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Rahul Caprihan
Dayalbagh Educational Institute

Ashok Kumar
Grand Valley State University
Seidman School of Business

Kathryn E. Stecke
University of Michigan Business School

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Effect of Information Delays on the Performance of Flexible Manufacturing Systems: An Empirical Investigation

RAHUL CAPRIHAN
Faculty of Engineering
Dayalbagh Educational Institute
Dayalbagh, Agra, India 282 005
Phone: 011 91 (562) 281224
Email: Rahulcap@vsnl.com
Fax: 011 91 (562) 281226

ASHOK KUMAR*
Seidman School of Business,
Grand Valley State University,
Grand Rapids, MI 49504-6495
Phone: (616) 336-7459
E-mail: Kumara@gvsu.edu
Fax: (616) 336-7445

KATHRYN E. STECKE
University of Michigan Business School,
Ann Arbor, MI 48109-1234
Phone: (734) 763-0485
E-mail: KStecke@umich.edu

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* Corresponding author

ABSTRACT

Routing flexibility is acclaimed as a significant contributor to the success of flexible manufacturing systems (FMSs). To harness the potential benefits of routing flexibility, system controllers must apply appropriate dispatching rules to determine the next workstation that a part type should visit after completion of each operation in its technological sequence. The successful deployment of dispatching rules requires accurate and timely shop floor status information. However, the acquisition, processing, and transfer of plant-wide status information is not a trivial task and is normally prone to time delays. We refer to these delays as *information delays* and believe that many contemporary flexible systems must cope with some level of information delay when implementing dispatching rules. We examine the extent of the adverse impact that such delays have on the performance of those FMSs that fail to operate in real time due to insufficient information automation.

FMSs that are affected by information delays are hard to formulate for optimal dispatching and sequencing decisions. Indeed, scheduling problems of such FMSs fall in the class of NP-hard in a strong sense. Hence, we use simulation to analyze the impact of information delays on the performance of these FMSs. Specifically, we use mean tardiness, percent tardiness, mean flowtime, and average machine utilization as the performance measures in the study. The choice of simulation experiments is determined using the Taguchi method of robust experimental design. The impact of information delays is captured using a metric called Information Delay Ratio (IDR), which relates the magnitude of information delays to the average processing time per operation of parts in an FMS. Using IDR as one of five experimental factors, the following key findings are established: (1) Information delay causes significant impairment of system performance for those FMSs that seek to optimize due date-based measures (mean tardiness, percent tardiness); and (2) FMSs that seek to optimize non-due date-based measures (mean flowtime and average machine utilization) are relatively insensitive to the adverse impact of information delays.

1. Introduction

Manufacturing organizations worldwide have used flexible manufacturing for a solution to a host of complex production related problems arising out of varying market demands, decreasing delivery lead times, exacting quality standards, and high production costs. Flexible manufacturing systems (FMSs) are able to adapt quickly and efficiently to changing customer requirements that impose dynamic changes in objectives and operating conditions. They epitomize the state-of-the-art in manufacturing system types and can accommodate the simultaneous processing of several part types as a consequence of a complex synergism between flexibility, integration, and automation.

For the most part however, the deployment of full-blown FMS installations has remained the domain of large corporations such as GM, IBM, and Ford among others, primarily because the investments required for such installations are quite substantial. Typically, with the cost of standard numerical-controlled machining centers ranging between $400,000 to $550,000, a complete FMS installation could be up to $30 million. Because of the significant investments, many smaller manufacturing organizations strive to attain the levels of information integration and automation extant within FMSs in a gradual, phased manner. Very often, this transition from a conventional to a fully integrated FMS could run into several years.

The efficient functioning of an FMS is dependent on a prudent choice of control strategies. The term control strategy here implies the choice and application of various dispatching rules to determine the next work center to which a part type that has just completed an operation should be routed. In an ideal flexible manufacturing environment, all of the information necessary for the execution of a control strategy is available in real-time, and consequently, good scheduling/dispatching decisions can be made quickly. Realistically however, most FMSs are limited in the degree of their automation. One of the ways this limitation manifests is through delays in information acquisition, transmission, processing, and execution. The focus of our study is on those FMSs where such delays are significant, i.e., a sum total of such delays may have the same order of magnitude as the processing times of operations. Thus, in this paper, we focus on FMSs that are in a transitional form, i.e., wherein the level of information integration and automation is not developed to the extent that dispatching decisions are made and executed in real time. Such FMSs may have islands of automation and employ various control strategies to harness the built-in flexibility for performance enhancement. These FMSs usually incur delays either in the collection and processing of shop floor status information or in the implementation of control decisions. These are *information delays* (Caprihan, 1995) and we believe that such delays are an essential, albeit undesirable, part of the scheduling environment of FMSs. The degree to which system performance is affected by such delays depends on system parameters, including the system status at the time of decision-making epochs, the control strategies employed, the performance measures of interest, as well as the extent of the information delay relative to processing times.

Information delays in manufacturing systems result both from unplanned activities (e.g., failure of a software system, unreliable networking conditions, or failure of communication equipment), as well as from planned activities. Our focus in this paper is on the impact of information delays arising from information-related planned activities. Towards this end, we look at the total amount of information delay in the system. These delays result at various decision epochs because of the time expended in: (i) the retrieval of status information from various sources in the system, (ii) the compilation of such information into an intelligible format, consistent with the needs of the control strategy being executed, (iii) the transmission of information to the decision-making node, (iv) the dissemination and subsequent processing of information for the generation of a control decision(s), and (v) the communication of the control decision(s) to the execution point.

Each of the above elements of information-related activities can constitute delays at each execution point of a control strategy. Gusikhin, Lewis, and Miteff (1996) and Gusikhin and Miteff (2000) present an excellent account of how delays manifest within real world manufacturing systems. Elaborating on a delay caused in the retrieval of information, Gusikhin et al. (1996) note, "Low level shop floor automation systems, in most cases, provide disjointed information originating from various controls scattered throughout the plant floor process. Many of these controls provide data that is limited to transactional information. Transactional information describes a single event in an operation. An event would include the start of an operation, the completion of an operation, signaling the start of part movement etc. The automation does not track parts by part number through the process. This lack of tracking greatly hinders the ability to follow a part through the entire process. It is also possible that controls may not exist in all areas, further complicating the problem by causing gaps in the information chain". Further, Gusikhin and Miteff (2000) observe, "Retrieving data representing a snapshot of the production process is problematic in several ways. Primarily, unsynchronized data retrieval between sources may lead to multiple or missed counts of parts, pallets, fixtures or other production units".

Furthermore, describing systemic information delays in general, Gusikhin and Miteff (2000) state, "Most production is non-serialized with islands of automation installed to meet the specific needs of the production line. Integration of this sparse and isolated data can be, and usually is, difficult. … Data may be obtained from programmable logic controllers, automatic guided vehicles, automated storage and retrieval systems, bar-code systems, manual input stations, special purpose personal computers, etc."

Clearly, the collection, dissemination, and transmission of information to the point of execution of a control strategy can result in significant information delays. This work highlights the fact that such delays can severely impair system performance.

Finally, the process of evolution of information technology has created numerous problems of integration and interfacing. Since information systems are typically upgraded sequentially, each module may gather, store, and communicate information at variance from other modules. Modules themselves may differ in the way information is acquired from them. Some modules may be queried for information while others may be programmed to send packets periodically (Gusikhin and Miteff, 2000). Further delaying factors could include the message formats that vary across modules, transmission failures such as lost messages, corrupted messages, delayed messages, and information traffic delays.

Information delays have been neglected in the many scheduling studies of dynamic and flexible job shops. Although considerable research effort has been devoted to the development of control strategies where information delays have been assumed implicitly to be insignificant (for instance in real-time scheduling), there has not been much research on the scheduling aspects of discrete part manufacturing systems while explicitly accounting for information delays (Caprihan, 1995; Caprihan, Kumar, and Wadhwa, 1997; Wadhwa, Caprihan, and Kumar, 1997; Caprihan, Wadhwa, and Kumar, 2000; Caprihan, Kumar, and Gursaran, 2000; Gusikhin et al., 1996, and Gusikhin and Miteff, 2000).

Information delays seem to be generic to all manufacturing systems. The magnitude of these delays may be reduced by using higher degrees of automation usually are not completely eliminated. Time is expended in the retrieval, formatting, processing, and communication of status information that is required for the execution of control strategies. Hence, it is important to understand both the effect and temporal nature of the impact of information delays on system performance. That is the focus of this work.

The paper is organized as follows. Section 1 introduces the concept of information delays. Section 2 reviews the relevant literature on FMS scheduling and information delays. Section 3 provides an information delay perspective on the synergy of flexibility, integration, and automation and defines a specific modal manifestation of information delay - the status-review delay. Section 4 defines terminology, performance measures, and details of the simulation experiment. In section 5 we summarize the results and key findings of the simulation experiments. Section 6 provides concluding remarks.

2. Review of the literature

In the literature, significant manufacturing scheduling contributions have been made. Panwalker and Iskander (1977), Blackstone, Phillips, and Hogg (1982), and Ramasesh (1990) present excellent surveys of scheduling studies in the conventional job shop context while Harmonosky and Robohn (1991), Basnet and Mize (1994), Sabuncuoglu and Hommertzheim (1993), and Rachamadugu and Stecke (1994) comprehensively review scheduling applications in the FMS domain.

Through an industry survey, Smith, Dudek, Ramesh, and Blair (1986) highlighted the importance of due date related criteria in FMSs. Traditionally, a variety of decision rules have been used for setting due dates in job shops. Ramasesh (1990) provides a classification scheme and identifies thirteen different approaches to schedule operations. Due dates can be specified both externally by a customer or set internally by a vendor. Most studies however, have investigated the performance of scheduling rules with due dates being set internally. Among the static policies, several studies conclude that total work content (TWK) is the best approach to set due dates internally (Ramasesh, 1990). Using TWK, due dates are set by adding a multiplier 'T' times the total work content for a part to its time of arrival in the shop. 'T' then determines the degree of due date tightness for the part. Typical values for 'T' range between 3 and 6. Due date-based studies in conventional job shops and FMSs are now reviewed.

Sabuncuoglu and Hommertzheim (1993) study the relative performance of several due date-based rules in an FMS of six machines. Performance measures include maximum tardiness, mean conditional tardiness, mean flowtime, proportion of tardy parts, and mean lateness. The modified due date rule gave best results.

Ballakur and Steudel (1984), in their review of job shop control systems when comparing several sequencing rules, conclude that the SIO (shortest imminent operation) rule appears to be the best sequencing rule for relatively loose due dates and moderate machine utilization; that combined rules involving SLACK and SIO are most promising and merit future research; and that due date assignment procedures and dispatching rules using current shop status information, such as work loads at machine centers, are very effective in improving system performance. Shanker and Tzen (1985) study make-to-order FMSs in which parts are scheduled according to due dates. Two heuristic algorithms are suggested with the work unbalance and machine utilization performance criteria. For a system of four machines, they conclude that their heuristic input method that balances workloads performs better than the FCFS rule. Ro and Kim (1990) use multiple criteria decision-making techniques to test alternate dispatching rules in an FMS with routing flexibility while simultaneously considering the makespan, mean flowtime, mean tardiness, maximum tardiness, and system utilization performance criteria. They highlight the superiority of a rule, called alternative routings directed dynamically, that delivers the current part to the next machine that has the shortest travel + queueing + operation time for that part among the candidate machines. Henneke and Choi (1990) experiment with a system with six machining centers, a turning cell including a robot, two vertical lathes, and a washing station capable of processing seven part families. Seven sequencing rules (including SPT, earliest due date (EDD), and SLACK) and four dispatching rules (including number-in-next-queue (NINQ) and work-in-next-queue (WINQ)) were evaluated using six performance measures. Machine breakdowns, material handling capacity, in-system storage capacity, and routing flexibility were also considered. The study concluded that the NINQ and WINQ rules outperformed the other dispatching rules. Karsiti, Cruz, and Mulligan (1992) suggest a two-level dynamic scheduling strategy for a system of ten machines, each capable of processing a number of operations, resulting in significant routing flexibility. The measures of performance examined include number of jobs tardy and normalized tardiness. They suggest a combination of the EDD input sequencing rule with the NINQ machine selection rule for best results. Kim and Kim (1994) simulate an FMS with six machines using several due date-based scheduling rules. The three performance criteria of mean flowtime, mean tardiness, and a bi-criterion measure combining these two with weighting factors were used. Contrary to expectations, a non-due date sequencing rule gave the best results across all three measures. Ovacik and Uzsoy (1994) propose a heuristic for sequencing complex job shops that used computerized shop floor information systems. Four variants of the proposed heuristic were compared with three existing heuristics (EDD, operation due date (ODD), and apparent tardiness cost with setups) using a modified form of the maximum lateness performance measure. The superiority of the suggested heuristic was demonstrated within each of three different manufacturing environments.

Note that researchers who have considered routing flexibility have implicitly assumed the availability of real-time information when making on-line dispatch decisions. In this paper, however, we investigate the effect of information delays on the due date scheduling aspects of an FMS with routing flexibility. We determine whether or not actual routing flexibility (Browne, Dubois, Rathmill, Sethi, and Stecke, 1984) can be exploited by on-line control strategies in the presence of delayed information availability in an attempt to improve system performance.

3. Balance between flexibility, integration, and automation: An information delay perspective

While flexibility provides decision alternatives, information automation (through computerized processing of information for decision support) provides some efficiency with which the alternatives can be processed and an appropriate one selected and implemented. Consider, for example, routing flexibility. On completion of an operation, routing flexibility ensures that alternative machines may exist for processing the next operation for a part. Thus, after each operation, a decision is required for choosing an appropriate machine to which the part should be next dispatched. Dispatch decisions are made using specific rules that select a machine based on the system status and a particular performance criterion. Information integration (for instance, through a local area network of computers where operators enter machine-specific status data into dedicated computers) helps make system status information available to a controller to ensure that the choice made is effective from a systems point of view. Sophisticated shop floor information systems are often employed for making scheduling decisions that track inventory in real time by providing location information on in-process parts and machine status data (Ovacik and Uzsoy, 1994). Because of a significant capital investment associated with flexibility, integration, and automation, manufacturing system designers have to determine an appropriate combination of the three. If there are restrictions on the extent of integration and automation, it may well be that no increase in the level of flexibility can help improve system performance.

There is a need for an appropriate balance between flexibility, integration, and automation. For instance, a manufacturing system does not need much routing flexibility unless the dispatcher has access to system status information, that is, unless the information collection and transfer within a system is well integrated. Similarly it may be of little value to have a very flexible system that is well integrated in terms of instant availability of status information, but has an inadequate level of information processing and decision implementation automation. In the latter situation, the decision-making event could get delayed to such an extent that by the time the decision is processed, system status might have changed significantly.

Information integration and automation can be technologies that determine how rapidly system status information can be transferred to a controller, and how quickly this information can subsequently be processed for effecting a scheduling decision. The concept of information delays implies that it takes a finite time period to collect, collate, transfer, and process information. One would expect conventional manufacturing systems (with little or no integration and automation) to have substantial information delays associated with them. Most research on the control aspects of conventional job shops has ignored the presence of routing flexibility and has focused instead on static scheduling schemes (Sen and Gupta, 1984). Researchers and practitioners who have considered routing flexibility have implicitly assumed real-time system status availability and have suggested the adoption of dynamic scheduling approaches (Harmonosky and Robohn, 1991). Others who have questioned whether available technology can be automated to a level where an optimum scheduling decision can be exhaustively searched for whenever required, without entailing significant delays in processing, have supported the use of local priority dispatching rules or heuristics (Panwalker and Iskander, 1977; Stecke and Solberg, 1981; Blackstone, Phillips, and Hogg, 1982; Stecke, 1992) implementable in an on-line manner.

However, Chakravarty (1987) notes, "…a mixed production environment comprising of conventional and flexible machining cells is likely to arise in manufacturing facilities due to a phased changeover from conventional to newer technologies." This implies that conventional manufacturing systems can undergo transitional phases by increases in flexibility, integration, and automation, and the time frame for completion of this transition may run into several months or years. While undergoing this transformation, shop controllers may want to exploit flexibility using on-line control strategies, designed for real-time operation, by deploying them within the information-delayed environment. The transitional form of a manufacturing system that is the focus of our study here could benefit from routing flexibility, although the operational environment may need to cope with information delays in other manners as well.

3.1 Basic modes of information delay

In scheduling decisions, information delays occur in many ways. Caprihan (1995) defines three modes through which information delays can impact control strategies. Mode 1 delay, called the information-transfer delay, occurs when the transfer of information to the point of execution of the control strategy does not occur in real time due to the limited automation of information collection, collation, and transfer. Mode 2 delay, called the decision-implementation delay occurs when the implementation of control strategies is delayed due to unavailability of the required information in real time. Lastly, Mode 3 delay, called the status-review delay, occurs when the information is collected, transmitted, or reviewed only at fixed intervals of time (similar to periodic review systems in inventory theory). Dispatch decisions that are triggered by completion of operations in between successive review instants are made using (sometimes obsolete) status information monitored at the last review instant. This last mode of delay (Mode 3) is the focus of analysis in this work. Figure 1 is a schematic representation of this mode of information delay. Caprihan, Kumar, and Wadhwa (1997), Wadhwa, Caprihan, and Kumar (1997), and Caprihan, Wadhwa, and Kumar (2001) report on the development of new control strategies for the two-queue, single machine dynamic sequencing problem and highlight their superiority over the alternating priority sequencing rule (Conway, Maxwell, and Miller, 1967), using the mean flowtime performance measure for each mode of information delay.

From figure 1, system status information is updated at fixed time instants separated by a known, fixed, and discrete time interval called a review period (RP). On the occurrence of an information request epoch (IRE), which occurs at arbitrary points in time, a dispatch decision is made based on the system status monitored at the last periodic review instant. The dispatch decision subsequently gets implemented without any decision implementation delay. Clearly, the magnitude of the status-review delay (Δ_{SRD}) is variable and ranges from just above zero time units to the magnitude of the RP. It is evident that for a control strategy operating under the status-review mode, erroneous dispatch decisions are likely. In contrast, a control strategy operating in real time would have instantaneous access to real time status information, which in the present context would imply an infinitesimally small review period. In the following sections, we investigate the effects of the status–review information delays on the performance of an FMS using simulation.

4. System description and experimental details

The FMS is modeled as a job shop with Mode 3 delays incorporated into the status monitoring scheme. However, unlike the processing times, these delays are actually dependent on the sequence of operations. Consider, for example, the instant when a certain part type completes its first operation. A dispatch decision, say δ_2, is now required to route the part for its next operation. The decision maker uses the information furnished at the last review instant, which occurred, say, Δ_{SRD1} time prior to the current time instant, to determine where this part type should be next dispatched. Decision δ_2 is, therefore, a function of Δ_{SRD1}. Clearly, each dispatch decision is a function of the previous dispatch decision as well as the previous status review delay. Therefore, there is a nested dependence of all dispatch decisions to their predecessors, i.e., any decision δ_I, and the corresponding delay Δ_{SRDi}, is a function of all the previous dispatch decisions, δ_1, $\delta 2$, …, δ_{i-1}, and the corresponding previous status review delays Δ_{SRD1}, Δ_{SRD2}, …, Δ_{SRDi-1}. Since job shop scheduling problems that seek to optimize the objectives such as the ones used in this paper are known to be NP-hard, the problem addressed here is NP-hard in a strong sense. We, therefore, use simulation to study and analyze the impact of the Mode 3 information delays on the performance of FMSs with routing flexibility.

4.1 FMS description

We use an FMS of six machines, each capable of processing up to six different part types. Six machines are chosen based on Shanker and Tzen's (1985) observation that such a configuration occurs most frequently. Each part type to be processed requires between four to six operations. Routing flexibility in this FMS means that alternate machines are available for the operations.

We use the following routing flexibility index to vary the degree of routing flexibility for the FMS. The routing flexibility index for each part type i (RF_i) is defined as

$$RF_i = \frac{\sum_{j=1}^{J_i} |O_{ij}|}{J_i},$$

where $O_{i,j}$ = j^{th} operation of part type i, i = 1, … , N; j = 1, … , J; J_i = number of operations of part type i; and $| O_{i,j} |$ = cardinality of the set of machines that can process operation *j* of part type *i*.

RF_i, therefore, is a measure of the average number of machines capable of processing an operation. The system routing flexibility index (RF) is then defined as

$$\text{RF} = \frac{1}{N}\sum_{i=1}^{N} RF_i \ ,$$

where N = total number of part types produced. It can be seen that the routing flexibility reflects the average number of machines available per operation per part type.

Because routing flexibility is an experimental factor in this paper, the RF is varied from 1 to 5. Table 1 depicts the relevant part type/processing time details for a flexibility index of 5. Note that when RF = 1, part type sequences through the FMS are fixed, i.e., no alternate routes are possible.

Part entry into the system is controlled using pallets. Due dates are set using the total work content (TWK) rule, a rule found appropriate in previous studies (Ramasesh, 1990). Due dates are determined as:

$$D_i = A_i + TP_i \ ,$$

where D_i = due date for part i,

A_i = arrival time of part i into the system,

T = due date tightness factor, and

P_i = total processing time for part i.

Due dates can also be set for the individual operations for a part in the form of operation milestones (Baker, 1984). To do this, once a part's due date is assigned, we divide its original flow allowance (the time between its release date and due date) into as many segments as there are operations (Baker, 1984). Accordingly, operation due dates are then determined as:

$$d_{i,j} = d_{i,j-1} + Tp_{i,j}$$

where: $d_{i,j}$ = operation due date for j^{th} operation of part i,

$d_{i,j-1}$ = operation due date for the $(j-1)^{th}$ operation part i,

T = due date tightness factor, and

$p_{i,j}$ = operation processing time for the j^{th} operation of part i.

4.2 Simulation Details

Simulation experiments are performed using the Arena 3.0 simulation language (Systems Modeling Corp., 1997). User-written C++ code was used to capture the dispatching logic incorporated into the models. Each experiment is a single replication, which is justifiable on account of our having assumed the following: (i) all parts of all types are available at the start of the simulation run (i.e., part arrivals are not stochastically generated), although part arrivals into the system are dependent on pallet availability; and (ii) pre-specified operation processing times are deterministic. A total of 1000 parts of six types are simulated with the production mix assumed to be a predetermined constant (part type A – 15%, B – 15%, C – 20%, D – 15%, E – 15%, and F – 20%). Further, identical experimental testing conditions for each dispatching rule are ensured using the method of common random numbers (Kelton, Sadowski, and Sadowski, 1998).

Sequencing of parts of different types from the input buffers of each machine is done using one of the following five rules: SOPT, EDD, Slack, ODD, and OSlack. Dispatching of parts on completion of an operation is performed using one of the following two rules: WINQ and NINQ. In the case of a tie between parts of the same type, the FCFS rule is used to break the tie. (See Appendix A for details regarding these acronyms). The performance measures used in the study are mean tardiness, percent tardy, mean flowtime, and average machine utilization.

Note that since sequencing decisions essentially rely on local (queue) status data, sequencing of parts from input buffers is done in real-time, i.e., with no information delay. In contrast, since dispatching decisions require global status data, dispatching rules are applied in an environment of information delays (IDs).

We adopt the Taguchi experimental design technique for conducting the simulation experiments as well as for analyzing the results obtained. Taguchi methods were chosen because, for the given set of factors, factor levels, and their interactions, they provide almost the same amount of information as the full design of experiments but with significantly less number of experiments. A full-fledged design of experiments would have required performing 1000 (5 x 2 x 5 x 4 x 5) experiments even with a single replication. Such large number of experiments would be justified only if there were many interaction effects between factor levels that were statistically significant and were not captured through Taguchi's orthogonal array designs. The additivity assumption test (a test that analyzes the percentage of experimental variations explained by factor main effects), however, showed that interaction effects were minimal. Therefore, a full design of experiments would yield only marginally extra useful information. This implied that factor main effects alone could explain most of the experimental variations. In turn, this implied that a small fraction of the total of 1000 experiments conducted within the framework of Taguchi's robust design would provide the information needed to determine optimal levels of factors for best performance. Indeed, we ended up using a set of just 25 (2.5% of 1000) experiments to establish the optimal levels of experimental factors with a high confidence level. The following section provides a brief introduction to the Taguchi experimental design method.

4.3 Taguchi's experimental design framework

The Taguchi experimental design is based on specially designed matrices whose columns contain arrays that are orthogonal to each other (Phadke, 1989). Each array (represented by a row of the matrix) of these matrices represents a specific combination of factor levels and is called a “treatment”. The settings of factor levels (also called process parameters or settings in the literature) under study change from one array to another. The orthogonality of arrays guarantees that the results from each treatment are independent of the other, i.e., the variations of one treatment are not confounded with the other. Furthermore, the orthogonality of arrays also allows separation of partial effects of various factor levels within a treatment, thus permitting more information from a limited number of experiments. This greatly economizes the number of experiments needed to be performed provided we know which interactions between factor levels are insignificant in terms of their practical impact.

The purpose of conducting an orthogonal experiment is twofold:

1. To establish the relative significance of individual factors in terms of their main effects on the objective function;
2. To determine the factor combinations that result in near optimal objective function values (i.e., to determine the best level for each factor).

Taguchi suggests using a summary statistic ‘η’, called signal-to-noise (S/N) ratio, as the objective function for matrix experiments. Taguchi classifies objective functions into one of three categories: the smaller-the-better type, the larger-the-better type, and nominal-is-best type. S/N ratios are measured in decibels.

An important goal in conducting a matrix experiment is to determine the best factor levels. The best level for a factor is that which results in the highest value of η in the experimental region. The effect of a factor level (also called the main effect) is defined as the deviation it causes from the overall mean. This deviation is captured through the square of the variations contributed by each factor level. The process of estimating the main effects of each factor is called analysis of means.

Taguchi makes an assumption in the method suggested for determining the best factor combination (based on the best level for each factor) for a defined objective function. He assumes that the variation of η as a function of the factor levels is additive, that is, cross product terms involving two or more factors are allowed only if they can be represented as one of the treatments in one of the Taguchi robust design arrays. The assumption of additivity implies the absence of significant interaction effects between factors. Taguchi suggests that a verification experiment (with factors at their best levels) be run to validate the additivity assumption. After running a verification experiment, if the predicted and observed η are close to each other, we conclude that the additive model is adequate for describing the dependence of η on the various parameters. On the contrary, if the observation is drastically different from the prediction, we say the additive model is inadequate and that there is evidence of a strong interaction among the parameters. In fact, Taguchi considers the ability to detect the presence of interactions to be the primary reason for using orthogonal arrays to conduct matrix experiments.

The real benefit in using matrix experiments is the economy they afford in terms of the number of experiments to be conducted. In the present study, because we need to experiment with five factors, three of them at five levels, one at four levels, and the last at two levels, a full factorial experiment would have required $5^3 \times 4 \times 2 = 1000$ experiments. In contrast, having found the L_{25} orthogonal array to be suitable for our purposes, only 25 experiments needed to be conducted. Use of such limited number of experiments while ignoring other possible 975 experiments was justified by the validity of the additivity assumption.

4.4 Matrix experiment details

To highlight the impact of the status-review delays within the assumed FMS, standard orthogonal array experiments are performed. As mentioned in section 4.3, Taguchi's standard L_{25} orthogonal array is found suitable for experimentation purposes. This enables the simultaneous consideration of six factors at five levels. In the present case, only five factors are considered, so the first five columns of the L_{25} orthogonal array are used, with the sixth column being excluded for experimentation purposes without affecting the orthogonality of the matrix (Phadke, 1989). The five factors along with their assumed levels are:

FACTOR	LEVELS
Routing Flexibility	(1, 2, 3, 4, 5)
Due Date Tightness	(3, 4, 5, 6)
Dispatching Rule	(WINQ, NINQ)
Sequencing Rule	(SOPT, EDD, Slack, ODD, Oslack
Information Delay Ratio	(1, 1.25, 1.5, 1.75, 2)

The levels for each factor used in the matrix experiment are shown in table 2. Table 3 details the resulting matrix experiment tableau with the factor level assignment based on the treatments recommended in Taguchi array L_{25}.

We define the metric information delay ratio (IDR) as the ratio of the review period (RP) (see section 3.1) to the average processing time per operation of all parts ($\overline{PT}$) in the system. The motivation for using $\overline{PT}$ as the denominator in IDR stems from our intuition that the temporal response of the system to the presence of information delays can be related to the magnitude of part processing times.

Further, the specific range of values of factor levels for IDR are intentionally chosen so as to represent incremental penalties in terms of information loss. Specifically, it was felt that an IDR = 2 would highlight the worst case scenario. For comparison, a second matrix experiment was also conducted in which the range for IDR was varied from 0 to 1. Results for this sensitivity experiment are detailed in section 5.3.

To proceed with the matrix experiment, the chosen performance measures need to be suitably modified as S/N ratios. The following measures are classified in the smaller-the-better category (Phadke, 1989): Mean tardiness, percent tardy, and mean flowtime; while the measure, average machine utilization, is of the larger-the-better type. Accordingly, the modified versions of these performance measures (as S/N ratios) are defined below.

Smaller-the-better measures:

$\eta_i = -10 \log_{10} (\text{mean tardiness})^2$

$\eta_i = -10 \log_{10} (\text{percent tardy})^2$

$\eta_i = -10 \log_{10} (\text{mean flowtime})^2$

Larger-the-better measure:

$\eta_i = -10 \log_{10} (1/\text{average machine utilization})^2$

Because of our usage of only one replication of each treatment, we resort to the use of S/N ratios to maintain consistency with the conventional Taguchi method of experimentation.

5. Experimental results and analysis

The results of the 25 treatments based on the L_{25} array are detailed below. The data analysis procedure using the Taguchi experimental framework involves the analysis of means (ANOM) and analysis of variance (ANOVA). ANOM helps identify the best factor combinations whereas ANOVA establishes the relative significance of factors in terms of their contribution to the objective function. The ANOM and ANOVA for the mean tardiness performance measure are discussed at some length below.

5.1 Mean Tardiness

The simulation results are summarized in table 4. The first column shows the treatment number consistent with the L_{25} array. The second column provides mean tardiness and the third column provides the S/N value in decibels for each treatment enumerated in column 1.

(i) Analysis of means

The main factor effects, calculated using the formulae given in Phadke (1989), are summarized in table 5. The notational convention adopted for analysis is

$m_{j,k}$: main factor effect for the k^{th} level of factor j

η_i : observed S/N ratio for the i^{th} orthogonal experiment

m : overall mean value of $\eta = \dfrac{\sum_{i=1}^{n} \eta_i}{n}$, where j has the following labels: RF = routing flexibility, D = dispatching rule, S = sequencing rule, T = due date tightness, IDR = information delay ratio, and n = number of experiments performed (i.e., 25).

Based on the analysis of means, the best levels for each factor resulting from the matrix experiment is shown italicized under the mean tardiness column of table 5. Note that the main effects values are measured in decibels because they refer to S/N ratios. Accordingly, the predicted factor level combination that should minimize the mean tardiness is RF3, D1, S1, T4, IDR1, which means that the routing flexibility = 3, the dispatching rule is WINQ, the sequencing rule is SOPT, the due date tightness factor = 6, and information delay ratio = 1. Interestingly, the predicted best settings from the matrix experiment do not correspond to any of the rows in table 3. This demonstrates the power of Taguchi methods: Without conducting an experiment with actual settings, one could still determine the optimal process setting that would maximize system performance for a given objective.

Figure 2 plots the main effects of each factor level. The best level for each factor is identified as the level that results in the highest value of η in the factor-level range. Note that the prediction of the best factor level combination is conditioned by the variation of η as a function of the factor levels satisfying the additivity assumption. To justify the validity of this assumption, a verification experiment needs to be carried out with best factor-level settings. The result of the verification experiment then is compared with a predicted optimal value, resulting in a prediction error. If the prediction error happens to fall within a two-standard-deviation confidence limit of the variance of prediction error, the additivity assumption can be assumed justified (Phadke, 1989). Validation of the additivity assumption essentially implies the absence of significant interaction affects between factors. Results of the verification experiments are detailed in section 5.4.

The ANOM plots shown in figure 2 reveal the relative magnitude of the main effects of various factors on the mean tardiness. Judging from the variation of the S/N ratios for each factor, the information delay ratio affects mean tardiness the most, followed by the factors, routing flexibility and due date tightness. The effects of the two factors, sequencing rule and dispatching rule, are relatively less pronounced. However, a better feel for the relative effects is obtained by conducting the analysis of variance, which is described next.

(ii) Analysis of variance

The formulas and the numbers used in conducting the ANOVA for mean tardiness are detailed in Appendix B. Table 6 shows the values of the sum of squares of variation for each factor and for the residual error. The variance for each factor is simply the sum of squares of its variations from the mean divided by its degree of freedom. The same formula applies to the residual error.

As a first cut, assuming all factors to be significant, we obtain F values of 4.95, 1.78, 1.62, 0.22, and 0.00, respectively, for IDR, RF, T, S, and D (not shown in table 6). At a 5% significance level, only IDR is significant (probability = 2.6%). Other factors have a probability of obtaining their F values, respectively, 22.5%, 25.9%, 92.1%, and 100%. That leaves IDR to be the only significant factor at a 5% significance level. In the second iteration, all non-significant factors, RF, T, S, and D, are pooled with the error. The new sum of squares for the residual error = 521.66, with 20 degrees of freedom. See table 6. Based on the new value of the variance of error (with all insignificant factors pooled), the IDR has an F value of 4.74 (see table 6). At a 5% level, this is the only significant factor for the mean tardiness objective. Note that this procedure is consistent with the one recommended in Phadke (1989) for the pooling of insignificant factors.

Phadke (1989) suggests using the F value resulting from the ANOVA only to establish the relative magnitude of the effect of each factor on the objective function η and to estimate the error variance. However, probability statements regarding the significance of individual factors are not made. We have used the probabilities above only for sorting out significant factors from insignificant and in that sense, use of probabilities is only to evaluate the relative magnitude of their variations. From the ANOVA tableau, the relative effect of the factor information delay ratio is seen to be significant, followed by the factors routing flexibility, due date tightness, sequencing rule, and dispatching rule, in that order. This is in agreement with the ANOM results plotted in figure 2.

To highlight the statistical significance of the impact of individual factors on the mean tardiness, in table 7, we present the ANOVA using the original simulated results (i.e., without converting to S/N ratios). The resulting ‘F’ ratio, again calculated using the method of pooling, is seen to be critical only for the factor information delay ratio (F = 5.54). Importantly, none of the other factors are significant. This demonstrates the consistency between the analytical findings using direct values of mean tardiness and their S/N counterparts.

5.2 Results for percent tardy, mean flowtime, and average machine utilization

Having demonstrated how analyses of means (ANOM) and variance (ANOVA) were carried out for mean tardiness in detail, we skip the details of similar analyses for percent tardy, mean flowtime, and machine utilization. The matrix experiment results for these performance measures are summarized in table 11. The information contained in this table is explained in section 5.3. The main factor effects of these objective functions are plotted, respectively, in figures 3, 4, and 5. The findings of the analysis of means are described next.

(i) Analysis of means

The main factor effects highlight the relative contribution of each factor level to the respective performance measures. Based on the analysis of means, the best levels for each factor are shown highlighted, respectively, in the ANOM plots of figures 3, 4, and 5. Accordingly, the predicted factor level combination that should minimize the percent tardy is RF3, D1, S2, T4, IDR1, which means that routing flexibility = 3, the dispatching rule is WINQ, the sequencing rule is EDD, the due date tightness factor = 6, and information delay ratio = 1. Interestingly, the predicted factor level combinations for both mean flowtime and average machine utilization are identical. The ANOM plots of figures 4 and 5 highlight that the best factor combination that should minimize both of these performance measures is RF3, D2, S1, T4, IDR1, which means that routing flexibility = 3, the dispatching rule is NINQ, the sequencing rule is SOPT, the due date tightness factor = 6, and information delay ratio = 1.

For the percent tardy measure, the factors IDR and T appear to have a significant impact, while for the mean flowtime and average machine utilization measures, only IDR and RF seem to have a major impact. Notably, both the sequencing and dispatching rules do not appear to impact the above performance measures significantly. The rationale for T being significant for percent tardy is obvious. The tighter T gets, the greater the chance of being tardy and vice versa. The same logic does not apply to mean flowtime and machine utilization.

(ii) Analysis of variance

Tables 8, 9, and 10, respectively, show the ANOVA results for the above three performance measures, using the original simulated results. The analysis with S/N ratios was dropped for these three objectives for brevity, having demonstrated that the findings with the original results are consistent with those using S/N ratios. For the percent tardy measure, table 8 highlights the significance of the factors DT and IDR, as noted from their 'F' ratios, $F = 4.5$ and $F = 3.35$, respectively. Interestingly, none of the other factors have a significant impact. Further, for the mean flowtime measure, table 9 shows that both IDR ($F = 9.96$) and RF ($F = 4.64$) are significant. Also, for the average machine utilization measure, table 10 shows that both IDR ($F = 9.62$) and RF ($F = 4.58$) are significant. None of the remaining factors have a significant impact. It is noteworthy once again that IDR was the significant factor across the board.

5.3 Sensitivity experiment with reduced information delay ratio

To gain insights from a sensitivity viewpoint, a second matrix experiment was conducted by varying the levels of the factor information delay ratio, while retaining identical settings for the remaining factors. For this revised experiment, IDR was varied in the range 0 – 1, in contrast to the range 1 – 2, in the original experiment. The new range ($0 < IDR < 1$) was chosen so as to develop a sense of the degree to which the deleterious impact of information delay on system performance is reduced as the magnitude of information delay with respect to the processing times is decreased. The question we seek to answer here is: Is there a specific value of IDR below which the performance loss due to information delay becomes tolerable? This question is significant because by determining the tolerance level to information delays, investment decisions in automation could be made more judiciously. The specific values of IDR within the 0-1 range (0, .25, 0.50, 0.75, and 1) were chosen to provide a uniform spread over the interval.

5.3.1 Sensitivity results for revised matrix experiment

The observed values for each performance measure (for both the original and revised matrix experiments) are summarized in table 11. The table layout is as follows: The first column shows the experiment number (treatment) from the L_{25} array. Then, three columns are assigned to each of the four performance measures (MT, PT, MF, and AMU) in the table. The first column shows the value of the main effect for the treatment for that measure when information delay ratio has a “high” value and the second column shows the value of the main effect for the treatment when information delay ratio has a “low” value. The rows are so arranged that for each treatment, the ratio of “high” to “low” IDR is 2.0. Thus, the main effects in high and low columns represent the impact of IDR (IDR = 2 vs. IDR = 1) while the other four factors have identical levels in both columns for a given treatment. The third column shows the percent deterioration that occurs as a result of doubling the IDR. Finally, the last two rows represent the average and maximum values of each column over all 25 experiments. For the percent deterioration columns, maximum value represents the worst impact of IDR when it is doubled. Analytical findings from this table specifically with regard to the last two rows are available in section 5.6.

Table 12 details the ‘F’ ratios and the best factor level combinations for each performance measure, for both the original and the revised matrix experiments. For each performance measure, it is interesting to compare the ‘F’ ratios across the original and revised matrix experiments.

For the mean tardiness performance measure, whereas IDR (F = 5.54) was the only significant factor in the original matrix experiment, a reduction in the range of IDR (from 1 – 2 to 0 – 1) resulted in RF (F = 102.05) being the only significant factor in the revised matrix experiment. Furthermore, the best factor level combination for the revised matrix experiment is RF5, D1, S5, T4, and IDR1. This implies that the routing flexibility = 5, the dispatching rule is WINQ, the sequencing rule is OSlack, the due date tightness factor = 6, and information delay ratio = 0. Interestingly, note that in the original matrix experiment, when the IDR had a significant impact (F = 5.54), the best factor combination showed that a routing flexibility level of 3 gave best results. However, with reduced IDR levels, the best factor level for routing flexibility increased to 5.

For the percent tardy performance measure, it is interesting to note that while T (F = 4.5) and IDR (F = 3.35) were the only two significant factors in the original experiment, in the revised matrix experiment, RF (F = 10.17), IDR (F = 3.29), and T (F = 3.90) all have a significant impact. Further, the best factor combination is RF4, D1, S5, T4, and IDR1, implying that routing flexibility = 4, the dispatching rule is WINQ, the sequencing rule is OSlack, the due date tightness factor = 6, and information delay ratio = 0. Again, with reduced IDR levels, the best factor level for routing flexibility increased from 3 in the original experiment to 4 in the revised experiment.

For the case of mean flowtime, in the original matrix experiment, the only two significant factors were RF (F = 4.64) and IDR (F = 9.96). In the revised matrix experiment, the same two factors, RF (F = 68.93) and IDR (F = 11.62), remain significant. Note however, the reversal in the magnitude of the 'F' ratios across the experiments. Further, in the revised experiment, the best factor combination is RF5, D2, S5, T4, and IDR1, implying that the routing flexibility = 5, the dispatching rule is NINQ, the sequencing rule is OSlack, the due date tightness factor = 6, and information delay ratio = 0. Interestingly, the only difference in the best factor combinations between the experiments is in the levels of the factors routing flexibility and sequencing rule: whereas RF = 3 and the SOPT sequencing rule were the best levels in the original experiment, in the revised experiment, RF = 5 and the OSlack sequencing rule gave best results. Clearly, because of the mitigated effect of information delays in the revised experiment, enhanced routing flexibility levels appear to improve flowtime estimates.

Finally, for the average machine utilization measure, both RF (F = 4.58) and IDR (F = 9.62) are significant in the original as well as in the revised experiment, RF (F = 124.5) and IDR (F = 6.53). Note however, the reversal in the magnitudes of the 'F' ratios between the two experiments. Further, the best factor combination for the revised experiment is RF3, D1, S1, T4, and IDR1, implying that the routing flexibility = 3, the dispatching rule is WINQ, the sequencing rule is SOPT, the due date tightness factor = 6, and information delay ratio = 0. The only difference between the original and revised experiments for this performance measure is in the factor-dispatching rule: whereas NINQ gave best results in the original experiment, in the revised experiment, WINQ gave best results.

In summary, the sensitivity results highlight the fact that a reduction in the range of IDR causes the factor routing flexibility to become much more significant, and the factor information delay ratio relatively less significant, or not at all (as is observed for mean tardiness). Alternatively, system performance benefits significantly from the presence of routing flexibility so long as information delays are constrained to a magnitude below the average processing time per operation of parts in the system. This observation is consistent with the intuitive understanding of FMS performance. When information delay becomes relatively less severe as represented by the lower IDR value, routing flexibility plays a more significant role in determination of system performance. This is consistent with FMS/job shop literature where the impact of routing flexibility on system performance in the absence of information delays has been well established.

5.4 Testing for additivity

To validate the assumption of additivity, or even more fundamentally, the usage of Taguchi experimental design, a verification experiment needs to be conducted with the best factor settings (Phadke, 1989). The result of the verification experiment then is compared with a predicted optimal value, resulting in a prediction error. If the prediction error happens to fall within a two-standard-deviation confidence limit of the variance of prediction error, the additivity assumption can be assumed justified approximately at a 95% confidence level. Validation of the additivity assumption essentially implies the absence of significant interaction effects between factors. Results of the verification experiment for mean tardiness are presented below.

5.4.1 Verification experiment for matrix experiment

A verification experiment, performed with the best factor combination (RF3, D1, S1, T4, IDR1) resulted in an observed mean tardiness of 61.0 minutes, that is, $\eta_{obs.opt}$ = -35.706 dB. Further, the predicted optimum mean tardiness, $\eta_{pre.opt}$, calculated using the main effects of only the significant best factor levels (Phadke, 1989), can be shown to be:

$$\eta_{pre.opt} = m + (m_{IDR,1} - m) = -53.530 + (-46.046 + 53.530) = -46.046 \text{ dB.}$$

The resulting prediction error is:

$$\text{Prediction error} = \eta_{obs.opt} - \eta_{pre.opt} = -35.706 - (-46.046) = 10.34 \text{ dB.}$$

Further, using the following equation (Phadke, 1989), we calculate the variance of prediction error:

$$\text{Variance of prediction error } (\sigma_{e\ pred}^{2}) = (1/n_o)\ \sigma_e^2 + (1/n_r)\ \sigma_e^2,$$

where n_o = equivalent sample size for the estimation of $\eta_{pre.opt}$, n_r = number of repetitions of the verification experiment, and σ_e^2 is the error variance of mean tardiness.

In the present case, n_o is given by

$$1/n_o = 1/n + (1/n_{IDR} - 1/n) = 1/5,$$

since n = number of rows in the matrix experiment = 25

n_{IDR} = number of times factor IDR was repeated in the matrix experiment = 5.

Note that we use only the significant factors for the above computation. Further, because in our study, n_r = 1, the variance of prediction error is calculated to be:

$$\sigma_{e\ pred}^{2} = (1/n_o)\sigma_e^2 + (1/n_r)\ \sigma_e^2 = (1/5) \times 26.08 + 26.08 = 31.296\ (\text{dB})^2.$$

The corresponding two standard deviation confidence limits for the prediction error are $\pm 2 \times \sqrt{\sigma_e^2}_{pred}$ = ±11.189 (dB). Since the prediction error (=10.34 dB) is within the calculated confidence limits, the additivity assumption is justified.

Similar verification experiments were performed for each of the other performance measures, for both of the matrix experiments conducted. In each case, the prediction error was well within the two standard deviation confidence limits for the prediction error, thus justifying the additivity assumption. Details are skipped for brevity.

5.5 Analysis of the results

The ANOVA results from the original matrix experiment summarized in table 12 indicate that the factors information delay ratio and routing flexibility, in that order, are significant in terms of their effect on both the non-due date-based performance measures even at a significance level of 2.5%. It is also observed that the factors due date tightness, dispatching rule, and sequencing rule are not significant. However, for the due date-based measures, whereas the only significant factor for mean tardiness is information delay ratio, both due date tightness and information delay ratio significantly impact the percent tardy measure. From the viewpoint of a system designer, this is an important observation as it helps provide valuable insight into the possible synergy between flexibility, integration, and automation. Based on the results of the present study, it would appear more beneficial to focus on information integration with the intention of decreasing the magnitude of information delays in an attempt to improve system performance.

The result is noteworthy because system controllers might instead have focused on both the control parameters (dispatching rule and sequencing rule) in their endeavor to improve system performance. Although, for the assumed experimental conditions, it is evident that both of the control parameters do not play an important role in improving system performance, the result is context specific and should not be interpreted in a generic sense. Further, although earlier studies by Neimeier (1965) and Wayson (1967), and more recently by Benjaafar, Talavage, and Ramakrishnan (1995), also concluded that the relative superiority of sophisticated scheduling rules over naive rules such as FCFS decreased substantially even with a little use of routing flexibility, the case with information delays deserves due consideration. Judging by the superior performance of the sequencing heuristics reported in Caprihan, Kumar, and Wadhwa (1997) and Wadhwa, Caprihan, and Kumar (1997), it would seem a worthwhile research effort to develop alternative dispatching heuristics for deployment within FMSs with information delayed operational environments. Recent research results show promise in this regard (Caprihan, Kumar, and Gursaran, 2000; Caprihan, 2000).

The ANOM plots of figures 2 through 5 further highlight the relative contributions of the factors in terms of their effect on the assumed performance measures. For each of the measures, it is interesting to observe that increasing the RF from 1 to 3 results in a marked improvement in performance while subsequent increments in the levels of routing flexibility tend to be counterproductive. Clearly, higher levels of RF provide greater scope for erroneous dispatch decisions being made in the presence of information delays, leading to detrimental affects on the performance measures. In contrast to the factor routing flexibility, and consistent with intuition, IDR incrementally degrades performance across the board for all performance measures. Notably, as judged from the range of S/N ratios, it has significantly more impact on all performance measures except for the percent tardy measure for which the due date tightness factor is more significant. Further, the factors sequencing rule and dispatching rule do not appear to have much affect on the performance measures.

The sensitivity results with reduced IDRs are noteworthy. The factor RF, in contrast to the original matrix experiment, dominates in terms of impact across all performance measures. Intuitively, enhanced routing flexibility levels should improve system performance, especially with flexibility provided without a penalty on processing times (see table 1), and with information delays constrained to a magnitude below the average processing time per operation of parts in the system. For the mean tardiness and mean flowtime measures, RF continually improves performance up to a level of 5. However, the marginal benefit of enhancing routing flexibility levels for both these measures exhibits a decreasing trend. This observation is in agreement with the earlier results of Bobrowski and Mabert (1988), Chen and Chung (1991), and Benjaafar et al. (1995) who point out that the introduction of routing flexibility follows a *Law of Diminishing Returns*. Further, results for the percent tardy measure have a similar trend as with the original matrix experiment: increasing the RF from 1 to 4 causes a marked improvement in results while subsequent increments in the levels of routing flexibility prove to be detrimental. Further, it is interesting to note that information delay ratio is no longer significant for the mean tardiness measure. In fact, for this measure, RF is the only significant factor in the revised experiment. However, for the non-due date measures (mean flowtime and average machine utilization), IDR continues to remain significant.

5.6 Performance deterioration in the presence of information delays

The last two rows of table 11 summarize the results of the simulation experiments in terms of the average and maximum percent performance deterioration caused by information delays. Percent performance deterioration is defined as:

$$\frac{Performance\ \ measure\ \ value\ \ at\ \ high\ \ IDR\ -\ Performance\ \ measure\ \ value\ at\ low\ IDR}{Performance\ measure\ \ value\ \ at\ low\ IDR} * 100$$

for smaller-the-better performance measures. For the larger-the-better measure, the terms in the numerator are reversed. Also, as stated before, the performance measure value in the 'High' IDR column in the table refers to a range of 1 - 2 whereas the 'Low' IDR refers to a range of 0 - 1, and in each row (treatment), the table is so organized that the ratio of high IDR to low IDR is maintained exactly at 2.0 to allow us to obtain a clear estimate of the impact of information delays on the FMS performance. We note from the last two rows that, for the mean tardiness performance measure, the average percent deterioration of the FMS performance is 68.6%, and it deteriorates to 99.7% in the worst case. Similarly, for the percent tardy performance measure, the average percent deterioration in performance is 41.0%, and it deteriorates to 95.3% in the worst case. However, the penalties for the non-due date-based measures appear to be less severe. For the mean flowtime performance measure, the average percent deterioration in performance is 8.3%, with the worst case being 13.8%; for the average machine utilization measure, the average percent deterioration is only 5.6%, with a maximum deterioration of 13.3%. Based on the simulation experiments, it can be concluded that information delays cause deterioration in FMS performance for all considered performance measures, although the due date-based measures suffer much more significantly.

6. Conclusions

The role of flexibility in manufacturing systems has been well understood and extensively researched. The performance of such systems pivots on the quality and availability of system status information. Yet, researchers have paid little attention to issues that are at the interface of flexibility and information automation. The focus of this paper is the analysis of the impact of one such issue – information delay – on FMS performance. Towards this end, information delay is defined as the sum of the delays that occur in the retrieval of status information, compilation of this information into an intelligible format, transmission of information, dissemination of information for the generation of a decision, and communication of the control decision(s) to the point of execution. In this paper we use extensive simulation experimentation to study the impact of information delays on FMS performance.

Our key finding is that information delays significantly impair system performance, especially for due date-based objectives. The performance of FMSs suffers less severely for non-due date-based measures. Specifically, we find that for mean tardiness and percent tardiness, the FMS performance deteriorates by as much as 68.6% and 41.0%, respectively, on average. In contrast, for the non-due date-based measures, mean flowtime and average machine utilization, the performance deterioration was only 8.3% and 5.6%, respectively. The worst-case scenarios record deterioration in performance of up to 99.7%.

Given the fact that these results are based on simulation experiments, one may doubt the universality of these findings; there is little question, nevertheless, that our results serve to highlight the deleterious effect that information delays can have on FMS performance, and that managers can ill afford to ignore them in their scheduling endeavors. We believe that this work can constitute the proverbial small first step towards understanding the full impact and extent of information delays in FMS scheduling in particular, and in automated manufacturing systems scheduling at large.

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APPENDIX A

The following notation is used in defining scheduling rules used in the simulation study:

t	:	Time at which a scheduling decision is to be made
i	:	Part index
j	:	Operation index
$j(t)$	:	Imminent operation of part i
P_i	:	Total processing time of a part of type i
$P_{i,j(t)}$	:	Sum of processing times for all operations preceding (and including) the j(t)*th* operation of the *i*th part type
$p_{i,j}$	:	Processing time for the *j*th operation of a part of type i
D_i	:	Due date of a part of type i
$d_{i,j}$	:	Operation due date for the *j*th operation of a part of type i
T	:	Due date tightness factor
$N_{i,j}(t)$	:	Set of parts in a queue corresponding to the *j*th operation of the *i*th part type at time t
$W_{i,j}(t)$	:	Total work content of the queue, i.e., the sum of the operation times of the $N_{i,j}(t)$ parts in that queue
$Z_i(t)$	:	Priority of part type i at time t
$M_{i,j+1}$	:	Set of machines capable of processing the (j+1)*th* operation of the *i*th part type
$N_{i,j+1,m}(t)$	:	Set of parts in the *m*th machine queue, $m \varepsilon M_{i,j+1}$ corresponding to the (j+1)*th* operation of the *i*th part type at time t
$W_{i,j+1,m}(t)$	:	Total work content of the *m*th machine queue, $m \varepsilon M_{i,j+1}$, i.e., the sum of the imminent operation times of the $N_{i,j+1,m}(t)$ parts in that queue

Sequencing rules used:

SOPT	:	Select the part with the shortest operation processing time, i.e., choose minimum $Z_i(t)$, where $Z_i(t) = p_{i,j(t)}$.
EDD	:	Select the part with the earliest due date, i.e., choose minimum $Z_i(t)$, where $Z_i(t) = D_i$.
Slack	:	Select the part with the smallest remaining slack, i.e., choose minimum $Z_i(t)$, where $Z_i(t) = D_i - t - P_{i,j(t)}$.
ODD	:	Select the part with the smallest operation due date, i.e., choose minimum $Z_i(t)$, where $Z_i(t) = d_{i,j}$ given that $d_{i,j} = d_{i,j-1} + Tp_{i,j}$.
OSlack	:	Select the part with the smallest operation slack time, i.e., choose minimum $Z_i(t)$, where $Z_i(t) = d_{i,j} - t - p_{i,j}$.

Dispatching rules used:

WINQ	:	Select that machine to process the next operation for a part which has the least work, i.e., select minimum $Z_i(t)$, where $Z_i(t) = W_{i,j+1,m}(t)$ for $m \varepsilon M_{i,j+1}$.
NINQ	:	Select that machine to process the next operation for a part which has the shortest queue, i.e., select minimum $Z_i(t)$, where $Z_i(t) = \mid N_{i,j+1,m}(t) \mid$ for $m \varepsilon M_{i,j+1}$.

APPENDIX B

Formulae for the analysis of variance

We use the following formulae in conducting the ANOVA (Phadke, 1989). The ANOVA calculations are illustrated using the simulation results for mean tardiness shown in table 4.

Total sum of squares = SST

= Sum of the sums of squares due to various factors (SSB) + Sum of squares due to error (SSE).

Further, SST = Grand total sum of squares (GTSS) - Sum of squares due to the mean (SSM).

Now, from table 4, using the observed mean tardiness values as S/N ratios,

$$\text{GTSS} = \sum_{i=1}^{25} \eta_i^2 = (-57.26)^2 + (-59.99)^2 + ... + (-50.02)^2 \text{ (dB)}^2 = 72654.148 \text{ (dB)}^2.$$

Also, SSM = $n \times m^2 = 25 \times (-53.530)^2 = 71637.594$ (dB)^2.

Therefore, SST = GTSS - SSM = 1016.555 (dB)^2 and SSB = $\sum_{j=1}^{c} \left[l_j \sum_{k=1}^{l_j} (m_{jk} - m)^2 \right]$,

where c = the number of factors and l_j = the number of levels for factor 'j', which can essentially be broken up into SSB = $SSB_1 + SSB_2 + SSB_3 + ... + SSB_C$.

In our case, SSB = $SSB_{RF} + SSB_T + SSB_D + SSB_S + SSB_{IDR}$.

Now, $SSB_{RF} = 5[(-58.540 + 53.530)^2 + (-52.820 + 53.530)^2 + ...+ (-53.576 + 53.530)^2]$ (dB)^2 = 178.343 (dB)^2.

Similarly, the other components are, SSB_T = 121.594 (dB)^2, SSB_D = 0.014 (dB)^2, SSB_S = 21.850 (dB)^2, and SSB_{IDR} = 494.893 (dB)^2.

Therefore, SSB = (178.343 + 121.594 + 0.014 + 21.850 + 494.893) (dB)^2 = 816.693 (dB)^2.

Finally, SSE = SST - SSB = 1016.555 - 816.693 (dB)^2 = 199.861 (dB)^2 .

Table 1. Part type / processing time data (routing flexibility = 5)

Part type	Operation #	Alternate machines[1]					
		1	2	3	4	5	6
A	1	16	16	16	16	-	16
	2	-	20	20	20	20	20
	3	12	12	12	12	12	-
	4	10	10	10	10	10	10
	5	15	15	-	15	15	15
	6	22	-	22	22	22	22
B	1	25	25	25	25	-	25
	2	-	9	9	9	9	-
	3	10	10	10	10	10	10
	4	23	23	23	-	-	23
C	1	10	10	-	10	10	10
	2	-	24	24	24	24	24
	3	14	14	14	-	14	14
	4	19	-	19	19	19	19
	5	15	15	15	15	-	15
D	1	26	26	-	26	26	26
	2	-	20	20	20	20	20
	3	32	32	32	-	32	-
	4	8	8	8	8	8	8
E	1	-	9	9	9	9	9
	2	18	18	18	18	18	18
	3	30	-	30	30	30	-
	4	20	20	20	20	-	20
	5	11	11	11	-	11	11
F	1	10	10	10	10	10	10
	2	-	13	13	13	13	-
	3	12	-	12	-	12	12
	4	22	22	-	22	-	22
	5	9	9	9	9	9	9
	6	15	15	15	-	15	15

[1] Note : Cell entries marked “-” imply that the machine cannot process the specified operation

Table 2. Factor-level details used in the Taguchi experiment

Factor name (label)	Factor level	Factor-level details (name or value)
Routing Flexibility (RF)	1	1
	2	2
	3	3
	4	4
	5	5
Dispatching Rule (D)	1	WINQ
	2	NINQ
Sequencing Rule (S)	1	SOPT
	2	EDD
	3	Slack
	4	ODD
	5	OSlack
Due Date Tightness (T)	1	3
	2	4
	3	5
	4	6
Information Delay Ratio (IDR)	1	1
	2	1.25
	3	1.5
	4	1.75
	5	2

Table 3. Factor-level details per L_{25} orthogonal array

Experiment #	RF	D	S	T	IDR
1	1	WINQ	SOPT	3	1
2	1	NINQ	EDD	4	1.25
3	1	WINQ	Slack	5	1.5
4	1	NINQ	ODD	6	1.75
5	1	WINQ	OSlack	3	2
6	2	WINQ	EDD	5	1.75
7	2	NINQ	Slack	6	2
8	2	WINQ	ODD	3	1
9	2	NINQ	OSlack	3	1.25
10	2	WINQ	SOPT	4	1.5
11	3	WINQ	Slack	3	1.25
12	3	NINQ	ODD	3	1.5
13	3	WINQ	OSlack	4	1.75
14	3	NINQ	SOPT	5	2
15	3	WINQ	EDD	6	1
16	4	WINQ	ODD	4	2
17	4	NINQ	OSlack	5	1
18	4	WINQ	SOPT	6	1.25
19	4	NINQ	EDD	3	1.5
20	4	WINQ	Slack	3	1.75
21	5	WINQ	OSlack	6	1.5
22	5	NINQ	SOPT	3	1.75
23	5	WINQ	EDD	3	2
24	5	NINQ	Slack	4	1
25	5	WINQ	ODD	5	1.25

Table 4. Taguchi experiment simulation results: mean tardiness

Experiment number	**Observed Mean Tardiness** (minutes)	**Mean Tardiness (η_i)** (dB)
1	729.78	-57.26
2	998.91	-59.99
3	910.49	-59.19
4	684.75	-56.71
5	949.25	-59.55
6	589.85	-55.41
7	650.31	-56.26
8	295.93	-49.42
9	433.00	-52.73
10	326.65	-50.28
11	398.71	-52.01
12	546.44	-54.75
13	671.88	-56.55
14	542.56	-54.69
15	**63.04**	**-35.99**
16	980.53	-59.83
17	124.45	-41.90
18	117.02	-41.37
19	710.15	-57.03
20	939.25	-59.46
21	505.97	-54.08
22	651.19	-56.27
23	1237.30	-61.85
24	191.89	-45.66
25	316.78	-50.02

Table 5. Factor main effects for the Taguchi simulation results for mean tardiness

Factor-level main effects	Applicable formulae	Main effect value for mean tardiness (dB)
$m_{RF,1}$	$(\eta_1 + \eta_2 + \eta_3 + \eta_4 + \eta_5) / 5$	-58.540
$m_{RF,2}$	$(\eta_6 + \eta_7 + \eta_8 + \eta_9 + \eta_{10}) / 5$	-52.820
$m_{RF,3}$	$(\eta_{11} + \eta_{12} + \eta_{13} + \eta_{14} + \eta_{15}) / 5$	***-50.798***
$m_{RF,4}$	$(\eta_{16} + \eta_{17} + \eta_{18} + \eta_{19} + \eta_{20}) / 5$	-51.918
$m_{RF,5}$	$(\eta_{21} + \eta_{22} + \eta_{23} + \eta_{24} + \eta_{25}) / 5$	-53.576
$m_{D,1}$	$(\eta_1 + \eta_3 + \eta_5 + \eta_6 + \eta_8 + \eta_{10} + \eta_{11} + \eta_{13} + \eta_{15} + \eta_{16} + \eta_{18} + \eta_{20} + \eta_{21} + \eta_{23} + \eta_{25}) / 15$	***-53.485***
$m_{D,2}$	$(\eta_2 + \eta_4 + \eta_7 + \eta_9 + \eta_{12} + \eta_{14} + \eta_{17} + \eta_{19} + \eta_{22} + \eta_{24}) / 10$	-53.599
$m_{S,1}$	$(\eta_1 + \eta_{10} + \eta_{14} + \eta_{18} + \eta_{22}) / 5$	***-51.974***
$m_{S,2}$	$(\eta_2 + \eta_6 + \eta_{15} + \eta_{19} + \eta_{23}) / 5$	-54.054
$m_{S,3}$	$(\eta_3 + \eta_7 + \eta_{11} + \eta_{20} + \eta_{24}) / 5$	-54.516
$m_{S,4}$	$(\eta_4 + \eta_8 + \eta_{12} + \eta_{16} + \eta_{25}) / 5$	-54.146
$m_{S,5}$	$(\eta_5 + \eta_9 + \eta_{13} + \eta_{17} + \eta_{21}) / 5$	-52.962
$m_{T,1}$	$(\eta_1 + \eta_5 + \eta_8 + \eta_9 + \eta_{11} + \eta_{12} + \eta_{19} + \eta_{20} + \eta_{22} + \eta_{23}) / 10$	-56.033
$m_{T,2}$	$(\eta_2 + \eta_{10} + \eta_{13} + \eta_{16} + \eta_{24}) / 5$	-54.462
$m_{T,3}$	$(\eta_3 + \eta_6 + \eta_{14} + \eta_{17} + \eta_{25}) / 5$	-52.242
$m_{T,4}$	$(\eta_4 + \eta_7 + \eta_{15} + \eta_{18} + \eta_{21}) / 5$	***-48.882***
$m_{IDR,1}$	$(\eta_1 + \eta_8 + \eta_{15} + \eta_{17} + \eta_{24}) / 5$	***-46.046***
$m_{IDR,2}$	$(\eta_2 + \eta_9 + \eta_{11} + \eta_{18} + \eta_{25}) / 5$	-51.224
$m_{IDR,3}$	$(\eta_3 + \eta_{10} + \eta_{12} + \eta_{19} + \eta_{21}) / 5$	-55.066
$m_{IDR,4}$	$(\eta_4 + \eta_6 + \eta_{13} + \eta_{20} + \eta_{22}) / 5$	-56.880
$m_{IDR,5}$	$(\eta_5 + \eta_7 + \eta_{14} + \eta_{16} + \eta_{23}) / 5$	-58.436

Table 6. ANOVA for mean tardiness using the simulated results estimated as S/N ratios

Factor	Degrees of Freedom	Sum of Squares	Mean Square	F value
Information Delay Ratio	4	494.89	123.72	4.74
Routing Flexibility	4	178.34[b]	44.59	
Due Date Tightness	3	121.59[b]	40.53	
Sequencing Rule	4	21.85[b]	5.46	
Dispatching Rule	1	0.01[b]	0.01	
Error	8	199.86[b]	24.98	
Total	24	1016.56	42.36	
Pooled Error	(20)	(521.66)	(26.08)	

Table 7. ANOVA for mean tardiness using the original simulated results

Factor	Degrees of Freedom	Sum of Squares	Mean Square	F[a] value
Information Delay Ratio	4	1036981.13	259245.28	5.54
Routing Flexibility	4	541907.63	135476.91	2.89
Due Date Tightness	3	212671.39[b]	70890.46	
Sequencing Rule	4	172086.00[b]	43021.50	
Dispatching Rule	1	2476.39[b]	2476.39	
Error	8	361585.50[b]	45198.19	
Total	24	2327708.03	96987.83	
Pooled Error	(16)	(748819.28)	(46801.21)	

[a]The critical F ratio (at $\alpha = 0.05$; i.e., $F_{0.05,4,16}$) = 3.01.
[b]Indicates the sum of squares added together to estimate the pooled error sum of squares, indicated in parentheses. The F ratio is calculated using the pooled error mean square.

Table 8. ANOVA for percent tardy using the original simulated results

Factor	Degrees of Freedom	Sum of Squares	Mean Square	F[a] value
Due Date Tightness	3	1517.30	505.77	4.50
Information Delay Ratio	4	1504.05	376.01	3.35
Routing Flexibility	4	554.39	138.60	1.23
Sequencing Rule	4	100.56[b]	25.14	
Dispatching Rule	1	0.86[b]	0.86	
Error	8	1358.19[b]	169.77	
Total	24	3518.05	146.59	
Pooled Error	(13)	(1459.61)	(112.28)	

[a]The critical F ratio (at $\alpha = 0.05$; i.e., $F_{0.05,4,13}$) = 3.18.
[b]Indicates the sum of squares added together to estimate the pooled error sum of squares, indicated by parentheses. The F ratio is calculated using the pooled error mean square.

Table 9. ANOVA for mean flowtime using the original simulated results

Factor	Degrees of Freedom	Sum of Squares	Mean Square	F[a] value
Information Delay Ratio	4	735.10	183.78	9.96
Routing Flexibility	4	342.69	85.67	4.64
Sequencing Rule	4	91.41[b]	22.85	
Due Date Tightness	3	20.65[b]	6.88	
Dispatching Rule	1	0.91[b]	0.91	
Error	8	182.38[b]	22.80	
Total	24	1373.13	57.21	
Pooled Error	(16)	(295.34)	(18.46)	

[a]The critical F ratio (at $\alpha = 0.05$; i.e., $F_{0.05,4,16}$) = 3.01.
[b]Indicates the sum of squares added together to estimate the pooled error sum of squares, indicated by parentheses. The F ratio is calculated using the pooled error mean square.

Table 10. ANOVA for average machine utilization using the original simulated results

Factor	Degree of Freedom	Sum of Squares	Mean Square	F[a] value
Information Delay Ratio	4	133.96	33.49	9.62
Routing Flexibility	4	63.77	15.94	4.58
Sequencing Rule	4	18.87[b]	4.72	
Due Date Tightness	3	3.79[b]	1.26	
Dispatching Rule	1	0.16[b]	0.16	
Error	8	32.85[b]	4.11	
Total	24	253.41	10.56	
Pooled Error	(16)	(55.67)	3.48	

[a]The critical F ratio (at $\alpha = 0.05$; i.e., $F_{0.05,4,16}$) = 3.01.
[b]Indicates the sum of squares added together to estimate the pooled error sum of squares, indicated by parentheses. The F ratio is calculated using the pooled error mean square.

Table 11. Deterioration in FMS performance for the performance measures

Experiment number	Mean tardiness			Percent tardy			Mean flowtime			Average machine utilization		
	Information delay ratio		% Performance deterioration	Information delay ratio		% Performance deterioration	Information delay ratio		% Performance deterioration	Information delay ratio		% Performance deterioration
	High*	Low*		High	Low		High	Low		High	Low	
1	729.78	729.78	0.0	88.33	88.33	0.0	165.72	165.72	0.0	82.05	82.05	0.0
2	998.91	998.91	0.0	87.44	87.44	0.0	173.61	173.61	0.0	78.62	78.62	0.0
3	910.49	910.49	0.0	83.7	83.7	0.0	173.16	173.16	0.0	78.85	78.85	0.0
4	684.75	684.75	0.0	77.67	77.67	0.0	169.87	169.87	0.0	80.36	80.36	0.0
5	949.25	949.25	0.0	92.42	92.42	0.0	170.5	170.5	0.0	80.07	80.07	0.0
6	589.85	165.39	72.0	78.6	57.61	26.7	165.95	153.79	7.3	81.86	87.14	6.5
7	650.31	198.67	69.4	77.29	56.87	26.4	168.85	156.46	7.3	80.72	85.94	6.5
8	295.93	122.76	58.5	80.92	65.66	18.9	154.1	147.51	4.3	87.1	89.39	2.6
9	433	179.04	58.7	85.07	73.22	13.9	158.38	149.95	5.3	85.36	88.54	3.7
10	326.65	99.04	69.7	75.38	53.13	29.5	157.32	149.06	5.3	85.77	88.94	3.7
11	398.71	35.86	91.0	83.46	36.29	56.5	157.13	140.15	10.8	85.72	90.62	5.7
12	546.44	57.98	89.4	85.76	48.79	43.1	160.96	143.73	10.7	84.17	90.34	7.3
13	671.88	65.69	90.2	83.98	45.2	46.2	165.92	147.47	11.1	82.07	89.54	9.1
14	542.56	53.6	90.1	78.23	35.18	55.0	164.64	149	9.5	82.57	89.05	7.8
15	63.04	0.21	99.7	35.19	1.65	95.3	151.6	136.32	10.1	88.08	90.83	3.1
16	980.53	157.09	84.0	87.43	63.13	27.8	173.64	151.71	12.6	78.83	88.12	11.8
17	124.45	0.64	99.5	51.93	2.85	94.5	152.33	133.56	12.3	87.9	90.95	3.5
18	117.02	0.32	99.7	46.89	2.21	95.3	153.74	137.58	10.5	87.18	90.81	4.2
19	710.15	48.74	93.1	88.3	44.54	49.6	165.53	142.76	13.8	82.04	90.34	10.1
20	939.25	125.63	86.6	90.81	65.99	27.3	170.79	148.11	13.3	79.87	89.25	11.7
21	505.97	3.46	99.3	73.35	8.8	88.0	165.56	143.17	13.5	82.31	90.43	9.9
22	651.19	83.26	87.2	87.97	58.02	34.0	163.85	145.84	11.0	82.91	89.86	8.4
23	1237.3	252.35	79.6	93.36	78.32	16.1	176.88	152.76	13.6	77.26	87.52	13.3
24	191.89	2.32	98.8	65.61	6.06	90.8	152.95	132.71	13.2	87.49	91.01	4.0
25	316.78	2.39	99.2	70.44	6.85	90.3	158.44	138.09	12.8	85.28	90.82	6.5
Average	582.6	237.1	**68.6**	78.0	49.6	**41.0**	163.7	150.1	**8.3**	83.0	87.6	**5.6**
Maximum	1237.3	998.9	**99.7**	93.4	92.4	**95.3**	176.9	173.6	**13.8**	88.1	91.0	**13.3**

*The ratio of **'High'** IDR (1.0 - 2.0) to **'Low'** IDR (0.0 - 1.0) was 2.0 for each experiment.