Scheduling with Sequencing Flexibility*

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ABSTRACT

This study examines the effects of sequencing flexibility on the performance of rules used to schedule operations in manufacturing systems. The findings show that taking advantage of even low levels of sequencing flexibility in the set of operations required to do a job results in substantial improvement in the performance of scheduling rules with respect to mean flowtime. Differences in the mean flowtime measure for various rules also diminish significantly with increasing sequencing flexibility. Performance improvements additionally result for such due-date related performance measures as mean tardiness and the proportion of jobs tardy. At high levels of sequencing flexibility, some nonparametric scheduling rules outperform the shortest processing time rule in terms of the mean flowtime criterion. Rules based on job due dates also outperform rules based on operation milestones in terms of tardiness related criteria at high levels of sequencing flexibility. The implications of these findings for the design of manufacturing systems and product design are noted.

Subject Areas: Production/Operations Management and Scheduling.

INTRODUCTION

Global competitive pressures in the manufacturing sector have resulted in renewed efforts to improve manufacturing operations. Recently, attention has focused on flexibility and its beneficial effects on manufacturing at both strategic and operational levels. Not surprisingly, technologies such as flexible manufacturing systems (FMS), computer integrated manufacturing (CIM), and robotics have gained a good deal of attention. However, a review of the literature on flexibility indicates that there are various types of flexibilities, and some of these flexibilities can be advantageously used without necessarily investing in capital intensive hardware technologies such as FMS. In this paper we investigate the effects of one such type of flexibility, namely sequencing flexibility, on the performance of a manufacturing system. Sequencing flexibility is a measure of alternate feasible sequences that can be used to schedule the operations of a job in a manufacturing system, even though each operation of the job can be performed on only one of the machines in the shop.

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This type of flexibility exists in conventional manufacturing systems as well as in new technologies such as FMS. Our evaluative studies show that using this flexibility can significantly improve the performance of scheduling rules and of manufacturing systems. A surprising finding, which is contrary to most early job shop studies, is that the shortest processing time rule need not necessarily outperform competing nonparametric dispatching rules for reducing the mean flowtime. This phenomenon occurs when a large amount of sequencing flexibility is present in the system, and it is appropriately used for scheduling purposes. Also, there is substantial reduction in the performance differences between various rules when sequencing flexibility is used. This is true for the mean flowtime criterion, as well as for due date related measures such as average tardiness and proportion of tardy jobs. Also, earlier research indicated that using operation milestones generally improves the performance of due date based rules such as the earliest due date rule, critical ratio rule, and the modified due date rule. Our study shows that these conclusions do not necessarily carry over when sequencing flexibility is available in the system. These findings have implications for both manufacturing system design and product design.

Our paper is organized as follows. First the concept of sequencing flexibility is discussed in detail, as well as how it can be quantitatively measured. The next section provides a review of the prior literature on using sequencing flexibility in making scheduling decisions. Then the procedures and competing rules used in our study to schedule jobs in flexible environments are described. The next section discusses simulation modeling issues, and also provides details on how the operation graphs for the jobs are generated, after which experimental design details are provided. Then an analysis of the simulation results is provided. Finally, implications of our study for manufacturing system design and future research directions are provided. Notation and acronyms used in the paper are shown in Table 1.

SEQUENCING FLEXIBILITY

The term flexibility has been used widely in prior research studies. It encompasses various types of flexibilities such as volume flexibility, variety flexibility, sequencing flexibility, material handling flexibility, product flexibility, expansion flexibility, and machine (or routing) flexibility. Some earlier studies [4] [9] [10] [26] [27] categorized various types of flexibility. Also, some researchers [5] [6] [7] [8] [11] addressed the issue of measuring various types of flexibility.

This paper analyzes the effects of sequencing flexibility on the performance of scheduling rules. Sequencing flexibility refers to the number of alternate sequences in which the operations of a job can be performed. It can easily be seen that sequencing flexibility is inherent in product structure rather than machine hardware. Sequencing flexibility does not depend on the type of machines. Even when each operation of a job can be performed on no more than one machine in the shop, there can be many alternate feasible operation sequences. The number of alternate feasible sequences can range from one (when operations have strict serial precedence) to $n_i!$ (when no precedence exists at all among the operations), where n_i is the number of operations for job i. Hence sequencing flexibility is present in conventional machining systems as well as with modern technologies such as FMS and

Table 1: Notation.

Parameters and Variables

λ	= job arrival rate,
μ	= mean service rate (= $1/\bar{p}$),
ρ	= machine utilization,
Λ_i	= the number of transitive precedence arcs in the operation graph of job i,
d_{ji}	= operation due date for the jth operation of job i,
k	= a constant used in determing flow allowance factors,
n_i	= number of operations for job i,
$\bar{p}$	= mean processing time for the operations,
p_{ji}	= processing time for the jth operation of the ith job,
A_i	= arrival time of job i,
D_i	= due date for job i,
I_i	= set of remaining operations of job i,
M	= number of machines in the system,
$\bar{N}$	= mean number of operations per job,
R_i	= number of remaining operations of job $i(=\lvert I_i \rvert)$,
S_{ji}	= number of immediate successors to the jth operation of job i,
U_{ji}	= priority index for the jth operation of ith job under the maximum successor ratio rule,
FAF	= flow allowance factor (also used as an acronym).

Acronyms

CR is critical ratio rule.
EDD is earliest due date rule.
EODD is earliest operation due date rule.
FIQ is first in queue rule (also known as FCFS).
FIS is first in system rule.
LWR is least work remaining rule.
MDD is modified due date rule.
MODD is modified operation due date rule.
OCR is operation critical ratio rule.
SFM is sequencing flexibility measure.
SPT is shortest processing time rule.

CIM. However, material handling facilities may sometimes restrict the use of sequencing flexibility. In most conventional systems, material handling is largely manual and/or centralized. Hence jobs can be transported between any pair of machines in either direction, directly or indirectly. But in automated manufacturing systems, material handling may restrict certain operation sequences if access from one machine to another machine is difficult or impossible.

In order to study the effects of sequencing flexibility on the performance of scheduling rules, it is necessary to quantify sequencing flexibility. One measure of sequencing flexibility is the number of feasible operation sequences in a job [13] [26]. The number of alternate feasible sequences is dependent partly on the number of operations to be performed. Clearly, if two jobs have the same number of feasible sequences, the job with a smaller number of operations is more flexible than the other with a larger number of operations. Hence it is appropriate to scale the number of feasible sequences with respect to the number of operations in a job. Rachamadugu and Schriber [20] derived a measure of flexibility, called the sequencing flexibility measure (SFM) which takes into consideration both the number of operations, and the number of feasible operation sequences. The sequencing flexibility measure (SFM) for job i is defined as follows:

$$\text{Sequencing flexibility measure} = 1 - \frac{2\Lambda_i}{n_i(n_i - 1)} \tag{1}$$

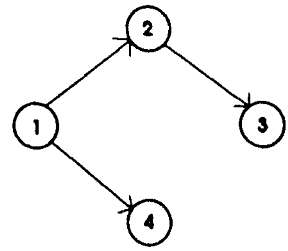
where Λ_i is the number of transitive precedence arcs in the operation graph of job i (see Table 1). The term transitive precedence arcs is used to represent precedence relations, both explicit and implicit, between all pairs of operations of a job. The denominator in the above expression is twice the potential number of acyclic precedence arcs that can exist in an operation graph of a job.

For example, consider the operation graph of a job shown in Figure 1. Though the figure shows only three explicit precedence arcs, an implicit precedence relation exists between operations 1 and 3. Hence the total number of precedence relations (both explicit and implicit), known as transitive precedence arcs, is four. The sequencing flexibility measure for the job shown in Figure 1 is therefore 1−(8/12), or .333. In the case of classical job shops, each job has a preassigned operation sequence, and hence the SFM value is zero. Gonzalez and Sahni [14] and Bitran, Dada, and Sisan [4] used the term open shops for situations in which each job visits all machines and there are no precedence restrictions among the operations of a job. The SFM value for open shops is 1. Clearly, the SFM value for most practical situations falls between 0 and 1. The expression shown in (1) is used as the measure of sequencing flexibility in this paper.

LITERATURE REVIEW

Baker [1], Conway, Maxwell, and Miller [10], and French [12] reviewed earlier research studies in job shop scheduling. Most studies treated the operations of a job as a fixed sequence. Very few researchers specifically addressed the impact of sequencing flexibility (when it exists and it is utilized) on the performance of scheduling rules in job shops. Russo [22] studied the effects of using sequencing flexibility on the performance of scheduling rules. He used both flowtime and due date (mean tardiness) related criteria to evaluate the performance of scheduling rules. His study identified different levels at which sequencing flexibility can be utilized. He showed that the greater the use of flexibility, the larger the improvement in the performance of scheduling rules. His studies were performed at a shop utilization level of 80 percent. Neimeier [17] studied the effect of sequencing flexibility on the performance of first come first serve (FCFS) and shortest processing Time (SPT) rules at various levels of sequencing flexibility. His study assigned operations to machines earlier than necessary, and hence did not fully exploit sequencing flexibility inherent in the jobs. He concluded that using sequencing flexibility improved the performance of the rules, and narrowed the performance differences between SPT and FCFS. However, SPT performed better than FCFS in all his studies. His conclusions were similar to those reported by Russo [22].

Figure 1: Operation graph.



Rachamadugu [19], Rachamadugu and Schriber [20], and Schriber [24] [25] investigated the effectiveness of sequencing flexibility on the performance of scheduling rules in job shops and generalized open shops (in a generalized open shop, while operations of a job can be performed in any order, a job need not visit all the machines in the shop). These studies show that, while SPT performs better than competing rules in conventional job shop studies, better results can be obtained by using the least work remaining (LWR) rule in generalized open shops. However, in most practical situations, manufacturing systems are neither as restrictive as the classical job shop studied in the literature (SFM value of zero), nor as flexible as the generalized open shop (SFM value of one) studied by Rachamadugu and Schriber [20]. Exploratory studies reported in [19] [20] [24] [25] were conducted using GPSS/H [23].

Lin and Solberg [16] recently studied flexibility issues in the context of flexible manufacturing systems. They concluded that utilizing both software and hardware flexibilities inherent in the system significantly improves the performance of scheduling rules. However, their study involved using combinations of routing flexibility, sequencing flexibility, and process flexibility available in the jobs and processes. Also, their findings were based on a specific flexible manufacturing system configuration. They observed that SPT and FIQ performed better than competing rules. Their study provides interesting insights into how the managerial control system can influence the effectiveness of flexibility. Their study did not explore the effects of flexibility on due date related criteria.

Our research extends earlier studies in the following ways. First, this study isolates and controls for the effects of sequencing flexibility. This is important because potential benefits which can be gained by using sequencing flexibility is independent of the manufacturing system hardware (unless there are very severe material handling restrictions). Hence it can be used in conventional systems as well as FMSs to improve system performance. Second, our study also addresses the effects of due date allowance (or flow allowance) on the performance of various rules when sequencing flexibility is utilized in making scheduling decisions. Third, our study also examines the interactive effects of using sequencing flexibility and setting operation due dates (milestones) on the performance of scheduling rules. This aspect of our study extends the earlier works of Kanet and Hayya [15], Baker and Kanet [3], and Baker [2] on operation milestones to more general situations.

Performance criteria used in this study are mean flowtime (an excellent surrogate for the system responsiveness and the level of inventories), average tardiness, and proportion of tardy jobs (good measures of customer service).

SCHEDULING WITH SEQUENCING FLEXIBILITY

Our study examined the performance of eleven scheduling rules at various levels of sequencing flexibility. These rules were chosen based on their use in the literature and their relevance to flexible situations and are described below:

1. First in queue rule (FIQ). Whenever a machine is available, highest priority is assigned to the job which arrived at this machine earliest. When a job has more than one assignable operation, it can be queued at more than one machine simultaneously. Note that the machine queues are virtual, not real. When one of these operations is assigned, the job is removed from the virtual queues at other machines. Hence a job may be queued at a machine more than once. Priority for a job at a machine is based on its most recent entry time into the machine queue. For classical job shops, this rule reduces to the well-known first-come-first-serve (FCFS) rule.
2. First in system rule (FIS). Highest priority is assigned to eligible operations of the job with the earliest system arrival time.
3. Shortest processing time rule (SPT). Highest priority is assigned to the job with the least processing time at the machine.
4. Least work remaining rule (LWR). Highest priority is assigned to the job with the least total remaining work to be performed.
5. Earliest due date rule (EDD). Highest priority is assigned to the job with the earliest due date.
6. Modified due date rule (MDD). Highest priority is assigned to the job with the earliest modified due date, where modified due date equals the maximum of the job's due date, and the earliest finish time of the job [3].
7. Critical ratio rule (CR). Highest priority is assigned to the job with the least ratio of remaining time until due date (dynamic slack) to the remaining processing time.
8. Earliest operation due date rule (EODD). Highest priority is assigned to the operation with the earliest operation due date. Procedure for setting operation due dates is shown in equation (4).
9. Modified operation due date rule (MODD). Highest priority is assigned to the operation with the earliest modified operation due date, where modified operation due date equals the maximum of the operation due date, and the earliest finish of the operation [2].
10. Operation critical ratio rule (OCR). Highest priority is assigned to the operation which has the least ratio of operation slack to the operation time.
11. Maximum successor ratio rule (MSUC). A priority index (U_{ji}) for the jth eligible operation of the ith job is determined as follows:

$$U_{ji} = \frac{S_{ji} + 1}{R_i} \tag{2}$$

where S_{ji} is the number of immediate successors to the jth operation of job i, and R_i is the total number of remaining operations of job i. Numerator is incremented by 1 to ensure that the last operation of a job is not left unfinished. Whenever a machine becomes available, an operation with the highest U_{ji} is assigned for processing on the machine. Since an operation with a large ratio tends to make eligible for assignment a large proportion of its successors, it is anticipated that it will lead to faster completion of the job.

Earlier job shop studies found that using operation milestones instead of job due dates improved the performance of scheduling rules. Also, Baker [2] found the total work content procedure to perform better than competing alternatives for setting due dates. This scheme was used to set the job due dates in our study. Job due date is given by the following:

$$D_i - A_i = (\text{Flow allowance}) \sum_{k=1}^{n_i} p_{ki} \tag{3}$$

where A_i and D_i denote the arrival time and the due date of job i, respectively, and p_{ki} represents the processing time for the kth operation of job i. In job shop studies, the operation sequences for jobs are fixed, and hence the operation due dates can be set at the time of job arrival [2] [15]. When flexibility exists in sequencing the operations, and it is used in scheduling operations, it is not known a priori in which sequence the operations will be executed. Hence the operation due date for an operation needs to be computed whenever it becomes eligible for assignment. Operation due date for the jth operation of job i (d_{ji}) is given by the following expression:

$$d_{ji} = A_i + \frac{D_i - A_i}{\sum_{k=1}^{n_i} p_{ki}} \left(p_{ji} + \sum_{l \in I_i} p_{li}\right) \tag{4}$$

where I_i represents the set of remaining operations of job i. Clearly, schedules generated using operation due dates and job due dates need not be identical. Note that (4) results in the same operation milestones as those suggested by Kanet and Hayya [15] and Baker [2] for classical job shops. However, (4) extends those concepts to more general situations in which the scheduler has no a priori knowledge of the sequence to be used in dispatching the jobs. Other operation due date setting procedures are possible, but they are not explored here.

MODELING ISSUES

The first part of this section describes how operation graphs are generated and then issues relating to modeling sequencing flexibility are discussed. The first step in generating an operations graph is to detemine the number of operations n_i randomly for the job. The operations of a job are indexed sequentially, 1, 2, ..., n_i. Next, two integers x and y in $[1,n_i]$ are randomly sampled such that $x \neq y$. Without loss of generality, assume that $x<y$. If a transitive precedence arc already exists between x and y, then x and y are discarded, and a new random pair of operations is sampled. Else, a direct precedence is imposed between the operations x and y, with x preceding y. This ensures that the operation graph is acyclic. Also, implicit precedence arcs are recognized by making x (and all its predecessors) be predecessors of y (and all its successors). This process is repeated until enough transitive precedence arcs have been generated, as needed by the sequencing flexibility measure value (1).

As an example, consider how operation graph shown in Figure 1 can be generated. Its SFM value is 1/3. Hence four transitive precedence arcs (1) need to be generated. Let the first chosen random pair be (1,4). Operation 1 is restricted to be performed before operation 4. Let the next chosen random pair be (2,3). This results in the precedence restriction that operation 2 should precede operation 3. Suppose the next randomly chosen pair is (1,4). Since a precedence relation exists between (1,4), this pair is discarded, and another pair is sampled. Let (1,2) be the next chosen pair. Hence operation 1 is restricted to precede operation 2. Since a precedence already exists between 2 and 3, this results in an additional transitive precedence arc, (1,3). Now there are four transitive precedence arcs, (1,2), (2,3), (1,3), and (1,4). Hence the operation graph is now complete.

Modeling sequencing flexibility proved challenging. Whenever a job had more than one eligible operation (an operation whose predecessor operations had been completed), a copy of the job was created for each of the eligible operations. Each copy joined the virtual queue at the machine at which the corresponding operation had to be performed. When processing began on any one of these operations, all other copies of the job were destroyed. This ensured that no two operations of a job would be carried out simultaneously. Later, when the ongoing operation was completed, copies of the job were then created for each remaining eligible operation, and so on, until all operations had eventually been completed. The set of steps followed in moving a job through its life cycle is summarized in the flowchart in Figure 2.

EXPERIMENTAL DESIGN

The shop simulated in our model consisted of ten machines. The number of operations in each arriving job was chosen from a discrete [4,8] uniform distribution. Because operations are randomly assigned to machines, a job may visit a machine more than once. Operation processing times were sampled from a negative exponential distribution with a mean of 5.0 time units. Because earlier studies [16] [20] found that the performance differences between scheduling rules were not significant at low utilization levels, job arrival rate was set to result in a high utilization of 90 percent. Resource input, work output, and the system utilization are related by the following expression

$$\text{System utilization} = \frac{\text{Work output}}{\text{Resource input}} = \frac{\lambda(1/\mu)\overline{N}}{M} \tag{5}$$

where λ, $\overline{N}$, μ, and M denote the mean arrival rate, mean number of operations per job, service rate at each machine center, and the number of machines in the system, respectively. Using (5), the mean arrival rate was set at 3/10 jobs per time unit to result in a system utilization of 90 percent. The corresponding interarrival times were also sampled from a negative exponential distribution.

There are three factors in the experiment: the level of sequencing flexibility (SFM), the flow allowance factor (FAF), and the scheduling rule. SFM values can range from 0 to 1, the former representing no sequencing flexibility (classical job shops) while the latter permits operations of a job to be performed in any order (open shops and generalized open shops). Because product structures in practice do not necessarily fall at the two extremes, we varied SFM values from 0 to 1, in increments of .2. Hence we have six SFM values. Flow allowances were set using a procedure earlier suggested by Baker and Kanet [3]. Flow allowances were set at $.25k$, $.5k$, k, $2k$, and $4k$ where k is a factor such that k times the mean machine processing time p equals the mean flowtime for a job in an M/M/1 queueing system with the same utilization as in our study (90 percent). From the basics of queueing theory [26],

$$\text{Mean flowtime} = k\bar{p} = \frac{1}{\mu(1-\rho)} \tag{6}$$

where ρ represents the expected machine utilization. Since $\bar{p}=1/\mu$, (6) can be rewritten as

$$k = \frac{1}{1-\rho} \tag{7}$$

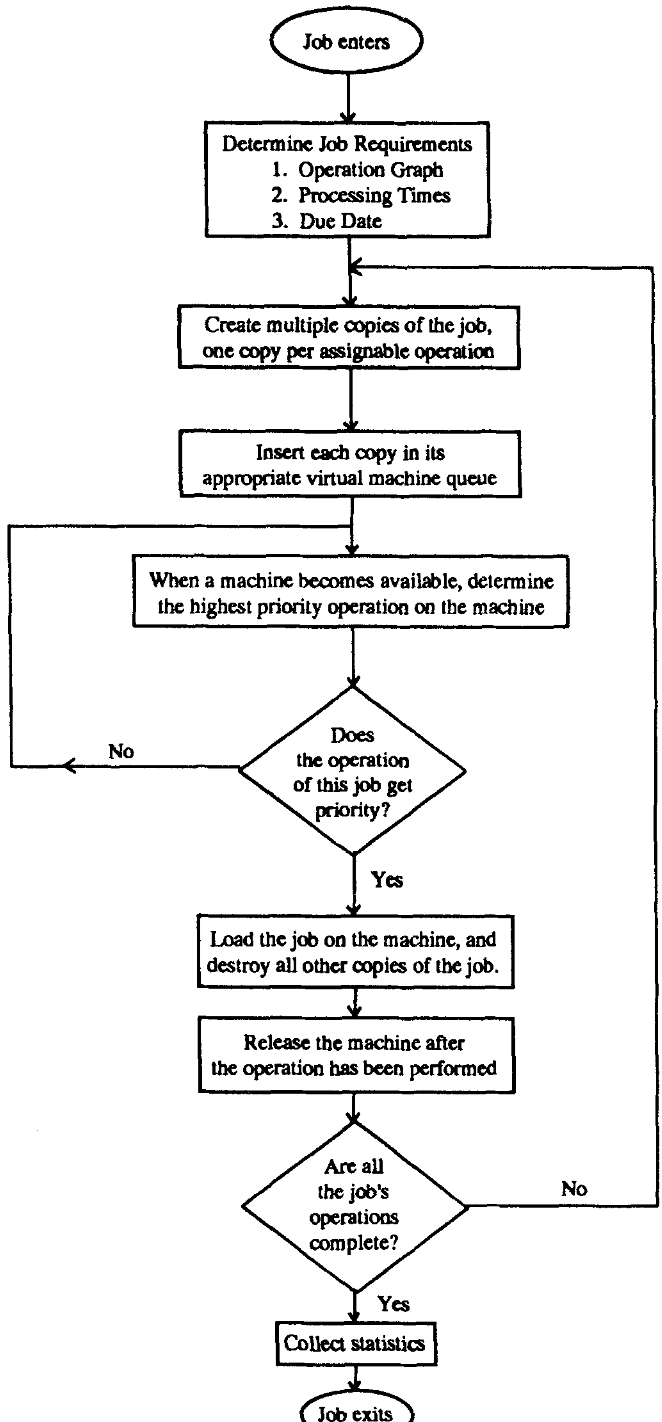
Using ρ=.9 in (7), k equals 10. Hence we used flow allowance values of 2.5, 5, 10, 20, and 40 in our experiments.

A full factorial design was used to study the performance of various scheduling rules. Six SFM values, five flow allowance factors, and eleven scheduling rules resulted in 330 experimental settings. A single replication was performed for each experimental setting. For purposes of testing for steady state, a replication was partitioned into a sequence of twelve consecutive, nonoverlapping batches, each corresponding to 20,000 time units (approximately 6,667 jobs). The performance measures of interest were then averaged over the last ten batches, giving the results reported here.

Common random numbers [23] were used in the experiments. This was done by dedicating independent random number generators to each source of randomness in the model. The net effect was that from experiment to experiment, any given job moving through the system had the same time of arrival, same number of operations, same set of required machines, and the same set of operation times. Job sets under different SFM settings were therefore identical to each other, except that for larger SFM values jobs had additional transitive precedence arcs imposed on them. This use of common random numbers sharpens the contrast in the performance measures achieved by the alternate scheduling rules.

The model was written in SIMAN [18], and was supported in part by subroutines coded in Fortran 77. The experiments were run on an Hitachi Data Systems 9080 computer.

Figure 2: Job life cycle in the simulation model.



VERIFICATION OF RESULTS

Three aspects of our study were used to verify the simulation results. First, the realized machine utilization was compared with the expected utilization. While the expected machine utilization was 90 percent, the realized mean machine utilization was 90.1 percent, and the range was 89.2 to 91.6 percent. Second, the batch mean flowtimes in each experiment were tested for autocorrelation using the Durbin-Watson statistic. In all cases, the existence of autocorrelation could not be confirmed for the batch mean flowtimes at a significance level of 5 percent. Details are shown in Table A1. Similar results were observed for the mean tardiness and proportion of tardy jobs, with some exceptions. These exceptions occurred when the tardiness and the proportion of tardy jobs were driven to very small values (close to zero, when flow allowances are large). Also, in cases where the performance measures were identical, the Durbin-Watson statistic could not be computed. Third, the special cases of no sequencing flexibility correspond to classical job shop studies. Our results for these special cases are similar to those derived by earlier researchers.

ANALYSIS OF RESULTS

This section analyzes the results of the simulation experiments (detailed results are provided in Table B1). The first part of the analysis focuses on the effect of sequencing flexibility on the mean flowtime performance of the alternative scheduling rules.

Figure 3 compares the mean flowtimes for scheduling rules at different flexibility levels. FIQ was excluded from Figure 3 since it performed worse than FIS under all settings. Also, the MSUC rule was eliminated from the figure since its performance was worse than well known rules from the prior literature. Results for due date based rules are shown at a flow allowance factor value of 1, which corresponds to the average flowtime for a job with average processing time. Note the beneficial effects of using sequencing flexibility. All rules included in our study improve their flowtime performance as the SFM value increases. It is clear that even a small degree of sequencing flexibility provides improvements in the mean flowtime performance. Relative to classical job shops, Table 2 lists the reduction in flowtimes for various rules at SFM values of .2 and 1. With the exception of the operation critical ratio rule (OCR), rules which perform poorly with no sequencing flexibility achieve large improvements at an SFM level of 1.0. For example, an arbitrary rule such as FIS improves its mean flowtime by 52.2 percent while the improvement for SPT is only 23.6 percent.

Classical job shops have an SFM value of zero. While SPT performs better than competing rules in classical job shops (see a recent survey by Ramasesh [21]), the least work remaining rule provides superior performance at high SFM values. Earlier job shop studies did not address perfect sequencing flexibility (SFM=1). Hence those studies did not uncover the superior performance of LWR at high SFM values.

Our study focuses on the interaction between the flowtime performance of due date related rules and flow allowances. As the flow allowance factor increases, due date based rules improve their performance with respect to due date related criteria. However, earlier research did not focus on the effects of flow allowance on flowtime

Figure 3: Mean flow time as a function of sequencing flexibility measure for selected scheduling rules.

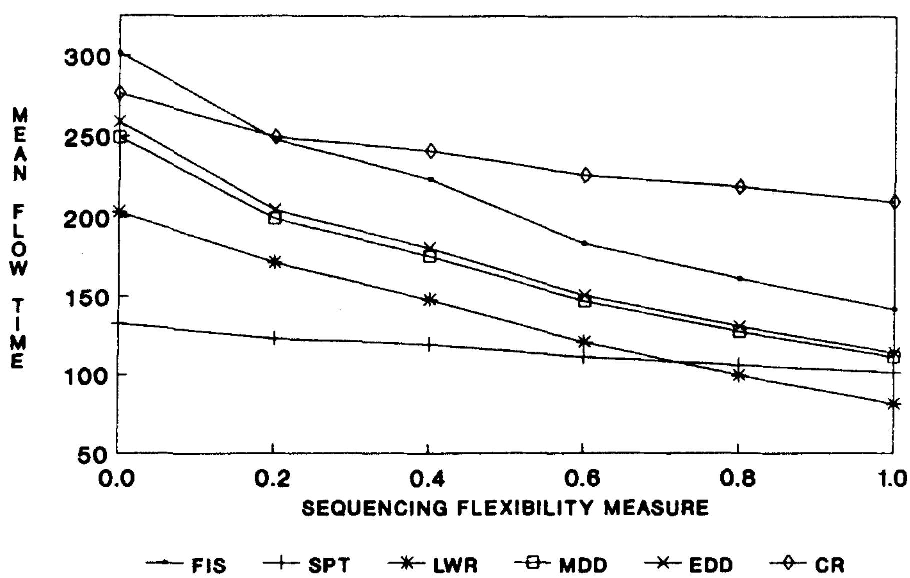


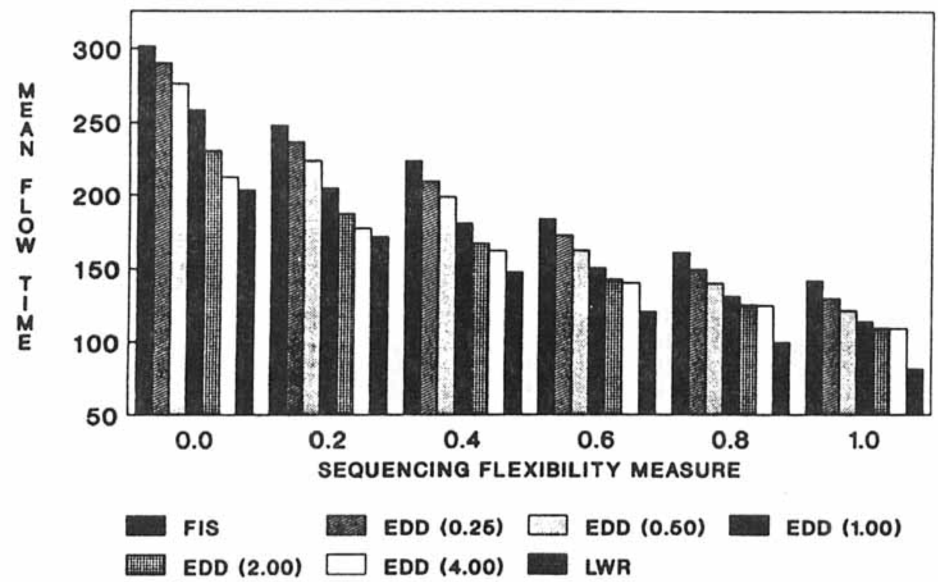
Table 2: Percent reduction in mean flowtimes.

Scheduling Rule	Mean Flowtime at SFM=0 (Job Shops)	Reduction in Mean Flowtime in Comparison with No Flexibility (in Percent)	
		SFM=.2	SFM=1.0
FIS	301.6	17.7	52.2
MSUC	297.6	24.4	63.8
CR*	276.4	9.7	24.0
EDD*	258.6	20.8	55.9
OCR*	254.8	4.8	10.8
MDD*	249.2	19.9	55.3
EODD*	213.9	11.8	36.8
LWR	203.2	15.5	59.9
MODD*	196.7	9.3	32.5
SPT	132.8	7.2	23.7

Note: the performance of rules marked * is reported at a flow allowance factor of 1.

performance of due date based rules. First, let us consider the EDD rule. Clearly, at very low flow allowances, priorities assigned by EDD and FIS are similar. If FAF is zero, EDD reduces to FIS. However, EDD imitates LWR at very large flow allowances. Hence the flowtime performance of EDD improves as FAF increases, and is also bounded by LWR and FIS, as shown in Figure 4.

Figure 4: Variation in mean flow time for earliest due date rule (with FIS and LWR as bounding cases).

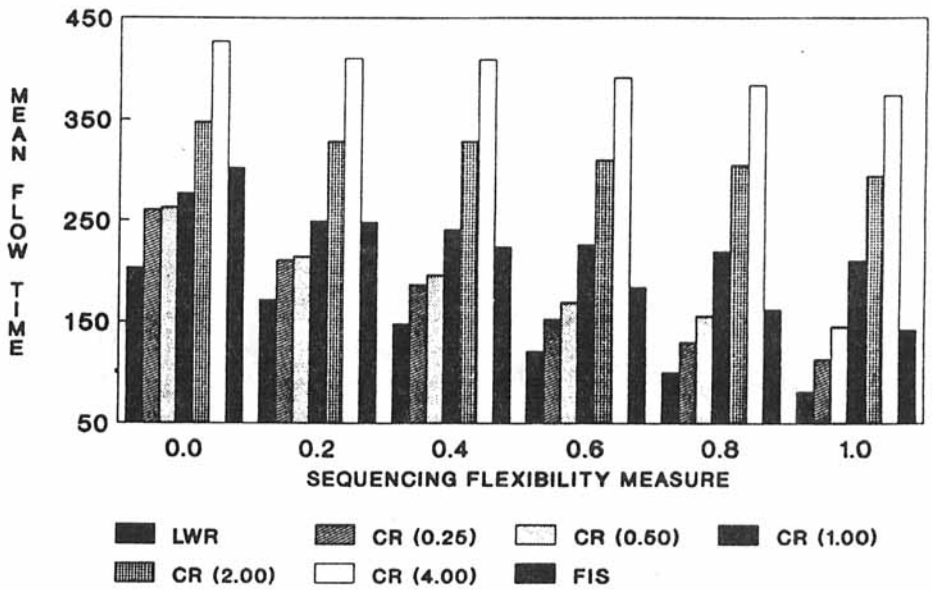


The flowtime performance of the CR rule deteriorates at all SFM values as the FAF increases (Figure 5). This means that EDD and CR perform in opposite ways for the flowtime criterion as FAF increases (compare Figures 4 and 5). This can be explained as follows. As the FAF decreases, jobs tend to have negative slack, and hence CR tends to assign jobs with a small amount of remaining work higher priority (some implementations of the CR rule disregard critical ratio indexes and invoke the shortest remaining processing time rule when one or more jobs have negative slack). When FAF values are large, slack tends to be positive, and hence jobs with the most remaining work are assigned higher priority (unless the queue at the machine has some tardy jobs). This explains the deteriorating performance of the CR rule at high FAF values. Though large FAF values improve the tardiness performance of the CR rule, those benefits are partly offset by an increase in inventories. This aspect of CR merits further investigation.

Next consider the flowtime performance of the modified due date rule. By definition, it is clear that MDD tends to imitate LWR at low FAF values. However, at high FAF values, MDD behaves more like the EDD rule. These patterns are evident from Table 3, which compares the performance of these rules at different SFM values.

Kanet and Hayya [15] noted in their job shop studies that when operation milestones are used, the performance of job due date based rules and the slack based rules improve. Our results lead to somewhat different conclusions, as shown in Figures 6, 7, and 8. In the case of EDD and EODD rules (Figure 6), our study reaffirms the conclusions of Kanet and Hayya [15] for the classical job shop. However, where flow allowances are large, setting operation due dates results in

Figure 5: Variation in mean flow time for the critical ratio rule (with LWR and FIS shown for comparison).



deteriorating performance even when small amounts of sequencing flexibility is present, and utilized. At extremely high SFM values, operation milestones worsen the performance of EDD for all FAF values in our study. Similar patterns can also be observed for MDD (Figure 7). In the case of the critical ratio rule, using operation due dates can increase mean flowtimes even in classical job shops (Figure 8). This has implications for tardiness performance as well, as discussed below.

The rest of our analysis relates to due date related criteria. Since FIS, FIQ and MSUC performed significantly worse than competing rules, their tardiness performance is excluded from further analysis. Figure 9 shows the average tardiness results for competing rules at a low FAF value of .25. It can be seen that as the SFM value increases, performance differences between the rules diminish significantly. At low SFM values, SPT and MODD perform extremely well. However, when the SFM value is high, MDD outperforms competing rules. This is not surprising, since in tight due date settings MODD and MDD emulate SPT and LWR, respectively. Our prior analysis indicates that while SPT yields the smallest flowtimes at low SFM values, LWR results in the least flowtime at high SFM values. This explains the superior performance of MODD at low SFM and MDD at high SFM values. Similar patterns can also be observed for the CR and EDD rules. While operation due date versions perform well at low SFM values (classical job shops), job due date versions dominate at high SFM values.

Figure 10 shows the tardiness performance of selected rules when FAF equals 1. Though SPT and LWR were competitive at the low FAF of .25, they are clearly dominated by due date based rules when FAF equals 1. Once again, it can be seen that

Table 3: Comparison of MDD with LWR and EDD (mean flowtime).

Flow Allowance		SFM VALUE					
		0	.2	.4	.6	.8	1.0
Low	LWR	203.21	171.55	147.81	120.75	99.71	81.43
(.25)	MDD	209.37	173.27	154.74	124.96	104.65	87.59
High	EDD	212.24	177.23	162.37	140.29	124.87	109.41
(4.0)	MDD	213.51	177.60	160.61	138.57	123.70	107.99

performance differences between various due date related rules diminish rapidly as the level of flexibility in sequencing the operations increases. MODD performs the best at low SFM values, while MDD dominates the other rules at high SFM values (also see the shaded cells in Table B2). In generalized open shops, MDD outperforms other rules. However, performance differences between MDD and MODD at this SFM value are insignificant. Increasing flow allowances beyond 1 results in all due date rules performing well, with the differences becoming insignificant from a practical point of view (for details, see Table B2). However, at high flow allowance values (FAF=2 or 4), operation milestone versions are clearly dominated by job due date versions of rules for all SFM values. Earlier, Baker and Kanet [3] commented on this phenomenon for job shops. Our study shows that those conclusions can be generalized to precedence constrained operations as well.

Our study not only reaffirms earlier research conclusions that MODD is a good choice for classical job shops, but also extends its usefulness to situations where sequencing flexibility exists in the system. At extremely high SFM values, MDD is a better choice than MODD.

The proportion of tardy jobs is yet another measure of performance which is of interest to practitioners. For example, in some industries such as the furniture industry, the manufacturer incurs freight expense if the delivery is late. In such situations, the proportion of tardy jobs is a better surrogate for profit than tardiness. Figure 11 shows the proportion of tardy jobs for the rules at a low FAF value of .25. All rules improve their performance as the SFM increases. SPT outperforms all other rules at low SFM values ($\leq$.6), and LWR performs the best at high SFM values. Superior performance of SPT for the proportion tardy criterion was noted earlier by Baker [2] for classical job shops. Our study extends its validity for low sequencing flexibility situations as well. However, at high SFM values, job based rules perform better than operation based rules. Unlike other measures, there is little convergence in the performance of rules as the SFM is increased. Figure 12 shows the results for a flow allowance value of 1. Though SPT dominates the other rules for job shop situations, MODD provides not only comparable performance for job shops, but also dominates other rules for low SFM values ($\leq$.6). MDD provides superior performance for high SFM values ($>$.6). At higher flow allowances (FAF=3,4), performance differences between the rules diminish rapidly (details are shown in Table B3).

Figure 6: Mean flow time difference, EDD-EODDD.

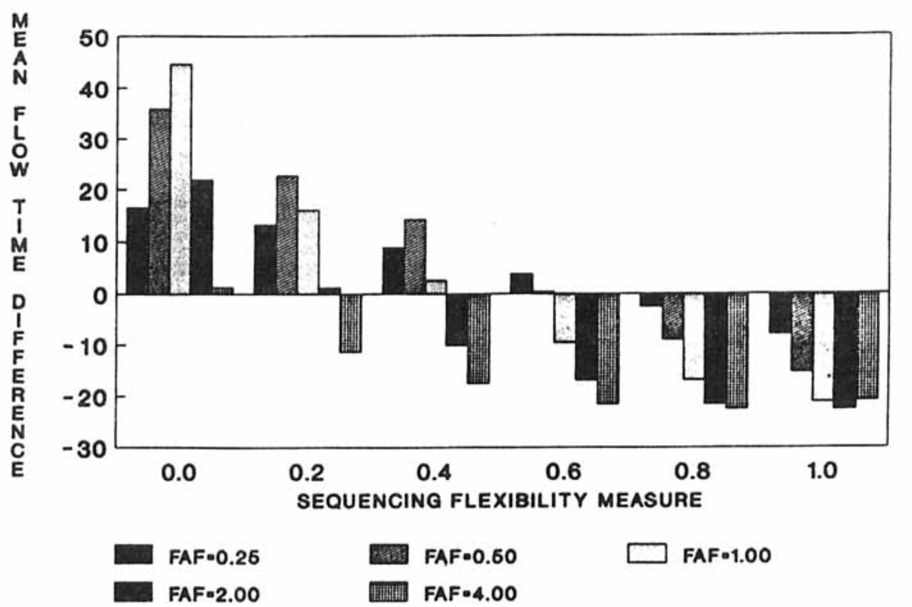


Figure 7: Mean flow time difference, MDD-MODD.

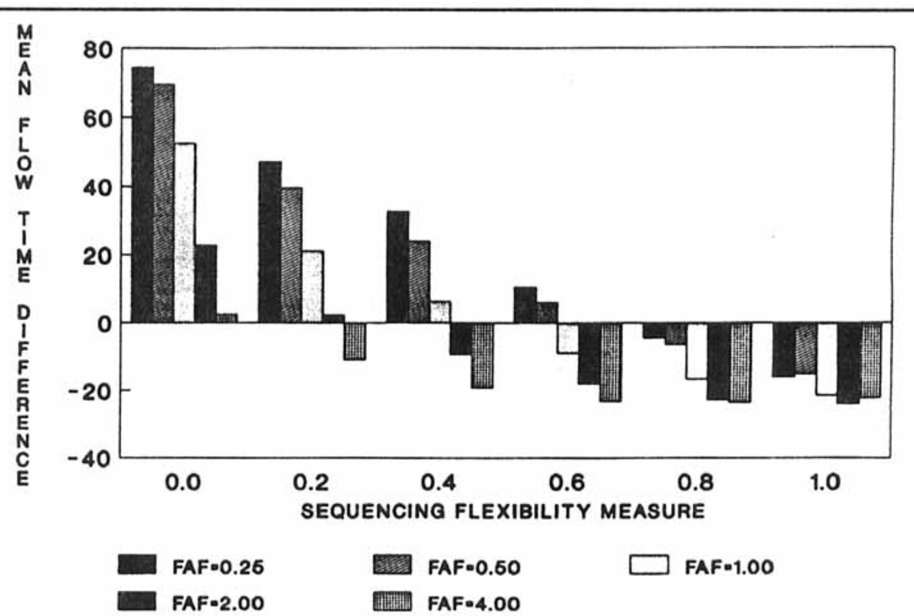


Figure 8: Mean flow time difference, CR-OCR.

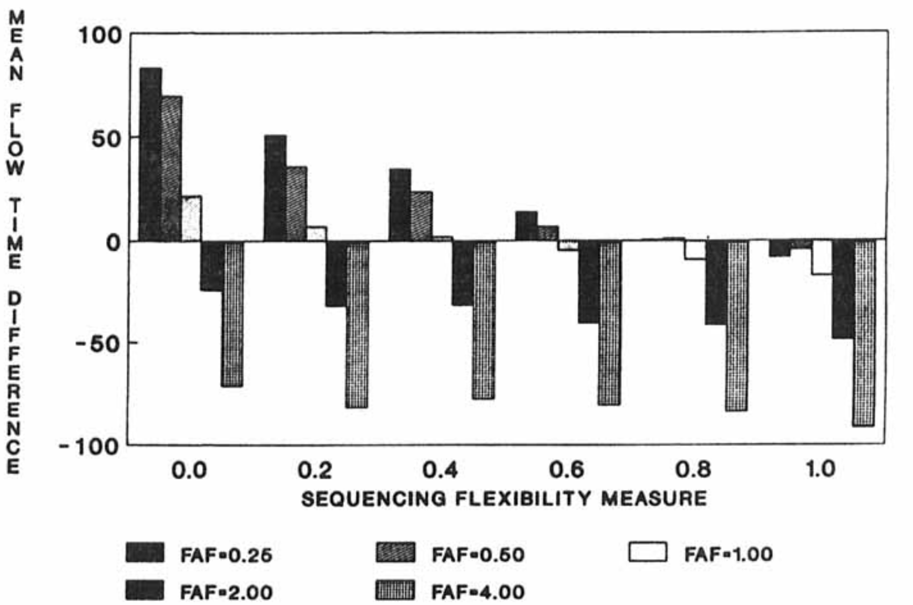


Figure 9: Tardiness performance of selected scheduling rules, flow allowance factor, .25.

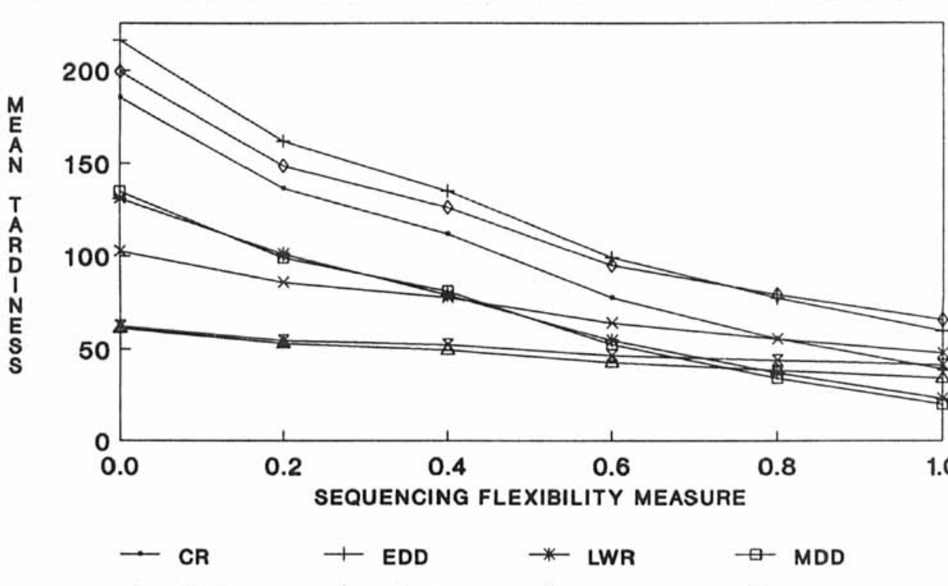


Figure 10: Tardiness performance of selected scheduling rules, flow allowance factor, 1.00.

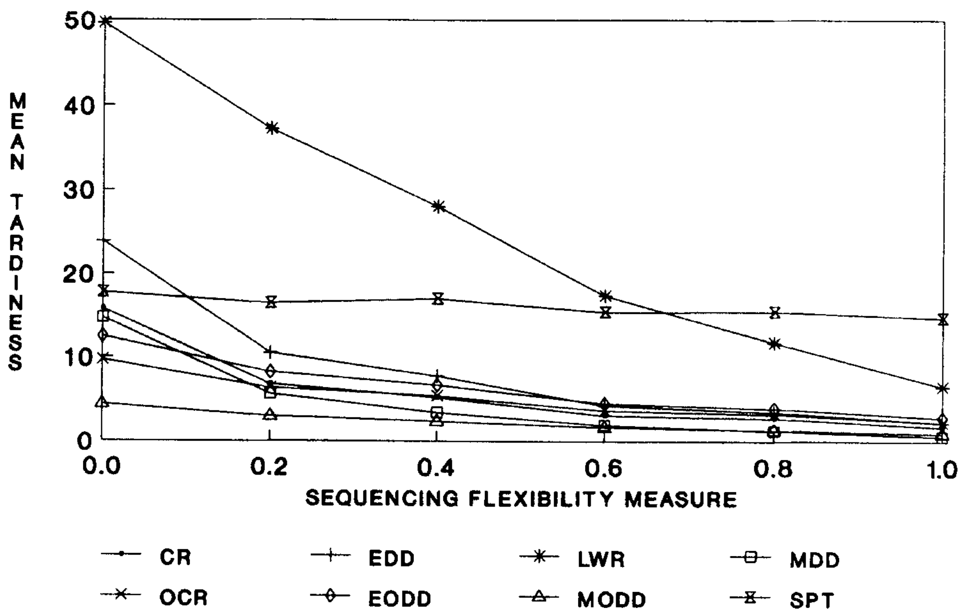


Figure 11: Proportion of tardy jobs for selected scheduling rules, flow allowance factor, .25.

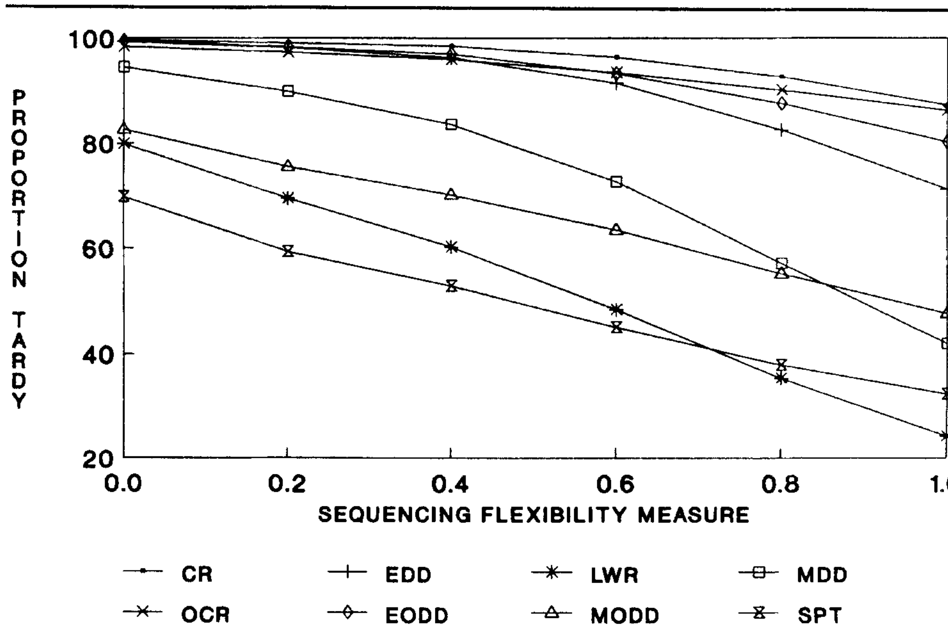
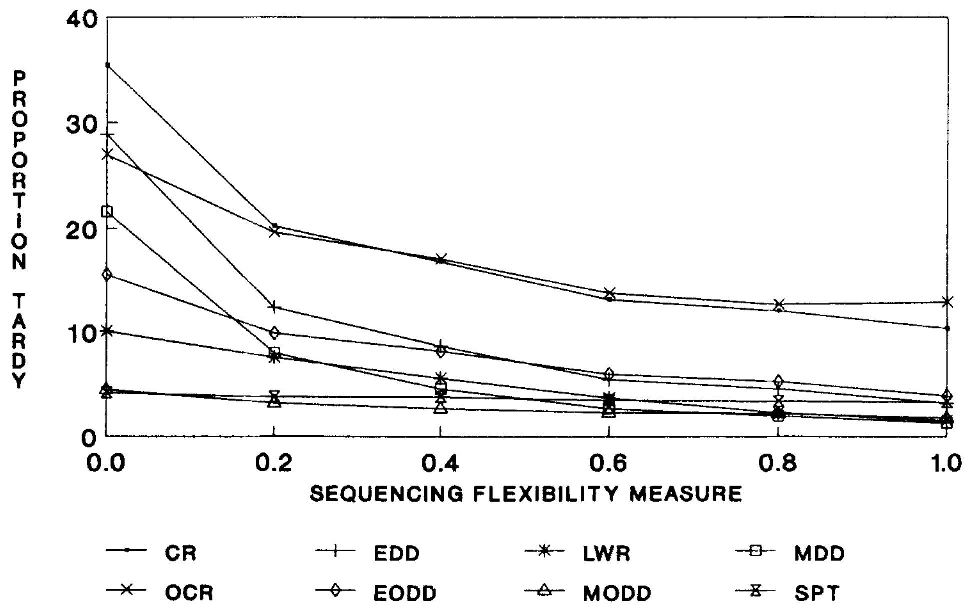


Figure 12: Proportion of tardy jobs for selected scheduling rules, flow allowance factor, 1.00.



CONCLUSIONS

Our study shows that manufacturing system performance can be improved by utilizing the sequencing flexibility inherent in the operations of jobs. The performance measures studied included mean flowtime, average tardiness, and proportion of tardy jobs. All rules in our study improve their performance at increasing levels of sequencing flexibility. However, performance differences between the rules also diminish significantly at high flexibility values. Results of our study have implications for the choice of scheduling rules, production control, economic justification of manufacturing information systems, and product design.

When operations have a high level of sequencing flexibility, the least work remaining rule performs better than the SPT rule in reducing the mean flowtime (and inventories). The importance of this criterion warrants its investigation using an approximate analytical model, if an exact model is mathematically or computationally intractable. Our investigations also highlighted the effects of flow allowance on the flowtime performance of EDD and CR. While the earliest due date rule improves its performance as flow allowance is increased, the critical ratio rule performance worsens.

Earlier researchers concluded that MODD performs well in job shops for the tardiness criterion. This superior performance carries over also to situations in which sequencing flexibility is used in scheduling. However, at high SFM values, MDD performs better than its operation due date version. For the proportion tardy criterion, there was no distinct choice. Depending on the flexibility and flow allowance values, one of the four rules (SPT, LWR, MODD, and MDD) performed best in our studies.

Our findings have implications for the design of production planning and control systems. A major factor in the design of shopfloor control systems is the choice of appropriate dispatching rules. Since utilizing sequencing flexibility (when available) results in diminishing differences between dispatching rules, shop floor control systems can shift their focus to other relevant criteria such as load control, predictability of flowtimes, schedule stability, etc.

Analysis provided in this paper is also useful in the economic evaluation of investments in realtime manufacturing information systems. Availability of these systems facilitates utilizing sequencing flexibility in production scheduling. Resulting benefits such as reduced inventories and improved customer service (from reduced tardiness and proportion of tardy jobs) can be used in the economic justification of manufacturing information systems.

Finally, our analysis has interesting implications for product design. If the sequencing flexibility measure can be increased (or the density of the operations graph can be decreased) at the product design stage, it will lead to improvements in shop operations. Product designers need to take this into consideration while choosing among alternate product designs. [Received: May 20, 1992. Accepted: October 9, 1992.]

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APPENDIX A

Table A1: Durbin-Watson statistic for mean flow time.

Scheduling Rule*	Sequencing Flexibility Measure .00	.20	.40	.60	.80	1.00
FIQ	2.684	2.650	2.501	2.650	2.445	2.495
FIS	2.959	2.546	2.503	2.651	2.491	2.523
SPT	2.958	2.499	2.438	2.623	2.491	2.509
LWR	2.955	2.294	2.324	2.523	2.271	2.581
EDD(.25)	2.856	2.615	2.446	2.600	2.428	2.482
EDD(.50)	2.873	2.316	2.353	2.676	2.397	2.456
EDD(1.0)	2.857	2.156	2.346	2.559	2.472	2.347
EDD(2.0)	2.806	2.374	2.423	2.508	2.438	2.302
EDD(4.0)	3.113	2.418	2.466	2.426	2.424	2.354
OCR(.25)	2.830	2.679	2.322	2.570	2.535	2.353
OCR(.50)	2.680	2.620	2.289	2.478	2.497	2.304
OCR(1.0)	2.776	2.365	2.227	2.443	2.373	2.444
OCR(2.0)	2.619	2.386	2.266	2.409	2.315	2.533
OCR(4.0)	2.858	2.389	2.155	2.489	2.393	2.543
CR(.25)	2.873	2.264	2.501	2.545	2.398	2.376
CR(.50)	2.769	2.236	2.303	2.500	2.322	2.349
CR(1.0)	2.852	2.306	2.315	2.566	2.427	2.494
CR(2.0)	2.798	2.648	2.251	2.576	2.547	2.505
CR(4.0)	2.845	2.614	2.431	2.615	2.395	2.537
EODD(.25)	2.864	2.674	2.430	2.648	2.585	2.465
EODD(.50)	2.911	2.683	2.594	2.732	2.600	2.437
EODD(1.0)	2.730	2.645	2.485	2.618	2.566	2.415
EODD(2.0)	2.462	2.616	2.235	2.561	2.456	2.212
EODD(4.0)	2.312	2.402	2.340	2.532	2.383	2.359
MODD(.25)	2.841	2.511	2.399	2.629	2.544	2.433
MODD(.50)	2.895	2.600	2.393	2.472	2.388	2.395
MODD(1.0)	2.823	2.561	2.437	2.648	2.573	2.441
MODD(2.0)	2.514	2.495	2.272	2.561	2.456	2.212
MODD(4.0)	2.612	2.402	2.340	2.532	2.383	2.359
MSUC	2.515	2.581	2.566	2.803	2.491	2.779
MDD(.25)	2.832	2.429	2.420	2.695	2.580	2.558
MDD(.50)	2.940	2.141	2.400	2.458	2.391	2.464
MDD(1.0)	2.784	2.169	2.392	2.595	2.432	2.425
MDD(2.0)	2.744	2.282	2.390	2.440	2.432	2.277
MDD(4.0)	2.980	2.312	2.465	2.512	2.415	2.347

Note: The numbers in parenthesis indicate flow allowance factors used to determine due dates.

APPENDIX B

Table B1: Mean flow time.

Scheduling Rule*	Sequencing Flexibility Measure .00	.20	.40	.60	.80	1.00
FIQ	309.80	262.23	241.90	206.67	181.44	156.55
FIS	301.68	248.02	223.64	183.72	161.67	142.06
MSUC	297.62	224.92	187.58	150.60	127.08	107.63
SPT	**132.80**	**123.12**	**119.40**	**111.30**	106.29	101.36
LWR	203.21	171.55	147.81	120.75	**99.72**	**81.43**
OCR(.25)	177.34	160.43	152.26	138.27	129.24	121.14
CR(.25)	260.45	211.23	186.65	152.20	129.69	112.77
EODD(.25)	274.24	223.36	200.65	169.07	152.18	137.72
EDD(.25)	290.74	236.64	209.52	172.87	149.66	129.77
MODD(.25)	134.95	126.09	122.36	114.39	109.14	103.69
MDD(.25)	209.37	173.27	154.74	124.96	104.65	87.59
OCR(.50)	193.19	179.06	172.54	162.41	155.04	149.63
CR(.50)	262.87	214.76	196.07	169.15	156.02	145.31
EODD(.50)	241.01	201.19	184.37	162.58	149.21	137.07
EDD(.50)	276.93	223.94	198.60	162.89	140.22	121.74
MODD(.50)	159.84	149.64	144.89	134.98	127.84	120.68
MDD(.50)	229.39	189.26	168.85	140.92	121.45	105.65
OCR(1.0)	254.83	242.51	239.42	231.04	228.89	227.22
CR(1.0)	276.41	249.49	241.17	226.24	219.39	209.89
EODD(1.0)	213.96	188.67	178.28	160.26	148.06	135.15
EDD(1.0)	258.63	204.77	180.89	150.70	131.15	114.03
MODD(1.0)	196.73	178.36	169.44	155.98	144.30	132.72
MDD(1.0)	249.23	199.40	175.72	147.10	127.63	111.28
OCR(2.0)	371.97	360.46	360.14	350.54	346.18	342.27
CR(2.0)	347.37	328.11	328.22	309.88	304.43	293.61
EODD(2.0)	280.76	187.19	177.42	159.62	147.09	132.40
EDD(2.0)	230.63	187.37	167.35	142.77	125.57	109.88
MODD(2.0)	207.85	186.55	177.19	159.62	147.09	132.40
MDD(2.0)	230.60	188.80	167.90	141.63	124.32	108.49
OCR(4.0)	498.22	492.07	486.64	471.85	467.70	465.44
CR(4.0)	426.83	410.24	409.03	391.16	383.82	373.78
EODD(4.0)	210.99	188.58	179.87	161.82	147.32	130.25
EDD(4.0)	212.24	177.23	162.37	140.29	124.87	109.41
MODD(4.0)	210.99	188.58	179.87	161.82	147.32	130.25
MDD(4.0)	213.51	177.60	160.61	138.57	123.70	107.99

Notes: The numbers in parenthesis indicate flow allowance factors used to determine due dates. Bold numbers indicate minimum values for each column.

Table B2: Mean tardiness.

Scheduling Rule*	Sequencing Flexibility Measure					
	.00	.20	.40	.60	.80	1.00
FIQ(.25)	235.14	187.79	167.55	133.06	108.68	85.22
FIS(.25)	226.90	173.56	149.50	110.71	90.29	73.01
MSUC(.25)	225.26	154.65	118.53	83.44	62.26	45.79
SPT(.25)	62.33	54.74	52.54	46.57	44.04	41.48
LWR(.25)	131.00	101.06	79.15	54.87	37.44	23.28
OCR(.25)	102.54	85.80	77.62	64.20	55.62	47.97
CR(.25)	185.61	136.44	111.85	77.74	55.69	39.46
EODD(.25)	199.40	148.72	126.11	95.15	79.17	65.99
EDD(.25)	215.92	161.99	135.07	99.20	77.48	59.95
MODD(.25)	**61.28**	**53.04**	**49.59**	**42.82**	38.66	34.53
MDD(.25)	134.87	99.08	81.09	52.63	**34.45**	**20.21**
FIQ(.50)	166.79	123.73	104.94	76.28	58.17	42.28
FIS(.50)	156.64	108.21	88.73	58.73	46.05	35.69
MSUC(.50)	173.73	113.78	82.69	53.52	37.91	26.75
SPT(.50)	33.68	30.66	30.89	27.89	27.29	26.27
LWR(.50)	87.18	65.70	49.95	32.72	21.79	12.89
OCR(.50)	49.21	37.63	32.77	25.45	20.70	16.49
CR(.50)	114.43	68.38	51.29	28.83	19.86	13.38
EODD(.50)	96.62	62.32	50.11	35.54	29.02	23.49
EDD(.50)	130.28	82.08	62.29	37.71	27.20	19.81
MODD(.50)	**26.29**	**20.59**	**18.60**	**14.37**	12.03	9.87
MDD(.50)	83.69	49.23	35.01	18.07	**10.43**	**5.60**
FIQ(1.0)	76.99	49.92	39.82	25.32	18.53	12.56
FIS(1.0)	64.58	38.38	30.15	17.82	14.04	10.44
MSUC(1.0)	114.14	73.88	50.95	29.73	20.31	13.78
SPT(1.0)	17.79	16.43	16.99	15.41	15.44	14.73
LWR(1.0)	49.64	37.20	28.00	17.38	11.76	6.55
OCR(1.0)	9.67	6.34	5.40	3.65	3.21	2.30
CR(1.0)	15.80	6.77	5.19	3.07	2.72	1.75
EODD(1.0)	12.48	8.12	6.69	4.48	3.93	2.85
EDD(1.0)	23.88	10.45	7.74	4.26	3.49	2.21
MODD(1.0)	**4.39**	**2.96**	**2.36**	**1.70**	1.33	.95
MDD(1.0)	14.70	5.59	3.40	1.95	**1.23**	**.59**
FIQ(2.0)	18.23	10.42	7.71	4.47	3.14	2.13
FIS(2.0)	12.47	6.76	5.08	2.74	2.20	1.61
MSUC(2.0)	59.48	40.51	26.76	13.79	9.28	6.25
SPT(2.0)	7.64	7.29	7.64	6.84	7.12	6.55
LWR(2.0)	21.65	16.51	12.54	7.03	5.32	2.66
OCR(2.0)	.54	.27	.16	.14	.14	.18
CR(2.0)	.12	.10	.10	.10	.10	.10
EODD(2.0)	.20	.05	.01	**.00**	**.00**	**.00**
EDD(2.0)	**.02**	**.00**	**.00**	**.00**	**.00**	**.00**
MODD(2.0)	.09	.02	.00	**.00**	**.00**	**.00**
MDD(2.0)	**.02**	**.00**	**.00**	**.00**	**.00**	**.00**

Table B2: (continued).

Scheduling Rule*	Sequencing Flexibility Measure					
	.00	.20	.40	.60	.80	1.00
FIQ(4.0)	2.10	1.20	.83	.42	.31	.16
FIS(4.0)	1.17	.57	.47	.21	.16	.10
MSUC(4.0)	22.62	17.29	11.22	5.23	3.59	2.53
SPT(4.0)	2.23	2.27	2.49	2.09	2.35	2.02
LWR(4.0)	5.87	4.78	3.99	1.60	1.76	.81
OCR(4.0)	.03	.03	.03	.04	.04	.05
CR(4.0)	.03	.03	.02	.03	.03	.03
EODD(4.0)	**.00**	**.00**	**.00**	**.00**	**.00**	**.00**
EDD(4.0)	**.00**	**.00**	**.00**	**.00**	**.00**	**.00**
MODD(4.0)	**.00**	**.00**	**.00**	**.00**	**.00**	**.00**
MDD(4.0)	**.00**	**.00**	**.00**	**.00**	**.00**	**.00**

Notes: The numbers in parenthesis indicate flow allowance factors used to determine due dates. Bold number cells indicate minimum values for each flow allowance setting.

Table B3: Proportion tardy (%).

Scheduling Rule*	Sequencing Flexibility Measure .00	.20	.40	.60	.80	1.00
FIQ(.25)	98.5	97.2	96.5	93.8	89.8	83.6
FIS(.25)	99.2	97.9	96.2	91.7	85.5	77.7
MSUC(.25)	87.1	78.3	73.0	66.2	58.6	48.6
SPT(.25)	**69.7**	**59.4**	**52.9**	**45.1**	37.9	32.4
LWR(.25)	79.9	69.5	60.3	48.4	**35.4**	**24.3**
OCR(.25)	98.4	97.3	96.0	93.5	90.2	86.3
CR(.25)	99.6	99.1	98.5	96.4	92.7	87.3
EODD(.25)	99.5	98.3	97.0	93.3	87.6	80.3
EDD(.25)	99.3	98.2	96.3	91.5	82.6	71.3
MODD(.25)	82.7	75.6	70.2	63.5	55.2	47.7
MDD(.25)	94.5	89.9	83.7	72.7	57.2	42.0
FIQ(.50)	86.4	80.0	75.1	66.6	56.7	46.6
FIS(.50)	90.3	81.3	73.6	60.3	50.5	42.0
MSUC(.50)	58.8	44.9	38.1	30.9	24.7	18.3
SPT(.50)	**16.5**	**13.8**	**12.6**	**10.9**	10.1	9.7
LWR(.50)	32.1	23.4	17.7	12.3	**7.9**	**5.0**
OCR(.50)	79.7	71.7	65.8	57.5	49.3	44.4
CR(.50)	94.7	86.3	78.8	64.3	53.3	45.1
EODD(.50)	83.5	69.6	59.8	48.0	38.5	32.3
EDD(.50)	90.3	77.1	64.6	45.9	32.8	24.5
MODD(.50)	33.5	26.9	24.6	20.0	17.3	15.5
MDD(.50)	78.4	59.9	44.8	28.1	17.0	10.9
FIQ(1.0)	49.7	38.7	33.4	24.7	18.9	13.9
FIS(1.0)	51.1	36.7	30.5	20.5	16.2	12.7
MSUC(1.0)	31.3	21.1	16.2	12.0	9.0	6.1
SPT(1.0)	**4.2**	3.8	3.8	3.5	3.4	3.3
LWR(1.0)	10.1	7.6	5.6	3.7	2.3	1.5
OCR(1.0)	27.0	19.6	17.1	13.8	12.7	12.9
CR(1.0)	35.4	20.2	16.8	13.2	12.1	10.4
EODD(1.0)	15.6	9.9	8.2	6.0	5.3	3.9
EDD(1.0)	28.9	12.4	8.7	5.5	4.6	3.2
MODD(1.0)	4.5	**3.2**	**2.7**	**2.3**	2.2	1.8
MDD(1.0)	21.6	8.0	4.6	2.7	**2.0**	**1.3**
FIQ(2.0)	13.4	8.7	7.0	4.4	3.2	2.3
FIS(2.0)	11.9	7.4	5.7	3.5	2.8	2.1
MSUC(2.0)	12.9	8.5	6.1	3.9	2.7	1.7
SPT(2.0)	1.2	1.1	1.1	1.1	1.1	1.0
LWR(2.0)	3.0	2.2	1.6	1.0	.7	.4
OCR(2.0)	3.4	2.8	2.6	2.6	2.8	3.3
CR(2.0)	2.2	2.0	2.0	1.9	1.9	1.9
EODD(2.0)	.5	.1	**.0**	**.0**	**.0**	**.0**
EDD(2.0)	**.1**	**.0**	**.0**	**.0**	**.0**	**.0**
MODD(2.0)	.2	.1	**.0**	**.0**	**.0**	**.0**
MDD(2.0)	**.1**	**.0**	**.0**	**.0**	**.0**	**.0**

Table B3: (continued).

Scheduling Rule*	Sequencing Flexibility Measure					
	.00	.20	.40	.60	.80	1.00
FIQ(4.0)	1.7	1.0	.8	.5	.3	.2
FIS(4.0)	1.3	.7	.6	.3	.2	.2
MSUC(4.0)	4.0	2.8	1.8	1.0	.6	.4
SPT(4.0)	.3	.3	.3	.2	.3	.2
LWR(4.0)	.6	.5	.4	.2	.2	.1
OCR(4.0)	.5	.6	.6	.7	.7	1.0
CR(4.0)	.5	.5	.5	.5	.5	.5
EODD(4.0)	**.0**	**.0**	**.0**	**.0**	**.0**	**.0**
EDD(4.0)	**.0**	**.0**	**.0**	**.0**	**.0**	**.0**
MODD(4.0)	**.0**	**.0**	**.0**	**.0**	**.0**	**.0**
MDD(4.0)	**.0**	**.0**	**.0**	**.0**	**.0**	**.0**

Notes: The numbers in parenthesis indicate flow allowance factors used to determine due dates. Bold numbers indicate minimum values for each flow allowance setting.