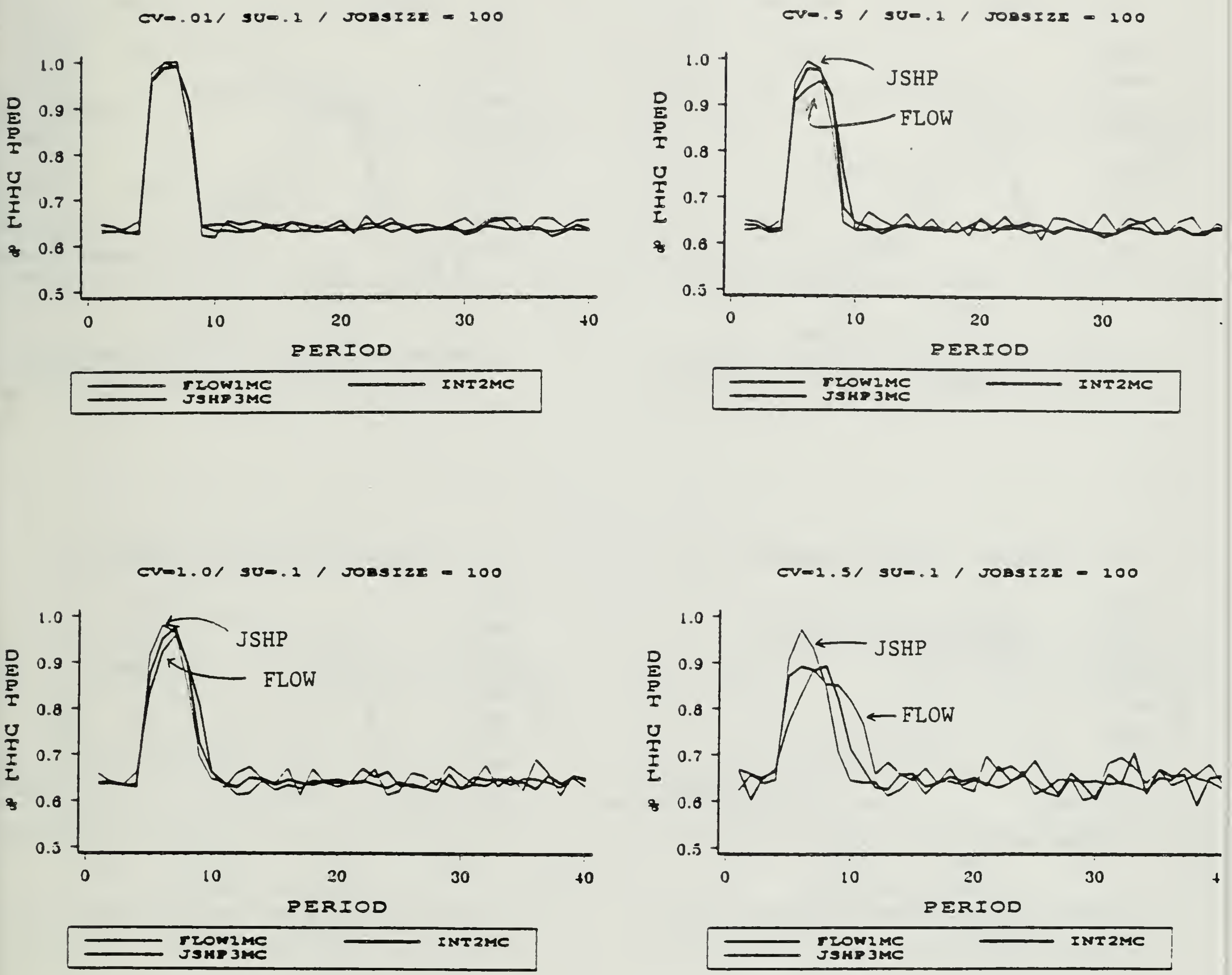
Interaction of Flow Dominance,
Number of Machines and Product Mix
Job Size = 100 Units

Figure 3



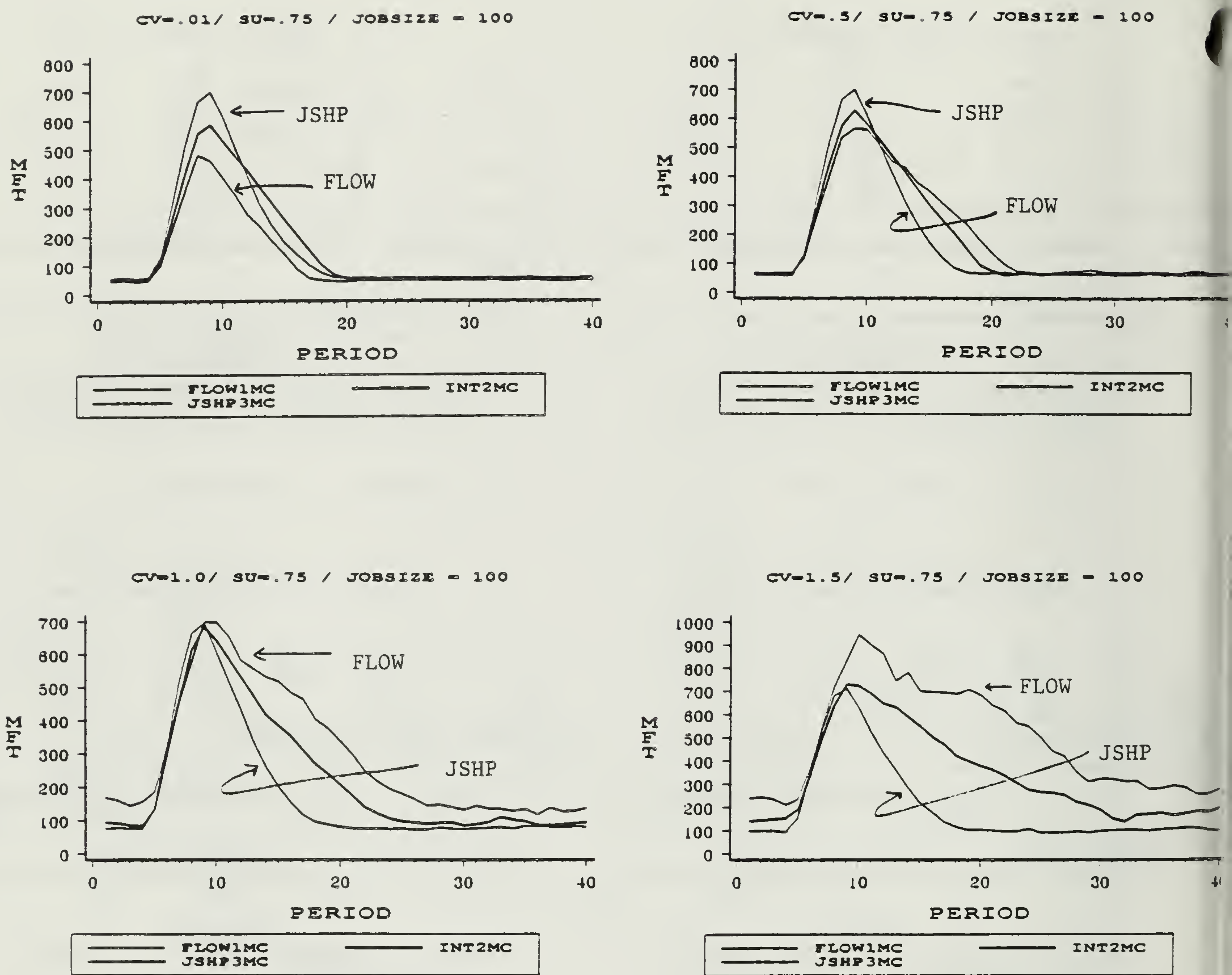
Time Series of Mean Flow-Time Performance for Shock Scenario
Low Setup

Figure 4



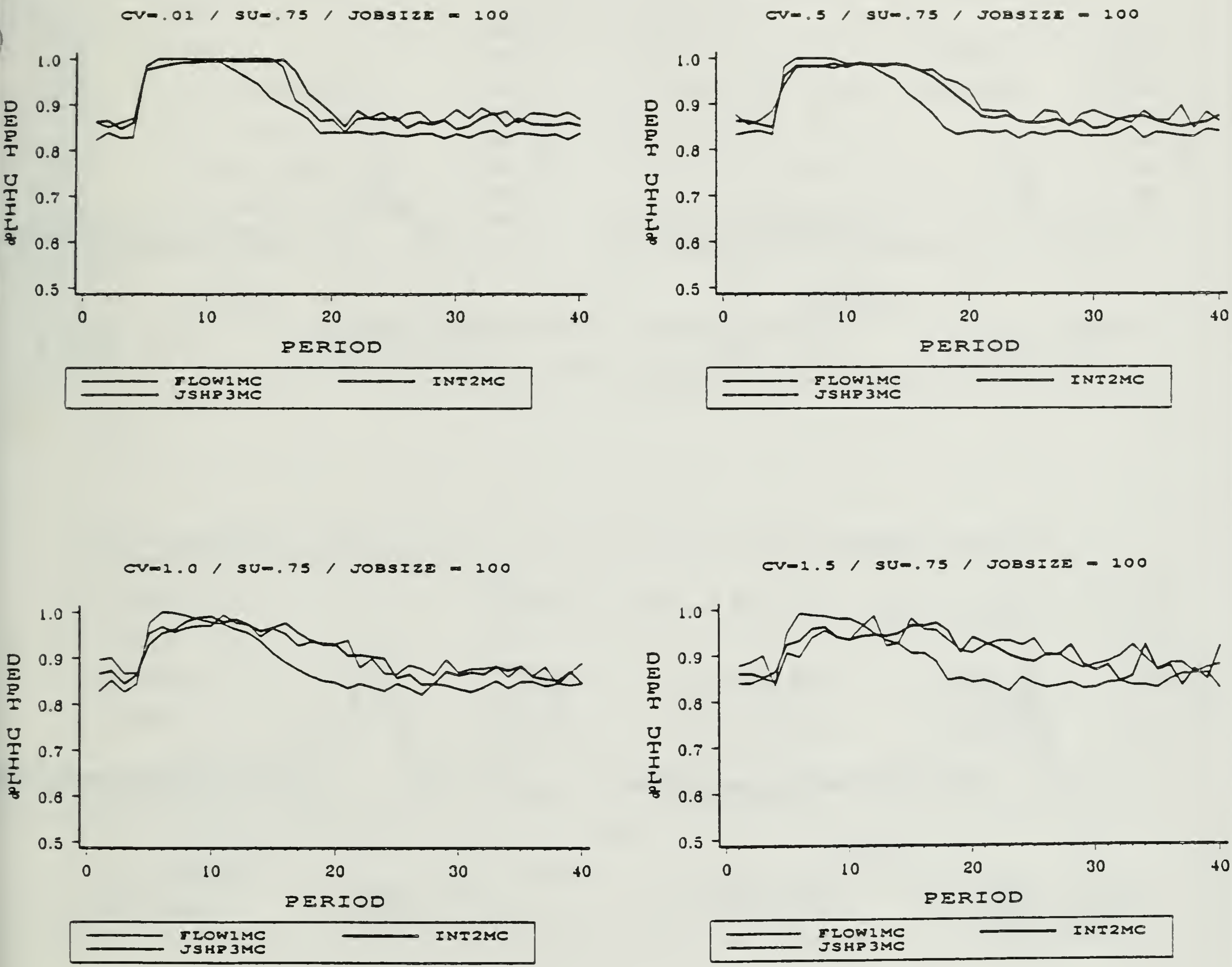
Time Series of Utilization Percentage for Shock Scenario
Low Setup

Figure 5



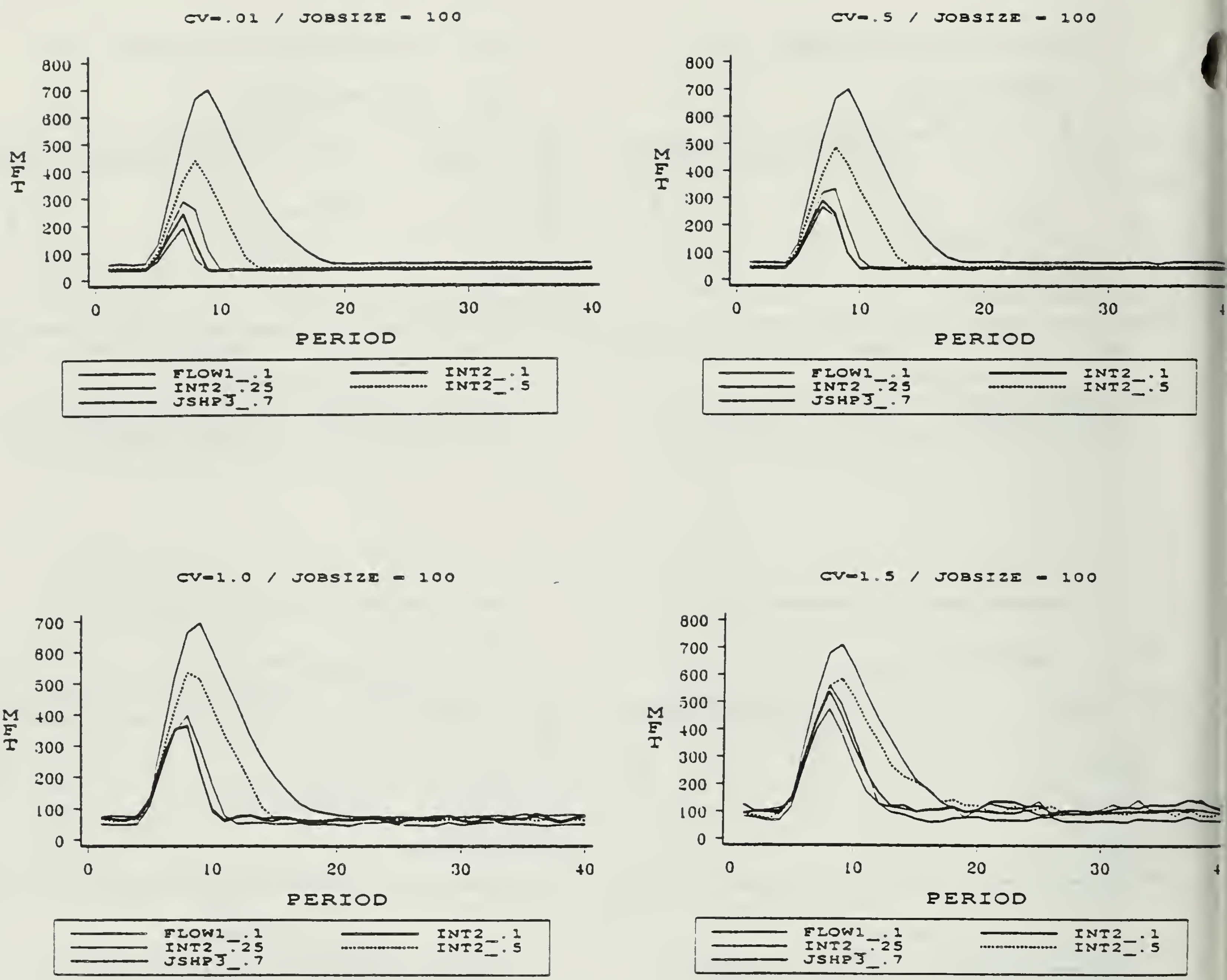
Time Series of Mean Flow-Time Performance for Shock Scenario
High Setup

Figure 6



Time Series of Utilization Percentage for Shock Scenario
High Setup

Figure 7



Time Series of Mean Flow-Time Performance for Shock Scenario Specific Process Designs

Figure 8

Appendix A – ANOVA

Class Level Information		
Class	Levels	Values
S (flow)	3	Flow shop, Int. Shop, Job Shop
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

Source	DF	ANOVA SS	F Value	Pr > F
S	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
S*L	4	472782.525	297.26	0.0
S*M	4	39921.473	25.10	0.0001
S*SU	8	606010.108	190.51	0.0
S*CV	6	708894.985	297.14	0.0
S*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
S*L*M	8	8647.920	2.72	0.0054
S*L*SU	16	264974.940	41.65	0.0
S*L*CV	12	334202.452	70.04	0.0
S*L*JS	16	47236.317	7.42	0.0001
S*M*SU	16	57664.512	9.06	0.0001
S*M*CV	12	6679.872	1.40	0.1574
S*M*JS	16	21072.817	3.31	0.0001
S*SU*CV	24	460832.966	48.29	0.0
S*SU*JS	32	163172.575	12.82	0.0
S*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

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