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ABSTRACT

Routing flexibility is acclaimed as a contributor in the success of flexible manufacturing systems. To harness the potential benefits of routing flexibility, system controllers often use dispatching rules. The successful deployment of dispatching rules desires accurate and timely shop floor status information. However, the acquisition, processing, and transfer of plant-wide status information is not a trivial task and can be 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.

In this paper, we present analytical models for static (off-line) and dynamic (real-time) scheduling of flexible manufacturing systems in the presence of information delays that yield optimal schedules with respect to four performance measures: mean tardiness, percent tardiness, mean flowtime, and average machine utilization. The computational complexity of such models permits the development of optimal solutions only for small manufacturing systems. Consequently, we use simulation to analyze the impact of information delays on the performance of larger manufacturing systems possessing routing flexibility. Towards this end, we define a metric, information delay ratio (IDR), which relates the magnitude of information delays to the average processing time per operation of parts in a system. Simulation experiments, performed on a flexible system using IDR as one of five experimental factors, reveal the following key findings: (1) information delays cause significant impairment of system performance with respect to due-date based measures, and (2) non due-date based measures are relatively insensitive to the adverse impact of information delays.

1. Introduction

Manufacturing organizations worldwide have acclaimed the flexible manufacturing concept as a panacea for a host of complex production related problems arising out of constantly varying market demands, decreasing delivery lead times, exacting quality standards, and soaring production costs. Flexible manufacturing systems (FMSs) are able to adapt quickly and efficiently to changing customer requirements that impose 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 large FMS installations has largely remained the domain of big companies such as Boeing, IBM, and John Deere 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 $350,000 to $450,000, a complete FMS installation could be $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. This transition from a conventional to a fully integrated FMS could run into several years.

In an ideal flexible manufacturing environment, all of the information necessary for execution of a control strategy is available in real-time, and consequently, good scheduling decisions can be made quickly. We define a *semi-automated flexible manufacturing system (SAFMS)* as a transitional form of manufacturing system wherein the level of information integration and automation is not developed to the extent that is prevalent within FMSs. An SAFMS then has a few islands of automation and employs various scheduling or control strategies to harness the built-in flexibility for performance enhancement. Most SAFMSs and FMSs can 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 SAFMSs. 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 scheduling and control strategies employed, the performance measures of interest, as well as the extent of the information delay.

Information delays in manufacturing systems can 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 at each of many decision epochs due to 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 finally (v) the communication of the control decision(s) to the execution point.

Each of the above elements of information-related activities constitute delays at each execution point of a control strategy. Gusikhin, Lewis, and Miteff (1996) and Gusikhin and Miteff (1999) 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 which is limited to transactional information. Transactional information describes a single event in an operation. An event includes 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 (1999) 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 (1999) 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 could 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, 1999). 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 not been considered 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; Caprihan and Wadhwa, 1999; Gusikhin *et al.*, 1996, and Gusikhin and Miteff, 1999).

Information delays seem to be generic to all manufacturing systems. The magnitude of these delays may be reduced using higher degrees of automation but cannot be completely eliminated. Time is expended in the retrieval, formatting, processing, and communication of status information that is required for 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.

This 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. In section 4, three modes of information delays are defined. Section 5 presents static and dynamic formulations to schedule FMSs in the presence of information delays. Section 6 defines terminology, performance measures, and details of a simulation experiment. In section 7, we summarize the results and key findings of the simulation experiment. Section 8 provides concluding remarks.

2. Review of the literature

In FMSs, the definition of flexibility is important (see Browne, Dubois, Rathmill, Sethi, and Stecke, 1984). Routing flexibility implies the existence of multiple sequencing routes for individual part types as a means of improving system performance. Browne *et al.* (1985) refers to this manifestation of routing flexibility as actual routing flexibility. Our interpretation is similar to that of some other researchers (Stecke and Solberg, 1981; Stecke, 1992).

Through an industry survey, Smith, Dudek, Ramesh, and Blair (1986) highlight the importance of due date related criteria in the FMS context. Due dates can be specified both externally by a customer or set internally by the vendor. Most studies however, have investigated the performance of scheduling rules with due dates being set internally. There is a host of literature on due date-based research in the traditional job shop environment (Panwalkar and Iskander, 1977; Blackstone, Phillips, and Hogg, 1982; Sen and Gupta, 1984; Ramasesh, 1990). Due date-based studies in FMSs are now reviewed.

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. 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.

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 the alternative routings directed dynamically rule that delivers the current part to the next machine which has the shortest [travel time + queueing time + operation time] for that part among the candidate machines. Montazeri and Wassenhove (1990) investigate the performance of several slack-based due date rules and conclude that the smallest remaining slack per operation rule performed the best. 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 routing flexibility. They suggest a combination of the earliest due date input sequencing rule with the number-in-next-queue machine selection rule for best results. 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. Kim and Kim (1994) use simulation to study an FMS with six machines using several due date based scheduling rules. Three performance criteria were used including mean flowtime, mean tardiness, and a bi-criterion measure combining the other two with weighting factors. Contrary to expectations, a non-due date dispatching rule gave the best results across all three measures. For an FMS of eight machines with routing flexibility, Byrne and Chutima (1997) study the relative performance of four machine selection rules using mean flowtime, mean lateness, mean shop utilization, number of parts completed, and percent tardy measures of performance.

Note that researchers who have considered the existence of 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 assumed SAFMS that possesses routing flexibility. We determine whether or not *actual routing flexibility* can be exploited by on-line control strategies operating 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 effected 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 consoles) 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 maybe 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 maybe of little value to have a very flexible system that is well integrated in terms of a ready 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 prolonged 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, 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. This is why 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. 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. Others who have questioned whether available technology can ever be automated to a level where an optimum scheduling decision can be exhaustively searched whenever required, without entailing significant delays in processing, have supported the use of local priority dispatching rules or heuristics (Panwalkar and Iskander, 1977) and Blackstone, Phillips, and Hogg, 1982) implementable in an on-line manner.

Significant manufacturing scheduling contributions have been made in the literature as reported in Panwalkar and Iskander (1977), Blackstone *et al.* (1982), Harmonosky and Robohn (1991), and Rachamadugu and Stecke (1994). 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. While undergoing this transformation, shop controllers may want to exploit flexibility using on-line control strategies, designed for real-time operation, by deploying these within information-delayed environments. The transitional form of a manufacturing system, which we have referred to as a semi-automated flexible manufacturing system, could permit use of routing flexibility, although the operational environment may need to cope with information delays. In section 4, we define some typical modes of information delays and their manifestations in the on-line scheduling of SAFMSs.

4. Basic modes of information delay

In scheduling decisions, information delays occur in many ways. We define three modes through which information delays can impact control strategies that enable scheduling decisions to be made in an on-line manner. For purposes of uniformity, in defining each information delay mode, we refer to the decision-maker as a controller. Figure 1 is a schematic representation of each information delay mode.

For each information delay mode, status information request epochs (IREs) occur at arbitrary points in time. The requested status information is subsequently furnished either without delay (in real time) or else after a finite period of time. Figure 1 depicts this occurrence as an information arrival epoch (IAE). This invokes a scheduling decision implementation epoch (DIE). The DIE, in turn, can occur instantaneously or else after a finite time period. Specific combinations of each of the above occurrences result in different modal manifestations of information delay.

(i) Mode 1 information-transfer delay

For a *Mode 1 delay*, after an IRE, it takes a finite magnitude of time (Δ_{ITD}) to transfer status information to the controller. IAEs therefore occur with a Δ_{ITD} time delay. It is clear from figure 1 that by the time the decision implementation epochs occur, system status could have changed resulting in an erroneous dispatch decision.

(ii) Mode 2 decision-implementation delay

For a *Mode 2 delay*, an information request epoch is followed by a real time information arrival epoch. However, it takes a finite magnitude of time (Δ_{DID}) to implement the dispatch decision. The decision implementation epoch therefore occurs after a Δ_{DID} time delay. From figure 1 it is clear that the Δ_{DID} time delay can result in system status changes so that erroneous dispatch decisions can result.

(iii) Mode 3 status-review delay

For a *Mode 3 delay*, system status information is updated at fixed discrete time intervals call review periods (RPs). On the occurrence of an information request epoch, a dispatch decision made based on the system status monitored on the last periodic review. Clearly, Mode 3 del (Δ_{SRD}) is a variable and its magnitude ranges from just above zero time units to the magnitude the RP.

Based on the definitions of the information delay modes, a control strategy operating in re time is likely to perform differently from one operating in an information delay mode. It is evide that for a control strategy operating in real-time, there would be no information delay associat with either the status information availability or the decision implementation time.

5. Formulation of the SAFMS scheduling problem with information delays

FMSs, like job shops, are designed to provide a competitive edge to manufacturing companies b economically producing a high variety of products. Yet, they are radically different in the production planning and control functions. The difference lies primarily in the degree of agili that an FMS can provide but job shops don't. Typically, the processing times and setup time associated with FMS environments are much smaller than for their job shop counterparts. As result, even small amounts of information delays affect an FMS's performance in a significar manner and have the potential of throwing them in disarray. It is important therefore, that jo shop scheduling be revisited to integrate information delays in the modeling of schedulin decisions. This is the purpose of this section. We propose new formulations that integrat information delays in FMS modeling and permit optimization of stated system objectives witl due accounting for information delays.

5.1 Static and dynamic control systems

Irrespective of the environment, production of parts can be scheduled in either a static o dynamic mode. The static mode, also referred to as off-line scheduling, implies that the inpu and movement of parts through the system is scheduled before the first operation is started. Part move through buffers and machines in a predetermined sequence and at predetermined times On the other hand, in a dynamic mode, also referred to as real-time or on-line scheduling, the next destination of parts is sequentially determined upon completion of each operation. Researchers have made arguments for and against dynamic control schemes for FMSs. Stecke and Solberg (1981) argue that static schemes are impractical because system capacity constraints make such an approach difficult. Also, Stecke and Solberg (1981) and Maley, Ruiz-Meir, and Solberg

(1988) suggest that literal "real-time" control may be seen as an ideal but not necessarily an achievable goal. Static schemes for making, detailed system decisions are recommended by some researchers (Hutchison, Leong, Snyder, and Ward, 1991) who suggest that they improve system performance because they consider the condition of the entire system when making scheduling decisions. Their argument is that dynamic schemes are rather myopic since they consider only current information about one small area of the system. In practice, however, most FMS installations use dynamic schemes.

We believe that, although both approaches should be used, the dynamic mode is particularly desirable in an FMS environment since it presents additional opportunities to readjust the schedule as the system evolves over time. Static scheduling may allow development of optimal schedules ahead of time (which are useful as benchmarks) but are limited in many ways. First, given the complexity of the scheduling problem, only small manufacturing systems can be solved optimally in a static mode. Second, in manufacturing systems that compete on flexibility, such as an FMS, system production generally does not evolve exactly as planned. This creates a need for revising the schedule, thereby forfeiting some of the advantages from operating in a static mode. The third problem is a consequence of delays that are incurred because of planned as well as unplanned activities. For FMSs specifically, such delays may cause a significant impairment in system performance. If a system is streamlined so that its processing and setup times have relatively small variances, static scheduling may provide a better choice, since the routing decisions made in advance permit managers the benefit of added lead-time to prepare for the raw material, assembly kits, tooling, etc., needed for production. However, in the face of significant uncertainty, dynamic scheduling seems to work better as it provides greater flexibility to cope with the changing environment. Therefore, dynamic scheduling is of greater interest to FMS managers since it allows better management of change that is a key to obtaining the best FMS performance.

A number of static and dynamic formulations of the job shop and FMS scheduling problems have been reported in the literature. Kimemia and Gershwin (1983) propose a routing algorithm for an FMS scheduling problem that allows identical machines to perform the same operation. Wilhelm and Shin (1985), Ro and Kim (1990), and Chen and Chung (1991) investigate the effectiveness of alternate operations in an FMS for minimizing makespan. Hutchison *et al.* (1991) examine the influence of two static and one dynamic scheme in scheduling FMSs with routing flexibility, using the makespan performance measure. Dolinska and Besant (1995) suggest a dynamic programming approach for the design, capacity balancing and real-time scheduling of FMSs. Liu and MacCarthy (1997) suggest two heuristic procedures using a mixed-integer linear program for FMS scheduling that takes into account constraints on storage and transportation. Daneils and Mazzola (1994) explore the improvements in manufacturing efficiency that can be achieved by considering flexibility of resource allocation in a flow shop.

We present both static as well as dynamic formulations below. We first describe some relevant terms.

Part Type: A part type is the final product that is subject to independent demand from the market. An example is a marker pen.

Parts: The number of parts that are required of the same part type have to be specified. For example, one may need to produce 100 parts of a marker pen.

Operation: Each part of a given part type undergoes a predetermined sequence of operations from raw material to completion. Operations are the steps needed to make a marker pen.

Order: An order requires production of a specified number of parts of a part type.

5.2 Operational assumptions

The formulations presented here make several assumptions, many of which are consistent with job shop scheduling as well. Specifically, we make the following assumptions.

1. *No preemption:* An operation once started on a part is completed without any interruption.
2. *Part type readiness:* Raw material for all part types is available at time zero in the system for processing of their first operation. This assumption can be relaxed quite easily.
3. *Known technological sequence:* The sequence in which operations must be performed on a part, from raw material to finished part, is known and the processing time for each operation is also known.
4. *Independence of processing times:* The processing time of any operation is independent of that of its preceding operation.
5. *Information delays are functions of part type, operation just completed, and machine:* Information delays are a function of the delays involved in each of the components of delays outlined in section 1. Total information delay is a function of the part type, operation, and the machine on which it is performed. This assumption is supported by practical experience. In some cases, these delays are observed to be a function of the

destination machine. However, since the destination may not be known at the time of decision-making, such delays are essentially the result of (i) an uncertainty in processing times, (ii) a random occurrence, (iii) result of a hardware breakdown, and/or (iv) a transportation delay between the current machine and the destination machine. All of these causes of delay are outside the scope of this work; we concentrate on the performance deterioration arising only from *planned information delays* that occur before a decision epoch.

6. *Tool availability:* All tools needed to perform an operation are available at the magazine when needed.
7. *Pallets:* Pallets are available as and when required and in the quantity needed.
8. *Dispatching:* Parts once dispatched to a machine for a given operation are processed at that machine for that operation. Thus, no operation is reconsidered for dispatching as a result of the change of a review period.

Since the processing time of an operation is also a function of the part type, operation, and the machine on which the operation is performed, information delay can be integrated with the processing time in an *additive* fashion. For the case of static modeling, this assumption has the effect of reducing the scheduling problem with delays to an equivalent one with processing times appropriately modified. Thus, we assume that there is a one to one mapping between processing time and information delay and that the two are additive in their impact on FMS performance. Furthermore, without loss of generality, we initially assume that each order is comprised of a single part. This is because an order requiring y parts may be modeled as y orders of one part with identical processing times. However, we present a more efficient formulation (in terms of number of variables) in section 5.4.2 which exploits such equivalence.

Regarding the formulation in section 5.3, assumptions 6 and 7 can be relaxed by adding appropriate constraints. However, this is out of the scope of this work whose primary goal is to analyze the impact of information delays. Table 1 describes the notation used in the formulation.

Table 1. Notation

i = Index for part types, $i \in I$ (also used equivalently, i = 1, 2, ..., I)

j = Index for operations

k = Index for machines, k = 1, ..., K

O_i = Ordered J_i-tuple of sequence of operations on part type I; $\{j_1^i, j_2^i, \ldots, j_{J_i}^i\}$, $i = i \in I$. When only the last operation is relevant in a discussion, J_i is used as the last operation of part type i for simplicity.

D_i = Due date for part type i

Y_i = Order size of part type i, i.e., number of parts needed of part type i

K_{ij} = Set of machines that can process operation j of part type i; $\forall$ i, j$\in O_i$

T_{max} = Upper bound on makespan

T_{min} = Lower bound on makespan

$$I_i = \begin{cases} 1, & \text{if } D_i - F_i^{J_i} \geq 0, \\ 0, & \text{otherwise.} \end{cases} \qquad \text{for all } i \in I, \text{ where } F_i^{J_i} = F_{iJ_ik} \text{ for some } k \in K_{iJ_i}$$

F_{ijk} = Completion time of operation j of part type i on machine k; $\forall$ i, j$\in O_i$, and k $\in K_{ij}$

$$F_{ijkt} = \begin{cases} 1, & \text{if operation j of part type i is completed on machine k at the end of time period t} \\ 0, & \text{otherwise.} \end{cases}$$

$\forall$ i, j$\in O_i$, k$\in K_{ij}$, and t = 1, 2, ..., T_{max}

$$X_{ijkt} = \begin{cases} 1, & \text{if operation j of part type i is scheduled on machine k in time period t} \\ 0, & \text{otherwise.} \end{cases}$$

$\forall$ i, j$\in O_i$, k$\in K_{ij}$, and t = 1, 2, ..., T_{max}

p_{ijk} = Processing time of operation j of part type i on machine k; k $\in K_{ij}$

p_{ij}^{max} = Maximum time that operation j of part type i will take to complete on any machine k $\in K_{ij}$; $p_{ij}^{max} = \max_{k \in K_{ij}}\{p_{ijk}\}$

p_{ij}^{min} = Minimum time that operation j of part type i will take to complete on any machine k $\in K_{ij}$; $p_{ij}^{min} = \min_{k \in K_{ij}}\{p_{ijk}\}$

Δ_{ijk}^{m} = Information delay at the completion of operation j of part type i on machine k in mode m

5.3 SAFMS scheduling problem with information delays: static formulation

The SAFMS scheduling problem is NP-hard in the strong sense since a special case of this problem with all information delays = 0 is the classic job shop problem which is known to be NP-hard. We now present the static formulation.

1. Minimize Mean Tardiness

$$Minimize \sum_{i \in I} I_i \left(D_i - F_i^{J_i}\right)$$

Subject to:

$$F_{ijk} = \sum_{t=1}^{T} t F_{ijkt}, \ \forall i \in I, j \in O_i, \text{and } k \in K_{ij} \qquad (1)$$

$$X_{ijk} = \sum_{u=t}^{t+P_{ijk}-1} tF_{ijkt}, \forall i \in I, j \in O_i, k \in K_{ij}, and\, t = 1,2,...T_{max} \tag{2}$$

$$F_{ij^i_{r+1}k_2} - p_{ij^i_{r+1}k_2} \geq F_{ij^i_r k_1} + \Delta_{ij^i_r k_1}, \tag{3}$$

$$\forall i \in I, j^i_{r+1}, j^i_r \in O_i, r = 1,2,...,J_i, and\, k_1 \in K_{ij^i_r}, k_2 \in K_{ij^i_{r-1}}$$

$$\sum_{i \in I}\sum_{j \in j} X_{ijkt} \leq 1, \forall i \in I, j \in O_i, k \in K_{ij}, and\; t = 1,2,...T_{max} \tag{4}$$

$$X_{ijkt} \in \{0,1\}, \forall i \in I, j \in O_i, k \in K_{ij}, and\, t = 1,2,...T_{max} \tag{5}$$

$$F_{ijkt} \in \{0,1\}, \forall i \in I, j \in O_i, k \in K_{ij}, and\, t = 1,2,...T_{max} \tag{6}$$

Constraint (1) yields the completion time of operation j of part type i on machine k, since F_{ijkt} will have a value of 1 only in period t in which operation j of part type i is completed. Constraint (2) states that an operation j of part type i is processed on machine k in period t if and only if that operation is completed between periods t and t + $p_{ijk} - 1$. Constraint (3) indicates that any operation j_{r+1} of a part type i cannot start on any machine k_2, unless its predecessor operation j_r is completed on a previous machine k_1, and an information delay corresponding to the operation/machine has been accounted for in the dispatching time. Constraint (4) insures that any machine k is busy doing at most one operation at any time t. Constraints (5) and (6) characterize the binary nature of X_{ijkt} and F_{ijkt}.

Some other objective functions are as follows.

2. Minimize Percent Tardy

$$Minimize\ 100 * \frac{1}{I}\sum_{i \in I} I_i, \text{ subject to equations (1) through (6).}$$

3. Minimize Mean Flowtime

$$Minimize\ \frac{1}{I}\sum_{i \in I} F_i^{J_i}, \text{ subject to equations (1) through (6).}$$

4. Maximize Average Machine Utilization

$$Maximize\ \frac{1}{KT_{max}}\left\{\sum_{i \in I, j \in O_i}\sum_{k \in K_{ij}}\sum_{t=1}^{t=T_{max}} X_{ijkt}\right\}, \text{ subject to equations (1) through (6).}$$

We now present two propositions that describe upper and lower bounds on makespan. The upper bound is needed for the dynamic programming algorithm that follows in section 5.5.

5.4 Upper and lower bounds on makespan

We present two results that provide upper and lower bounds on the makespan for all the part types that need to be scheduled. Proposition 1 provides an upper bound and Propositio provides a lower bound.

Proposition 1: An upper bound on makespan is given by:

$$T_{max}=\sum_{i=1}^{I}\sum_{j=1}^{J_i} p_{ijk^*}+\Delta_{ijk^*}, \text{ where } k^*: p_{ijk^*}+\Delta_{ijk^*}=\min_{k\in K_{ij}}\{p_{ijk}+\Delta_{ijk}\},\ \forall i\in I,\ j\in O.$$

Proof: It is sufficient to show that there exists a feasible sequence with a makespan of T_{max}. T following algorithm constructs such a sequence.

Step 1. Initialize: $i \leftarrow 0, T \leftarrow 0$

Step 2. $i \leftarrow i+1, r \leftarrow 0$

Step 3. $r \leftarrow r+1$

Step 4. Find k*: $p_{iJ_r^ik^*}+\Delta_{iJ_r^ik^*}=\min_{k\in K_{iJ_r^i}}\left\{p_{iJ_r^ik}+\Delta_{iJ_r^ik}\right\}$

Step 5. Assign operation J_r^i to machine k* for the period T to T+ $p_{iJ_r^ik^*}+\Delta_{iJ_r^ik^*}$

Step 6. $T \leftarrow T+ p_{iJ_r^ik^*}+\Delta_{iJ_r^ik^*}$

Step 7. If $r < J_i$, go to Step 3. Else, go to Step 8.

Step 8. If $i < I$, go to Step 2. Else, $T_{max} = T$, Stop.

Feasibility of the schedule follows due to the non-overlapping time windows allocated t different operations by Step 5. The sequence of operations for each part type i is guaranteed b Steps 2 and 3, and the makespan = T_{max} is guaranteed by Step 6.

QED

Note that this upper bound is tighter than the intuitive upper bound:

$$T_{max}=\sum_{i=1}^{I}\sum_{j=1}^{J_i} p_{ijk^*}+\Delta_{ijk^*}, \text{ where } \{k^*: p_{ijk^*}+\Delta_{ijk^*}=\max_{k\in K_{ij}}\{p_{ijk}+\Delta_{ijk}\} \text{ for } \forall i\in I,\ j\in O_i$$

by an amount $\sum_{i\in I}\sum_{r=1}^{J_i}\left(p^{max}_{iJ_r^i}+\Delta^{max}_{iJ_r^i}\right)-\left(p^{min}_{iJ_r^i}+\Delta^{min}_{iJ_r^i}\right)$.

Proposition 2: A lower bound on the makespan is given by

$$T_{min}=\max_{i\in I}\left\{\sum_{j=1}^{J_i}\min_{k\in K_{ij}}\{p_{ijk}+\Delta_{ijk}\}\right\}.$$

Proof: We show that a schedule, possibly infeasible, exists with a makespan = T_{min}. Let T_i be the minimum time taken to perform all operations of part type i in sequence. Then,

$$T_i = \sum_{j=1}^{J_i} \min_{k' \in K_{ij}} \{p_{ijk'} + \Delta_{ijk'}\}$$

Thus, any part type i takes at most $\max_i\{T_i\}$ time, but at least one part type, say i', takes exactly $\max_i\{T_i\}$ time. Hence, the makespan for all part types is at least $\max_i\{T_i\}$ time (=T_{min}), which is the case when all part types are processed in parallel, with i' finishing last . Since this may not always be feasible due to limited machine availability, the optimal value of makespan is $\geq T_{min}$ and therefore, T_{min} is a lower bound. QED

5.4.2 Modified formulation with order size >1.

Whereas the formulation presented in section 5.3 yields an optimal sequence for the general case considering the order size of each part type, additional computational efficiency is obtained by exploiting the fact that many parts of the same type can be processed as a batch. This can be accomplished through the following substitution in equalities (2) and (3):

$$p_{ijk} \leftarrow y_{ijk}\, p_{ijk}, \text{ for all } i \in I, j \in O_i, k \in K_{ij},$$

where y_{ijk} is the number of parts of type i whose operation j was processed on machine k. This formulation needs the following additional constraints.

$$\sum_{j=1}^{J} \sum_{k \in K_{ij}} y_{ijk} = Y_i \ , \forall i \in I.$$

Finally, the change in the interpretation of Fijk should be noted. It signifies the completion time of operation j of the last part in the order of parts of type i processed on machine k.

5.5 A dynamic SAFMS scheduling algorithm with information delays

As indicated previously, FMSs can benefit from a dynamic approach to scheduling since a primary goal of FMSs is to provide flexibility to meet changing demands in an evolving manufacturing environment. Therefore, we develop a general dynamic scheduling algorithm that works in an SAFMS environment. The decision making process is as follows.

System status is reviewed at constant intervals of time, referred to as review period in section 4(iii). At the beginning of each review period, a system status information report is generated that includes details about: (1) operations completed in the previous period, (2) operations waiting to be processed in front of each machine, (3) set of "next" operations that need to be undertaken, and (4) a list of unfinished operations. Based on the system objective, a machine sequencing rule is applied to operations completed in the previous period to determine on what machines the "next" operations will be performed, and an input buffer sequencing rule is applied to determine the sequence in which the operations already dispatched to a given machine will be processed on that machine.

In order to formulate an algorithm that captures both the above scheduling decisions, we need to define an expanded notation for operation j. The additional notation needed to develop the dynamic algorithm is provided in table 2.

Table 2. Additional notation for dynamic scheduling

n = Index for the review period.

T = Length of each review period.

$J^{i,n}_{j,k,r}$ = j^{th} operation of part type i which is in the r^{th} position in the sequence of operations waiting to be processed on machine k, at the beginning of the n^{th} review period. r = 0 signifies that the operation is being processed on machine k at the beginning of review period n.

$p^{i,n}_{j,k,r}$ = Processing times of $J^{i,n}_{j,k,r}$. For r = 0, this represents the remaining processing time for the current operation on machine k. (Although superscript n and position subscript r have no role in processing time description, these are needed for the formulation.)

$\Delta^{i,n}_{j,k,r}$ = Information delay corresponding to operation $J^{i,n}_{j,k,r}$.

$\Pi^{\sigma,n}_{k}$ = A sequencing rule used at the beginning of review period n to sequence operations at machine k.

$\Pi^{\delta,n}$ = A dispatching rule used at the beginning of period n to dispatch parts to machines for their next operation, consistent with the technological sequence of the operations.

$\Pi\langle X\rangle \Rightarrow Y$ This indicates that when a rule Π operates on an argument X, then Y is the outcome.

S^{n}_{k} = The state of machine k, defined as the set of operations in front of machine k at the beginning of review period n, k = 1, 2,..., K.

$f_n\{\Pi *^{\sigma,n}_{k}, \Pi *^{\delta,n}, S^{n}_{k}, k=1,2,...,K\}$ = Optimal value of the objective function at the beginning of n^{th} review period when machine state is $\{S^{n}_{k}\}$, and optimal sequencing and dispatching policies $\Pi *^{\sigma,n}_{k}, \Pi *^{\delta,n}$, k = 1, 2, ..., K are used throughout the horizon.

Df_n = Contribution of the n^{th} review period to the objective function based on an optimal scheduling and dispatching rule.

5.5.1 The dynamic scheduling algorithm for review period n

The optimality equation is:

$$f_n\left\{\Pi *_k^{\sigma,n}, \Pi *^{\delta,n}, S_k^n, k=1,2,\dots,K\right\} = Df_n + f_{n+1}\left\{\Pi *_k^{\sigma,n+1}, \Pi *^{\delta,n+1}, S_k^{n+1}, k=1,2,\dots,K\right\}. \quad (7)$$

The boundary conditions are:

$$f_1\left\{\Pi *_k^{\sigma,1}, \Pi *^{\delta,1}, S_k^1, k=1,2,\dots,K\right\} = 0 \quad (8)$$

$$S_k^1 = \left\{J_1^i, k \in K_{i1}, i=1,2,\dots,I\right\}, k = 1, 2, 3, \dots, K \quad (9)$$

$$S_k^{T_{max}+1} = \{\phi\}, k = 1, 2, 3, \dots, K. \quad (10)$$

result of pursuing optimal sequencing and dispatching rules in period n plus the optimal value of the performance measure if the optimal sequencing and dispatching rules are used for the remainder of the makespan. Equality (8) states that the optimal value of the objective function at the beginning of period 1 is 0. Equality (9) places the first operation of each part type that can possibly be processed at machine k, and equality (10) indicates the emptiness of the set of operations in front of any machine at the end of the scheduling horizon.

5.5.2 System dynamics

Let the system state at the beginning of review period n be defined as: $S_n = \left\{S_1^n, S_2^n, \dots, S_K^n\right\}$. In this section, we develop a methodology to determine S_n. It is sufficient to develop S_k^n given S_{n-1}^k, $\Pi_k^{\sigma,n}$, and $\Pi^{\delta,n}$, k = 1, 2, ..., K.

The system dynamics is described in six steps.

Step 1. *Identify unfinished operations at machine k in period n-1.*

Let $S_{n-1}^k = \left\{J_{j_0,k,[0]}^{i_0,n-1}, J_{j_1,k,[1]}^{i_1,n-1}, \dots, J_{j_{m_k},k,[m_k]}^{i_{m_k},n-1}\right\}$, where subscript 0 is assigned to the unfinished operation on machine k, [r] is the r^{th} operation in sequence to be performed on machine k, at the beginning of review period n-1. To simplify notations, let $p_{[r]}$ be the processing time of the r^{th} operation and Δ_r be the information delay for r^{th} operation, keeping in mind that they apply to machine k and appropriate part type and its operation.

For brevity, we drop the subscripts/superscripts i, n-1, k, and r from the RHS and pick them up later when needed. Thus, the operations in the RHS brackets are $\left\{j_{[1]}, j_{[2]}, \dots, j_{[m_i]}\right\}$, the corresponding processing times are $\left\{p_{[1]}, p_{[2]}, \dots, p_{[m_i]}\right\}$, and the information delays are $\left\{\Delta_{[1]}, \Delta_{[2]}, \dots, \Delta_{[m_i]}\right\}$. Then, the set of operations, O_k^{n-1}, completed during review period n-1 on machine k, is given by:

$$O_k^n = \begin{cases} \left\{ \begin{array}{l} J_{[u],k},\ u = 0, 1, 2, ..., l_k : \\ \left((p_{[0]} + \Delta_{[0]}) + (p_{[1]} + \Delta_{[1]}) + ... + (p_{[l_k]} + \Delta_{[l_k]}) \le T \le \right. \\ \left. \qquad (p_{[0]} + \Delta_{[0]}) + (p_{[1]} + \Delta_{[1]}) + ... + (p_{[l_k+1]} + \Delta_{[l_k+1]}) \right) \end{array} \right\}, \ if\ p_{[0]} + \Delta_{[0]} \ge T \\ \{\phi\},\ \ if\ \ p_{[0]} + \Delta_{[0]} \le T. \end{cases} \tag{11}$$

Inequality (11) shows that at any given machine k, the operations completed during a review period n are those whose processing times add up to the review period time or less, when a given sequencing rule is followed in processing parts.

Step 2. *Unfinished operations at machine k at the end of period n-1.*

The set of unfinished operations at machine k at the end of period n-1 constitutes a part of the set of all operations at the start of review period n at machine k. This set is determined by $O_k'^{n-1} = S_k^{n-1} \setminus O_k^{n-1}$, where A\B represents remainder of set A after deletion of the elements of set B from A.

Step 3. *Determination of the parts that will be dispatched at the beginning of period n for "next" operation.*

The set of all operations completed, O^{n-1}, during the (n-1)[st] review period is given by:

$$O^{n-1} = \{ O_1^{n-1} \bigcup O_2^{n-1} \bigcup ... O_K^{n-1} \}.$$

Recovering the subscripts and superscripts we get,

$$O^{n-1} = \begin{cases} \bigcup_{k=1}^{K} \left\{ J_{j_0,k,[0]}^{i_0,n-1}, J_{j_1,k,[1]}^{i_1,n-1}, ..., J_{j_{l_k},k,[l_k]}^{i_{l_k},n-1} \right\} \ if\ p_0 + \Delta_0 \ge T; \\ \{\phi\},\ p_0 + \Delta_0 \le T. \end{cases} \tag{12}$$

Equivalently, $O^{n-1} = \left\{ J_{j,k}^{i,n-1} \right\}$ for some i $\in$ I, j $\in$ O_i, k $\in$ K_{ij}.

Equality (12) states the fact that the totality of operations completed in any given review period is the union of all sets of operations completed on each machine.

Due to the periodic review nature of all decisions, the information delay occurs in this type of systems since the information about completion of each operation is held until the beginning of next review period when dispatching and scheduling decisions are made. Given the knowledge of the operations in set O^{n-1}, we can readily construct a set of "next" operations, O^{cn} using the sequence information given in O_i. Thus, for each part type i that has completed an operation $J_{j,k}^{i,n-1}$ on machine k in period n-1, the dispatching rule application would yield a machine (k') on which the next operation $J_{j+1,k'}^{i,n}$ shall be performed for that part.

$$\Pi^{*\delta,n} \left\langle \{ J_{j,k}^{i,n-1} \} \right\rangle = \{ J_{j,k'}^{i,n} \} = O^{cn} \tag{13}$$

Step 4. *Construct a subset of parts that will be processed at machine k.*

Form (13), identify parts in O^{cn} *that* will be routed to machine k at the beginning of period n.

$$O_k^{cn} = \{ J_{j,k'}^{i,n} \} : \{ k' = k, \ for \forall J_{j,k'}^{i,n} \in O^{cn} \} \quad (14)$$

Step 5. *Determine the total set of operations in front of machine k.*

The total set of operations to be completed on machine at the beginning of review period n is given by S'^{n}_{k}, where

$$S'^{n}_{k} = O'^{n-1}_{k} \bigcup O^{cn}_{k} \quad (15)$$

Step 6. *Sequence all operations in front of machine k to optimize system performance.*

Finally, since we are in a dynamic mode, we need to re-sequence S'^{n}_{k} to optimize the system performance. Hence,

$$S_k^n = \Pi_k^{\sigma,n} \left\langle S'^{n}_{k} \right\rangle$$

This completes the system dynamics.

Note that the algorithm stops at the beginning of review period N, defined by $N: S_k^T = \{\phi\}, for\ all\ k \in K$; $N \leq T_{max}$.

5.5.3 Characterization of Df_n

Df_n changes based on the performance measure used. We characterize this change below.

The value of DF_n for each objective function under study is presented.

1. Minimize Mean Tardiness

The contribution of review period n to mean tardiness is from those parts that ere competed late in period n. That yields,

$$Df_n = \frac{1}{I} \sum_{i \in I'} I_i (D_i - F_i^{J_i}).$$

2. Minimize Percent Tardiness: $Df_n = \frac{1}{I} \sum_{i \in I'} I_i * 100$

3. Minimize Mean Flowtime: $Df_n = \frac{1}{I} \sum_{i \in I'} F_i^{J}$

4. Maximize Utilization: $Df_n = \frac{1}{KT_{max}} \sum_{i \in I, j \in O_i} \sum_{k \in K_{ij}} \sum_{t=(n-1)T}^{nT} X_{ijkt}$.

The FMS scheduling problem with time delays is now mathematically defined. However, as only small instances of this problem can be solved optimally, we now turn to simulation to investigate the impact of information delay on system in greater details.

6. System description and experimental details

The computational complexity of the models detailed in section 5 precludes the development of optimal solutions for large manufacturing systems. Consequently, in this section we use simulation to analyze the impact of information delays on the performance of larger manufacturing systems possessing routing flexibility.

6. 1 Semi-automated FMS description

We use a hypothetical SAFMS 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 by the SAFMS requires between four to six operations. Routing flexibility in this SAFMS 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 SAFMS. The routing flexibility index for each part type (RF_i) is defined as

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

where O_{ij} = j^{th} operation of part type i, i = 1, ..., I; j = 1, ..., J_i, and $|O_{ij}|$ = 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 a part type's operation. The system's routing flexibility index (RF) is then defined as

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

From this definition, for a conventional job shop, RF = 1, while for a shop possessing alternative routing capability, RF > 1.

Because routing flexibility is an experimental factor in this paper, the RF varies from 1 to 5. Table 3 depicts the relevant part type/processing time details for a flexibility index of 5. Note that when RF = 1, part type sequences through the SAFS are fixed, i.e., no alternate routes are possible.

Part entry into the system is controlled using pallets to hold parts. *Part 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 $(j-1)^{st}$ operation part i,

T = due date tightness factor, and

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

6.2 Simulation details

Simulation experiments were performed using the Arena 3.0 simulation language (Systems Modeling Corp., 1997), into which user written C++ code was linked 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 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 were 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 scheduling rule were 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 was done using one of the following five rules: SOPT, EDD, Slack, ODD, and OSlack. Dispatching of parts on completion of an operation was 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 was used to break the tie. (See Appendix A for details regarding the above scheduling rules). The performance measures used in the present study are conditional mean tardiness, percent tardy, mean flowtime, and average machine utilization. The first performance measure estimates the average tardiness over only the late parts, while the second measures the proportion of tardy parts that exit the system.

Note that since sequencing decisions essentially rely on local (queue) status data, for this study, sequencing of parts from input buffers is done in real-time. In contrast, since dispatching decisions require global status data, dispatching rules are effected in an environment of information delays (IDs). Further, for ease of model implementation, we assume that IDs are deterministic in nature.

Models developed for each ID mode are similar as far as the application of the sequencing logic is concerned. The essential differences between them arise from the manner in which the user written dispatching logic is coded. Whereas the coding of the dispatching rules (WINQ and NINQ) using external C++ routines is a straightforward translation of their respective definitions, implementing the same within each defined ID mode requires careful design. For the purposes of this paper, we focus on the Mode 3 ID case only.

We adopt the Taguchi experimental design technique both for conducting the simulation experiments and for analyzing the results obtained. Section 6.3 provides an introduction to the Taguchi experimental design method.

6.3 Taguchi's experimental design framework

The Taguchi experimental design paradigm is based on the technique of matrix experiments (Phadke, 1989). A matrix experiment consists of a set of experiments where the settings of process parameters under study are changed from one experiment to another. The experimental data generated is subsequently analyzed to determine the effects of various process parameters. In the statistical literature, individual experiments in a matrix experiment are called treatments. Settings are also referred to as levels and parameters as factors.

Experimental matrices are special orthogonal arrays, which allow the simultaneous effect of several process parameters to be studied efficiently. The columns of an orthogonal array represent the individual factors under study, and the number of rows represent the number of experiments to be conducted.

The purpose of conducting an orthogonal experiment is twofold:

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

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. 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 optimal factor combination (based on the optimum 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 not allowed. 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 Taguchi experimental design 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 at five levels, one at four levels, and one 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 need to be conducted.

6.4 Matrix experiment details

To highlight the impact of the Mode 3 IDs within the SAFMS considered, standard orthogonal array experiments are performed. As mentioned in section 6.3, Taguchi's standard L_{25} orthogonal array is found suitable for experimentation purposes. The respective 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	(0, 0.5, 1.0, 1.5, 2.0)

The L_{25} array enables the simultaneous consideration of six factors at five levels or less. In the present case, first five columns of the L_{25} array are used, with the sixth column being excluded for experimentation purposes without affecting the orthogonality of the matrix (Phadke, 1989). The levels for each factor used in the matrix experiment are shown in table 4. Table 5 details the resulting matrix experiment tableau with the factor level details.

We define the metric information delay ratio (IDR) as the ratio of the review period (RP) (refer to section 4(iii)) to the average processing time per operation of parts ($\overline{PT}$) in the system. The motivation for using $\overline{PT}$ as the denominator in the defined metric stems from our intuition that the temporal response of the system to the presence of information delays could be related to the magnitude of part processing times. In this context, Harmonosky and Robohn (1991) observed, "...the speed needed for a response may actually depend on system parameters such as the magnitude of part processing times and the flexibility of the system. ... If part-processing times are on the order of an hour, a response within five minutes may still be considered as 'real-time'. On the other hand, if part processing times are on the order of fifteen minutes, a decision may be needed in one minute to be considered 'real-time'".

Further, the specific range of values for factor levels for the IDR were intentionally chosen so as to represent incremental penalties in terms of information loss. Specifically, it was felt that an IDR of approximately 2 would highlight the worst-case scenario. For comparison, a second matrix experiment was also conducted in which the range for IDR was restricted to 1. Results for this experiment are detailed in section 7.3.

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

Smaller-the-better measures:

1. $\eta_i = -10 \log_{10} (\text{conditional mean tardiness})^2$
2. $\eta_i = -10 \log_{10} (\text{percent tardy})^2$
3. $\eta_i = -10 \log_{10} (\text{mean flowtime})^2$

Larger-the-better measures:

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

Note that, although the real benefit in using S/N ratios is for situations where multiple replications are performed (Roy, 1990), we resort to their use in order to remain consistent with their conventional usage within the Taguchi method of experimentation.

7. Experimental results and analysis

The results of the matrix experiments 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 optimal 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 CMT performance measure are discussed in detail in section 7.1.

7.1 Conditional Mean Tardiness

The matrix experiment simulation results are summarized in table 6.

(i) Analysis of means

The main factor effects, calculated using the formulas given in Phadke (1989), are summarized in table 7. The notational convention adopted for analysis is

$m_{j,k}$: main factor effect for the k^{th} level of factor j[1]

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

m : overall mean value of $\eta = \frac{\sum_{i=1}^{n} \eta_i}{n}$,

where n = number of experiments performed (i.e., 25).

Based on the analysis of means, the optimum levels for each factor resulting from the matrix experiment is shown italicized under the conditional mean tardiness column of table 7. 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 optimize (i.e., minimize) the CMT is RF3, D2, S5, T4, IDR1 which means that the routing flexibility = 3, the dispatching rule is NINQ, the sequencing rule is OSlack, the due date tightness factor = 6, and information delay ratio = 0. Interestingly, the predicted best settings from the matrix experiment do not correspond to any of the rows in table 5.

Figure 2 plots the main effects of each factor level. The optimal 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 optimum 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 optimum 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 falls 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 7.4.

The ANOM plots shown in figure 2 reveal the relative magnitude of the main effects of factors on the CMT. Judging from the variation of the S/N ratios for each factor, the information delay ratio affects CMT the most, followed by the factors routing flexibility and due date tightness (please see the first and last segment of the plot). The effects of the 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.

(ii) Analysis of variance

The formulas used in conducting the ANOVA are detailed in Appendix B. Table 8 shows the resulting ANOVA tableau. From table 8, the error variance (σ_e^2), defined as

$$\text{Error variance} = \text{SSE/degrees of freedom for error}$$

is calculated to be $(\sigma_e^2)_{CMT} = 44.76\ (dB)^2$ (see the shaded box under the "mean square" column of table 8). Note that the error variance is calculated using the method of pooling (Phadke, 1989).

Phadke (1989) suggests using the F ratio 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. From the ANOVA tableau, the relative effects of the factors *information delay ratio* and *routing flexibility* are seen to be important, followed by the factors *due date tightness*, *sequencing rule*, and *dispatching rule*, in that order. This is in agreement with the ANOM results.

To highlight the statistical significance of the impact of individual factors on the conditional mean tardiness, in table 9 we present the ANOVA using the original simulated results (i.e., without converting to S/N ratios). The resulting F ratios (again calculated using the method of pooling) are seen to be critical for the factors *information delay ratio* (F = 9.25) and *routing flexibility* (F = 5.63).

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

The matrix experiment results for the above performance measures are summarized in table 10, while their main factor effects are shown in table 11.

(i) Analysis of means

The main factor effects highlight the relative contribution of each factor level to the respective performance measure. Based on the analysis of means, the optimum levels for each factor are shown italicized under each performance measure column of table 11. Accordingly, the predicted factor level combination that should minimize the percent tardy is RF4, D2, S2, T4, IDR1, which means that the routing flexibility = 4, the dispatching rule is NINQ, the sequencing rule is EDD, the due date tightness factor = 6, and information delay ratio = 0. Likewise, the predicted factor level combination that should minimize mean flowtime is RF3, D2, S5, T4, IDR1, and is interpreted to mean that the routing flexibility = 3, the dispatching rule is NINQ, the sequencing rule is EDD, the due date tightness factor = 6, and information delay ratio = 0. Finally, the optimum combination for average machine utilization is RF3; D2, S5, T4, IDR1, which means that the routing flexibility = 3, the dispatching rule is NINQ, the sequencing rule is OSlack, the due date tightness factor = 6, and information delay ratio = 0. Once again, the optimal combination that yielded the best performance for each of these measures was did not tally with any of the experiments in L_{25} array.

Figures 3, 4, and 5, respectively, show the main effect plots of each factor level for each of the above performance measures. For the percent tardy measure, the factors IDR, T, and RF 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, neither the sequencing and dispatching rules appear to impact the above performance measures significantly. It can be concluded that for all four measures, IDR was the most significant factor, RF was the next significant and that all other factors were relatively insignificant.

(ii) Analysis of variance

Tables 12, 13, and 14, respectively, show the ANOVA results for the above three performance measures, using the original simulated results (i.e., without converting to S/N ratios). For the percent tardy measure, table 12 highlights the significance of the factor IDR, as noted from its F ratio value (F = 6.71). Interestingly, none of the other factors have a significant impact. Further, for the mean flowtime measure, table 13 shows that both IDR (F = 12.31) and RF (F = 5.1) have a significant impact. Also, for the average machine utilization measure, table 14 shows that both IDR (F = 11.79) and RF (F = 6.41) have a significant impact. Interestingly again, none of the remaining factors have a significant impact.

7.3 Sensitivity experiment with reduced information delay ratio

In order to gain insights from a sensitivity viewpoint, a second matrix experiment was conducted by varying the levels for the factor information delay ratio, while assuming identical settings for the remaining factors. Accordingly, IDR varied in the range 0 – 1, in contrast to the range 0 – 2, in the previous experiment. The specific choice of the modified range values for IDR (i.e., 0.0, 0.25, 0.5, 0.75, 1.0) was made so as to analyze the performance deterioration of SAFMS under less severe conditions if information delays. It was conjectured that there may exist a cut-off point for information delays below which they could be regarded as tolerable.

7.3.1 Sensitivity results for revised matrix experiment

The observed values for each performance measure are shown in table 15. Table 16 gives the main effect values for each factor level, with the predicted optimal values shown highlighted and italicized under respective performance measure columns. Figures 6 through 9 depict the ANOM plots for each performance measure for the revised experiment.

(i) Analysis of means

For the CMT and percent tardy performance measures, figures 6 and 7 show that the optimal factor level combination is RF4, D1, S5, T4, and IDR1. Note however, that for both these measures, the effect of the factors routing flexibility and due date tightness appear much more significant than their corresponding effect in the previous matrix experiment (see figures 2 and 3) as judged from the variation in the S/N ratio values. A quantified estimate of these significance effects appears in the ANOVA section (ii) below.

For the case of mean flowtime, figure 8 highlights the significance of the factor routing flexibility in terms of its impact on this performance measure. Specifically, the optimal factor combination is: RF5, D2, S5, T4, and IDR1. Clearly, because of the mitigated detrimental effect of information delays, enhanced routing flexibility levels appear to improve flowtime estimates (see figure 4 for comparison). Finally for the average machine utilization measure, the ANOM plot of figure 9 highlights the significance of the factor routing flexibility in terms of its impact on this measure. The optimal factor combination for this case is: RF3, D1, S5, T4, and IDR1.

(ii) Analysis of variance

Tables 17 through 20 show the ANOVA details for the revised matrix experiment. For each performance measure, the ANOVA results highlight the significance of the factor routing flexibility. However, the factor IDR, although significant for the mean flowtime measure, is no longer significant at lower significance levels (i.e., at an α value of 1%). Specifically, for the CMT measure, although IDR is still significant at $\alpha = 0.05$ and 0.025, it is not so at $\alpha = 0.01$. For the percent tardy measure, IDR is significant at $\alpha = 0.05$, but not at $\alpha = 0.025$ or 0.01. Finally, for the average machine utilization measure, IDR is not significant even at $\alpha = 0.05$.

It is interesting to note that a reduction in the range of IDR from 2.0 to 1.0 causes the factor routing flexibility to become much more significant. Alternatively, the 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.

7.4 Testing for additivity

In order for the optimal combinations of factor levels determined for each performance measure to be true, we need to test the validity of what is called the validity assumption in Phadke (1989). To accomplish this, a verification experiment is conducted with the optimal 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 stands justified. Validation of the additivity assumption essentially implies the absence of significant interaction affects between factors. Results of the verification experiments for the CMT measure of performance matrix experiment is presented below.

7.4.1 Verification experiment for matrix experiment

A verification experiment, performed with the optimal factor combination (RF3, D2, S5, T4, IDR1) resulted in an observed CMT of 13.72 minutes, that is, $\eta_{obs.opt} = -22.75$ dB. Further, the predicted optimum CMT, $\eta_{pre.opt}$, calculated using the main effects of only the significant optimal factor levels (Phadke, 1989), can be shown to be

$$\begin{aligned}\eta_{pre.opt} &= m + (m_{RF,3} - m) + (m_{T,4} - m) + (m_{IDR,1} - m)\\ &= -50.452 + (-46.004 + 50.452) + (-44.706 + 50.452) + (-36.952 + 50.452)\\ &= -26.76 \text{ dB}.\end{aligned}$$

The resulting prediction error is:

$$\text{Prediction error} = \eta_{obs.opt} - \eta_{pre.opt} = -22.75 - (-26.76) = 4.01 \text{ dB}.$$

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 $\eta_{pre.opt}$ and n_r = number of repetitions of the verification experiment.

In the present case, n_o is given by

$$1/n_o = 1/n + (1/n_{RF} - 1/n) + (1/n_T - 1/n) + (1/n_{IDR} - 1/n) = 57/100,$$

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

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

n_T = number of times factor T was repeated in the matrix experiment = 4

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

Further, because in our study, $n_r = 1$, the variance of prediction error is calculated to be:

$$\sigma_{e\ pred}^2 = (1/n_o)\sigma_e^2{}_{CMT} + (1/n_r)\,\sigma_e^2{}_{CMT} = (57/100) \times 44.76 + 44.76 = 70.273\ (\text{dB})^2.$$

The corresponding two-standard-deviation confidence limits for the prediction error are $\pm 2 \times \sqrt{\sigma_{e\ pred}^2} = \pm 16.765$ (dB). The prediction error (= 4.01 dB) happens to be well within the calculated confidence limits, so the additivity assumption is justified.

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

7.5. Analysis of the results

With IDR varied in the range 0.0 – 2.0, the ANOVA results presented in tables 9, 12, 13, and 14 indicate that the factors information delay ratio and routing flexibility, in that order, are significant in terms of their effect on each considered performance measure, even at a significance level of 1%. It also is observed that the factors due date tightness, dispatching rule, and sequencing rule are not seen to be significant. From the viewpoint of a system designer, this is an important observation as it helps provide valuable insight into the possible synergism 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 SAFMSs with information delayed operational environments. Research is in progress in this regard (Caprihan, Kumar, and Gursaran, 1997).

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 the measures CMT, mean flowtime, and average machine utilization, it is interesting to observe that increasing the RF from 1 to 3, results in a marked improvement in results 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 on account of the presence of information delays, leading to detrimental affects on the performance measures. However, for the percent tardiness measure, RF positively impacts performance even up to a factor level of 4 (see figure 3). In contrast, and as per expectation, 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 the performance measures than the other factors. On the same basis, the factors due date tightness, 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 3), and with information delays constrained to a magnitude below the average processing time per operation of parts in the system. For the mean flowtime measure, while RF continually improves performance up to a level of 5, the case with the other measures has a similar trend as with the previous matrix experiment: increasing the RF from 1 to 3, results in a marked improvement in results while subsequent increments in the levels of routing flexibility prove to be detrimental. Interestingly, due date tightness appears to have a significant impact on percent tardiness, as seen from the variation in range of S/N ratios (see figure 6). In fact, the ANOVA table 18 reveals that due date tightness is significant ($F = 3.90$) at a significance of level $\alpha = 0.05$. For the factor IDR, in contrast to the previous matrix experiment, for all measures except mean flowtime, the factor was not significant in terms of impact at a significance of level 1%. In fact, for the average machine utilization measure, IDR was not even significant at $\alpha = 0.05$. Clearly, system performance improved appreciably with a reduction in the value of IDR.

7.6. Performance deterioration in the presence of information delays

In order to obtain an overall assessment of the deleterious effect of information delay, table 21 was constructed by extracting relevant results from tables 6, 10, and 15. The results are so arranged that for each objective, and for each row (representing an experiment in L_{25} array), the first column and second column main effects are based on an IDR ratio of exactly 2 to 1. The last two rows of table 21 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:

$$\frac{\textit{Objective functon value at high IDR} - \textit{Objective functon value at low IDR}}{\textit{Objective functon value at low IDR}} * 100$$

for smaller-the-better performance measures. For the larger-the-better measure, the terms in numerator are reversed. Also, the objective value in the high IDR column in the table refers to a range of 0 to 2 whereas the low IDR refers to a range of 0 to 1. However, in each row (experiment), the table is so organized that the ratio of high IDR to low IDR is 2.0 in order to obtain a clear estimate of the impact of information delays on the SAFMS performance. We note from the last two rows that, for the conditional mean tardiness performance measure, the average percent deterioration of the SAFMS performance is 40.9% , and it could deteriorate to 89.1% in the worst case. Similarly, for the percent tardy performance measure, the average percent deterioration in performance is 25.0%, though it could deteriorate to 84.8% in the worst case. However, the penalties for the non-due date-based measures, are less severe. For the mean flowtime performance measure, the average percent deterioration in performance is 4.9%, with the worst case being 13.6%; for the average machine utilization measure, the average percent deterioration in performance is only 3.5%, with a maximum deterioration of 13.3%. It can be concluded, based on the simulation experiments, that information delays cause deterioration in SAFMS performance in all performance measures, although the due date based measures suffer quite significantly in the presence of information delays.

8. 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 scant 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 SAFMS performance. For purposes of this paper, information delay is defined as the sum total of the planned delay that occurs 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.

We develop a mixed integer linear program for static scheduling in SAFMSs in the presence of information delays. We also develop a dynamic programming algorithm applicable in a real-time scheduling environment. Both these formulations yield an optimal schedule in the presence of information delays in SAFMSs. However, the problem complexity for both these programs is NP-hard. We therefore resort to extensive simulation experimentation to study the impact of information delays on the SAFMS performance.

Our key finding is that information delays significantly impair system performance especially for due date-based objectives but are significantly less severe for non-due date-based measures. Specifically, we find that for conditional mean tardiness and percent tardiness, the SAFMS performance deteriorates by as much as 40.9% and 25%, respectively, on average. In contrast, for the non-due date-based measures, mean flowtime and average machine utilization, the performance deterioration was only 4.6% and 3.5%, respectively. The worst-case scenarios record deterioration in performance of up to 89.1%.

Given the fact that these results are based on simulation experiments, one may doubt the universality of these findings. However, our results serve to highlight the deleterious effect that information delays can have on SAFMS performance and managers can ill afford to ignore them in their scheduling endeavors.

We believe that this work constitutes a small first step towards understanding the full impact and extent of information delays in SAFMS 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 the 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 the 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 the $Z_i(t)$, where $Z_i(t) = D_i$.

Slack : Select the part with the smallest remaining slack, i.e., choose the 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 the 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 the 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 the 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 the minimum $Z_i(t)$, where $Z_i(t) = | N_{i,j+1,m}(t) |$ 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 CMT shown in table 6.

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 6, using the observed CMT values as S/N ratios,

$$GTSS = \sum_{i=1}^{25} \eta_i^2 = (-58.34)^2 + (-61.16)^2 + ... + (38.41)^2 \text{ (dB)}^2 = 66861.445 \text{ (dB)}^2.$$

Also, SSM = $n \times m^2 = 25 \times (-50.452)^2 = 63635.125$ (dB)^2.

Therefore, SST = GTSS - SSM = 3226.320 (dB)^2.

$$\text{and SSB} = \sum_{j=1}^{c}\left[l_j \sum_{k=1}^{l_j} (m_{jk} - m)^2 \right],$$

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} = $5[(-59.874 + 50.452)^2 + (-51.812 + 50.452)^2 + ...+ (-47.886 + 50.452)^2]$ (dB)^2
= 655.953 (dB)^2.

Similarly, the other components are, SSB_T = 215.768 (dB)^2, SSB_D = 0.003 (dB)^2, SSB_S = 16.537 (dB)^2, and SSB_{IDR} = 1772.684 (dB)^2.

Therefore, SSB = (655.953 + 215.768 + 0.003 + 16.537 + 1772.684) (dB)^2 = 2660.946 (dB)^2.

Finally, SSE = SST - SSB = 3226.320 - 2660.946 (dB)^2 = 565.374 (dB)^2.

Notes:

[1] 'j' has the following abbreviations: RF = routing flexibility, D = dispatching rule, S = sequencing rule, T = due date tightness, IDR = information delay ratio.

Table 3. Part type / processing time data (routing flexibility = 5)

Part type	Operation Number	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
	2	-	9	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
	2	-	20	20	20	20	20
	3	32	32	32	-	32	-
	4	8	8	8	8	8	8
E	1	-	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
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

Table 4. 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	0
	2	.5
	3	1.0
	4	1.5
	5	2.0

Table 5. Factor-level details per L_{25} orthogonal array

Experiment #	RF	D	S	T	IDR
1	1	WINQ	SOPT	3	0
2	1	NINQ	EDD	4	.5
3	1	WINQ	Slack	5	1
4	1	NINQ	ODD	6	1.5
5	1	WINQ	OSlack	3	2
6	2	WINQ	EDD	5	1.5
7	2	NINQ	Slack	6	2
8	2	WINQ	ODD	3	0
9	2	NINQ	OSlack	3	.5
10	2	WINQ	SOPT	4	1
11	3	WINQ	Slack	3	.5
12	3	NINQ	ODD	3	1
13	3	WINQ	OSlack	4	1.5
14	3	NINQ	SOPT	5	2
15	3	WINQ	EDD	6	0
16	4	WINQ	ODD	4	2
17	4	NINQ	OSlack	5	0
18	4	WINQ	SOPT	6	.5
19	4	NINQ	EDD	3	1
20	4	WINQ	Slack	3	1.5
21	5	WINQ	OSlack	6	1
22	5	NINQ	SOPT	3	1.5
23	5	WINQ	EDD	3	2
24	5	NINQ	Slack	4	0
25	5	WINQ	ODD	5	.5

Table 6. Taguchi experiment simulation results: conditional mean tardiness

Experiment number	Observed CMT (minutes)	Observed CMT (η_i) (dB)
1	826.20	-58.34
2	1142.40	-61.16
3	1087.80	-60.73
4	881.62	-58.91
5	1027.10	-60.23
6	637.06	-56.08
7	841.39	-58.50
8	186.97	-45.44
9	292.36	-49.32
10	306.03	-49.72
11	142.13	-43.05
12	367.73	-51.31
13	677.22	-56.61
14	693.54	-56.82
15	12.93	-22.23
16	1121.50	-61.00
17	22.61	-27.09
18	43.50	-32.77
19	479.73	-53.62
20	884.70	-58.94
21	359.87	-51.12
22	616.14	-55.79
23	1325.30	-62.45
24	38.26	-31.66
25	83.25	-38.41

Table 7. Factor main effects for the Taguchi simulation results for CMT

Factor-level main effects	Applicable formulae	Main effect value CMT (dB)
$m_{RF,1}$	$(\eta_1 + \eta_2 + \eta_3 + \eta_4 + \eta_5) / 5$	-59.874
$m_{RF,2}$	$(\eta_6 + \eta_7 + \eta_8 + \eta_9 + \eta_{10}) / 5$	-51.812
$m_{RF,3}$	$(\eta_{11} + \eta_{12} + \eta_{13} + \eta_{14} + \eta_{15}) / 5$	***-46.004****
$m_{RF,4}$	$(\eta_{16} + \eta_{17} + \eta_{18} + \eta_{19} + \eta_{20}) / 5$	-46.684
$m_{RF,5}$	$(\eta_{21} + \eta_{22} + \eta_{23} + \eta_{24} + \eta_{25}) / 5$	-47.886
$m_{D,1}$	$(\eta_1 + \eta_3 + \eta_5 + \eta_6 + \eta_8 + \eta_{10} + \eta_{11} + \eta_{13} + \eta_{15} + \eta_{16} + \eta_{18} + \eta_{20} + \eta_{21} + \eta_{23} + \eta_{25}) / 15$	-50.475
$m_{D,2}$	$(\eta_2 + \eta_4 + \eta_7 + \eta_9 + \eta_{12} + \eta_{14} + \eta_{17} + \eta_{19} + \eta_{22} + \eta_{24}) / 10$	***-50.418***
$m_{S,1}$	$(\eta_1 + \eta_{10} + \eta_{14} + \eta_{18} + \eta_{22}) / 5$	-50.688
$m_{S,2}$	$(\eta_2 + \eta_6 + \eta_{15} + \eta_{19} + \eta_{23}) / 5$	-51.108
$m_{S,3}$	$(\eta_3 + \eta_7 + \eta_{11} + \eta_{20} + \eta_{24}) / 5$	-50.576
$m_{S,4}$	$(\eta_4 + \eta_8 + \eta_{12} + \eta_{16} + \eta_{25}) / 5$	-51.014
$m_{S,5}$	$(\eta_5 + \eta_9 + \eta_{13} + \eta_{17} + \eta_{21}) / 5$	***-48.874***
$m_{T,1}$	$(\eta_1 + \eta_5 + \eta_8 + \eta_9 + \eta_{11} + \eta_{12} + \eta_{19} + \eta_{20} + \eta_{22} + \eta_{23}) / 10$	-53.849
$m_{T,2}$	$(\eta_2 + \eta_{10} + \eta_{13} + \eta_{16} + \eta_{24}) / 5$	-52.030
$m_{T,3}$	$(\eta_3 + \eta_6 + \eta_{14} + \eta_{17} + \eta_{25}) / 5$	-47.826
$m_{T,4}$	$(\eta_4 + \eta_7 + \eta_{15} + \eta_{18} + \eta_{21}) / 5$	***-44.706***
$m_{IDR,1}$	$(\eta_1 + \eta_8 + \eta_{15} + \eta_{17} + \eta_{24}) / 5$	***-36.952***
$m_{IDR,2}$	$(\eta_2 + \eta_9 + \eta_{11} + \eta_{18} + \eta_{25}) / 5$	-44.942
$m_{IDR,3}$	$(\eta_3 + \eta_{10} + \eta_{12} + \eta_{19} + \eta_{21}) / 5$	-53.300
$m_{IDR,4}$	$(\eta_4 + \eta_6 + \eta_{13} + \eta_{20} + \eta_{22}) / 5$	-57.266
$m_{IDR,5}$	$(\eta_5 + \eta_7 + \eta_{14} + \eta_{16} + \eta_{23}) / 5$	-59.800

*Numbers in italics correspond to optimal levels.

Table 8. ANOVA for CMT using the simulated results estimated as S/N ratios

Factor	Degrees of Freedom	Sum of Squares	Mean Square	F value
Information Delay Ratio	4	1772.68	443.17	9.90
Routing Flexibility	4	655.95	163.99	3.66
Due Date Tightness	3	215.77	71.92	1.61
Sequencing Rule	4	16.54	4.13	
Dispatching Rule	1	0.02	0.02	
Error	8	565.38	70.67	
Total	24	3226.32	134.43	
Pooled Error	13	581.92	44.76	

Table 9. ANOVA for CMT using the original simulated results

Factor	Degrees of Freedom	Sum of Squares	Mean Square	F[a] value
Information Delay Ratio	4	1971438.50	492859.63	9.25
Routing Flexibility	4	1199749.88	299937.47	5.63
Due Date Tightness	3	133078.84[b]	44359.61	
Sequencing Rule	4	194612.09[b]	48653.02	
Dispatching Rule	1	2000.59[b]	2000.59	
Error	8	522939.00[b]	65367.38	
Total	24	4023818.90	167659.12	
Pooled Error	(16)	(852630.52)	(53289.41)	

[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. Taguchi experiment simulation results for percent tardy, mean flowtime, and average machine utilization

Experiment number	Observed Percent Tardy (%)	Observed Mean Flowtime (minutes)	Observed Av. M/C Utilization (%)
1	88.33	165.72	82.05
2	87.44	173.61	78.62
3	83.70	173.16	78.85
4	77.67	169.87	80.36
5	92.42	170.50	80.07
6	76.01	163.42	83.02
7	77.29	168.85	80.72
8	65.66	147.51	89.39
9	76.77	152.03	87.93
10	68.76	153.82	87.16
11	57.05	145.67	89.81
12	81.19	154.38	87.05
13	81.43	163.26	83.22
14	78.23	164.64	82.57
15	1.65	136.32	90.83
16	87.43	173.64	78.83
17	2.85	133.56	90.95
18	9.29	143.64	90.36
19	83.79	157.24	85.57
20	89.14	167.31	81.34
21	58.06	156.80	85.95
22	85.37	160.51	84.23
23	93.36	176.88	77.26
24	6.06	132.71	91.01
25	18.24	145.04	90.02

Table 11. Factor main effects for percent tardy, mean flowtime, and average machine utilization

Factor-level main effects	Main effect value for percent tardy (dB)	Main effect value for mean flowtime (dB)	Main effect value for av. m/c utilz. (dB)
$m_{RF,1}$	-38.666	-44.636	38.059
$m_{RF,2}$	-37.236	-43.916	38.648
$m_{RF,3}$	-30.752	*-43.664**	*38.754*
$m_{RF,4}$	*-28.950*	-43.770	38.616
$m_{RF,5}$	-30.836	-43.732	38.644
$m_{D,1}$	-33.480	-43.993	38.528
$m_{D,2}$	*-33.000*	*-43.869*	*38.568*
$m_{S,1}$	-34.306	-43.944	38.610
$m_{S,2}$	*-31.732*	-44.126	38.373
$m_{S,3}$	-33.198	-43.904	38.506
$m_{S,4}$	-35.280	-43.954	38.588
$m_{S,5}$	-31.924	*-43.790*	*38.643*
$m_{T,1}$	-38.110	-44.054	38.524
$m_{T,2}$	-33.656	-44.008	38.447
$m_{T,3}$	-29.652	-43.822	38.584
$m_{T,4}$	*-26.912*	*-43.780*	*38.642*
$m_{IDR,1}$	*-20.874*	*-43.086*	*38.966*
$m_{IDR,2}$	-31.248	-43.616	38.813
$m_{IDR,3}$	-37.426	-44.024	38.574
$m_{IDR,4}$	-38.256	-44.342	38.321
$m_{IDR,5}$	-38.636	-44.650	38.048

*Numbers in italics correspond to optimal levels.

Table 12. ANOVA for percent tardy using the original simulated results

Factor	Degrees of Freedom	Sum of Squares	Mean Square	F[a] value
Information Delay Ratio	4	10404.39	2601.10	6.71
Due Date Tightness	3	3410.82	1136.94	2.93
Routing Flexibility	4	3995.95	998.99	2.58
Sequencing Rule	4	133.62[b]	33.40	
Dispatching Rule	1	0.97[b]	0.97	
Error	8	4905.77[b]	613.22	
Total	24	22851.51	952.15	
Pooled Error	(13)	(5040.35)	(387.72)	

[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 13. 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	2355.05	588.76	12.31
Routing Flexibility	4	1034.43	258.61	5.41
Sequencing Rule	4	101.06[b]	25.27	
Due Date Tightness	3	70.90[b]	23.63	
Dispatching Rule	1	4.61[b]	4.61	
Error	8	588.52[b]	73.57	
Total	24	4154.57	173.11	
Pooled Error	(16)	(765.09)	(47.82)	

[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 14. ANOVA for average machine utilization using simulated results

Factor	Degree of Freedom	Sum of Squares	Mean Square	F[a] value
Information Delay Ratio	4	262.59	65.65	11.79
Routing Flexibility	4	142.75	35.69	6.41
Sequencing Rule	4	20.91[b]	5.23	
Due Date Tightness	3	7.85[b]	2.62	
Dispatching Rule	1	0.13[b]	0.13	
Error	8	60.20[b]	7.53	
Total	24	494.43	20.60	
Pooled Error	(16)	(89.09)	(5.57)	

[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 15. Sensitivity experiment simulation results for conditional mean tardiness, percent tardy, mean flowtime, and average machine utilization

Experiment number	Observed CMT (minutes)	Observed percent tardy (%)	Observed mean flowtime (minutes)	Observed avg. m/c utilization (%)
1	826.20	88.33	165.72	82.05
2	1142.40	87.44	173.61	78.62
3	1087.80	83.70	173.16	78.85
4	881.62	77.67	169.87	80.36
5	1027.10	92.42	170.50	80.07
6	287.09	57.61	153.79	87.14
7	349.34	56.87	156.46	85.94
8	186.97	65.66	147.51	89.39
9	244.53	73.22	149.95	88.54
10	186.42	53.13	149.06	88.94
11	98.82	36.29	140.15	90.62
12	118.83	48.79	143.73	90.34
13	145.33	45.20	147.47	89.54
14	152.35	35.18	149.00	89.05
15	12.93	1.65	136.32	90.83
16	248.84	63.13	151.71	88.12
17	22.61	2.85	133.56	90.95
18	14.63	2.21	137.58	90.81
19	109.44	44.54	142.76	90.34
20	190.38	65.99	148.11	89.25
21	39.27	8.80	143.17	90.43
22	143.51	58.02	145.84	89.86
23	322.20	78.32	152.76	87.52
24	38.26	6.06	132.71	91.01
25	34.87	6.85	138.09	90.82

Table 16. Factor main effects for conditional mean tardiness, percent tardy, mean flowtime, and average machine utilization

Factor-level main effects	Main effect value for CMT (dB)	Main effect value for percent tardy (dB)	Main effect value for mean flowtime (dB)	Main effect value for avg. m/c utilzn. (dB)
m_{RE1}	-59.874	-38.666	-44.636	38.059
m_{RE2}	-47.728	-35.692	-43.600	38.888
m_{RE3}	-38.108	-26.670	-43.120	***39.090***
m_{RE4}	***-36.936***	***-24.272***	-43.080	39.074
m_{RE5}	-37.538	-24.880	***-43.068***	39.077
m_{D1}	***-43.626***	***-29.611***	-43.518	***38.844***
m_{D2}	-44.653	-30.673	***-43.475***	38.829
m_{S1}	-42.770	-29.304	-43.474	***38.898***
m_{S2}	-44.698	-29.850	-43.598	38.768
m_{S3}	-45.748	-31.358	-43.492	38.791
m_{S4}	-44.924	-32.128	-43.510	38.862
m_{S5}	***-42.044***	***-27.540***	***-43.430***	38.871
m_{T1}	-47.285	-35.937	-43.546	***38.862***
m_{T2}	-45.880	-31.618	-43.542	38.803
m_{T3}	-42.298	-26.080	-43.456	38.815
m_{T4}	***-37.436***	***-20.608***	***-43.414***	38.848
m_{IDR1}	***-36.952***	***-20.874***	***-43.086***	***38.966***
m_{IDR2}	-40.596	-26.184	-43.362	38.865
m_{IDR3}	-44.060	-31.720	-43.520	38.856
m_{IDR4}	-48.010	-35.556	-43.680	38.806
m_{IDR5}	-50.566	-35.846	-43.856	38.698

Table 17. CMT ANOVA for the revised matrix experiment

Factor	Degrees of Freedom	Sum of Squares	Mean Square	F[a] value
Routing Flexibility	4	2932646.50	733161.63	112.48
Information Delay Ratio	4	104270.72	26067.68	4.00
Due Date Tightness	3	18504.28[b]	6168.09	
Sequencing Rule	4	41719.88[b]	10429.97	
Dispatching Rule	1	42.14[b]	42.14	
Error	8	44020.25[b]	5502.53	
Total	24	3141203.77	130883.49	
Pooled Error	(16)	(104286.55)	(6517.91)	

[a]The critical F ratio at $\alpha = 0.05$ (i.e., $F_{0.05,4,16}$) = 3.01; at $\alpha = 0.025$ (i.e., $F_{0.025,4,16}$) = 3.73; at $\alpha = 0.01$ (i.e., $F_{0.01,4,16}$) = 4.77.
[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 18. Percent tardy ANOVA for the revised matrix experiment

Factor	Degrees of Freedom	Sum of Squares	Mean Square	F[a] value
Routing Flexibility	4	11163.81	2790.95	10.17
Due Date Tightness	3	3212.59	1070.86	3.90
Information Delay Ratio	4	3614.29	903.57	3.29
Sequencing Rule	4	287.82[b]	71.96	
Dispatching Rule	1	0.82[b]	0.82	
Error	8	3278.81[b]	409.85	
Total	24	21558.13	898.26	
Pooled Error	(13)	(3567.45)	(274.42)	

[a]The critical F ratio (at $\alpha = 0.05$; i.e., $F_{0.05,4,13}$) = 3.18; at $\alpha = 0.025$ (i.e., $F_{0.025,4,13}$) = 4.00; at $\alpha = 0.01$ (i.e., $F_{0.01,4,13}$) = 5.21.
[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 19. Mean flowtime ANOVA for the revised matrix experiment

Factor/ Source	Degrees of Freedom	Sum of Squares	Mean Square	F[a] value
Routing Flexibility	4	2890.56	722.64	68.93
Information Delay Ratio	4	487.33	121.83	11.62
Sequencing Rule	4	24.34[b]	6.08	
Due Date Tightness	3	13.52[b]	4.51	
Dispatching Rule	1	0.36[b]	0.36	
Error	8	129.52[b]	16.19	
Total	24	3545.63	147.73	
Pooled Error	(16)	(167.74)	(10.48)	

[a]The critical F ratio (at $\alpha = 0.05$; i.e., $F_{0.05, 4, 16}$) = 3.01; at $\alpha = 0.025$ (i.e., $F_{0.025, 4, 16}$) = 3.73; at $\alpha = 0.01$ (i.e., $F_{0.01, 4, 16}$) = 4.77.
[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 20. Average machine utilization ANOVA for the revised matrix experiment

Factor/ Source	Degrees of Freedom	Sum of Squares	Mean Square	F[a] value
Routing Flexibility	4	374.37	93.59	22.41
Information Delay Ratio	4	19.65	4.91	1.18
Sequencing Rule	4	5.74[b]	1.44	
Due Date Tightness	3	0.85[b]	0.28	
Dispatching Rule	1	0.02[b]	0.02	
Error	8	60.20[b]	7.52	
Total	24	460.83	19.20	
Pooled Error	(16)	(66.81)	(4.18)	

[a]The critical F ratio (at $\alpha = 0.05$; i.e., $F_{0.05, 4, 16}$) = 3.01; at $\alpha = 0.025$ (i.e., $F_{0.025, 4, 16}$) = 3.73; at $\alpha = 0.01$ (i.e., $F_{0.01, 4, 16}$) = 4.77.
[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.

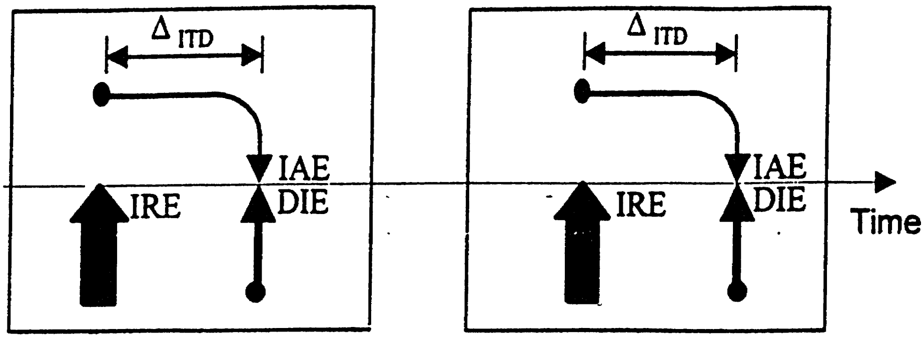
Table 21: Deterioration of performance of SAFMS under different objectives

Expt No.	Conditional mean tardiness			Percent tardy			Mean flowtime			Average machine utilization		
	Information delay ratio		% Performance	Information delay ratio		% Performance	Information delay ratio		% Performance	Information delay ratio		% Performance
	High*	Low*	Deterioration	High	Low	Deterioration	High	Low	Deterioration	High	Low	Deterioration
1	826.2	826.2	0.0	88.33	88.33	0.0	165.72	165.72	0.0	82.05	82.05	0.0
2	1142.4	1142.4	0.0	87.44	87.44	0.0	173.61	173.61	0.0	78.62	78.62	0.0
3	1087.8	1087.8	0.0	83.7	83.7	0.0	173.16	173.16	0.0	78.85	78.85	0.0
4	881.62	881.62	0.0	77.67	77.67	0.0	169.87	169.87	0.0	80.36	80.36	0.0
5	1027.1	1027.1	0.0	92.42	92.42	0.0	170.5	170.5	0.0	80.07	80.07	0.0
6	637.06	287.09	54.9	76.01	57.61	24.2	163.42	153.79	5.9	83.02	87.14	5.0
7	841.39	349.34	58.5	77.29	56.87	26.4	168.85	156.46	7.3	80.72	85.94	6.5
8	186.97	186.97	0.0	65.66	65.66	0.0	147.51	147.51	0.0	89.39	89.39	0.0
9	292.36	244.53	16.4	76.77	73.22	4.6	152.03	149.95	1.4	87.93	88.54	0.7
10	306.03	186.42	39.1	68.76	53.13	22.7	153.82	149.06	3.1	87.16	88.94	2.0
11	142.13	98.82	30.5	57.05	36.29	36.4	145.67	140.15	3.8	89.81	90.62	0.9
12	367.73	118.83	67.7	81.19	48.79	39.9	154.38	143.73	6.9	87.05	90.34	3.8
13	677.22	145.33	78.5	81.43	45.2	44.5	163.26	147.47	9.7	83.22	89.54	7.6
14	693.54	152.35	78.0	78.23	35.18	55.0	164.64	149	9.5	82.57	89.05	7.8
15	12.93	12.93	0.0	1.65	1.65	0.0	136.32	136.32	0.0	90.83	90.83	0.0
16	1121.5	248.84	77.8	87.43	63.13	27.8	173.64	151.71	12.6	78.83	88.12	11.8
17	22.61	22.61	0.0	2.85	2.85	0.0	133.56	133.56	0.0	90.95	90.95	0.0
18	43.5	14.63	66.4	9.29	2.21	76.2	143.64	137.58	4.2	90.36	90.81	0.5
19	479.73	109.44	77.2	83.79	44.54	46.8	157.24	142.76	9.2	85.57	90.34	5.6
20	884.7	190.38	78.5	89.14	65.99	26.0	167.31	148.11	11.5	81.34	89.25	9.7
21	359.87	39.27	89.1	58.06	8.8	84.8	156.8	143.17	8.7	85.95	90.43	5.2
22	616.14	143.51	76.7	85.37	58.02	32.0	160.51	145.84	9.1	84.23	89.86	6.7
23	1325.3	322.2	75.7	93.36	78.32	16.1	176.88	152.76	13.6	77.26	87.52	13.3
24	38.26	38.26	0.0	6.06	6.06	0.0	132.71	132.71	0.0	91.01	91.01	0.0
25	83.25	34.87	58.1	18.24	6.85	62.4	145.04	138.09	4.8	90.02	90.82	0.9
Average	563.9	316.5	40.9	65.1	49.6	25.0	158.0	150.1	4.9	84.7	87.6	3.5
Maximum	1325.3	1142.4	89.1	93.4	92.4	84.8	176.9	173.6	13.6	91.0	91.0	13.3

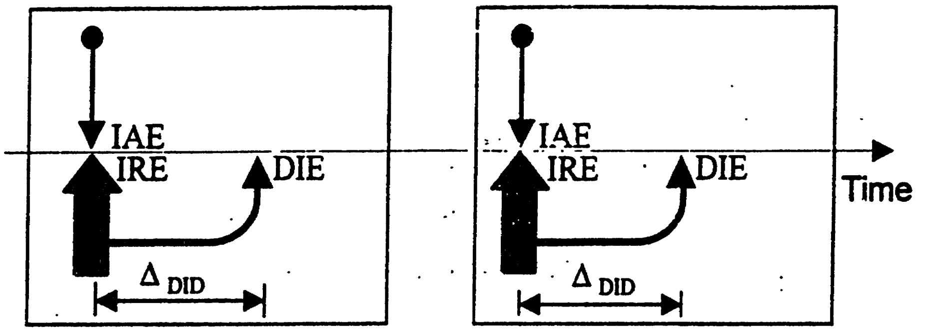
*The ratio of high IDR to low IDR was 2.0 for each experiment.

Fig. 1: Schematic Representation of Information Delay Modes

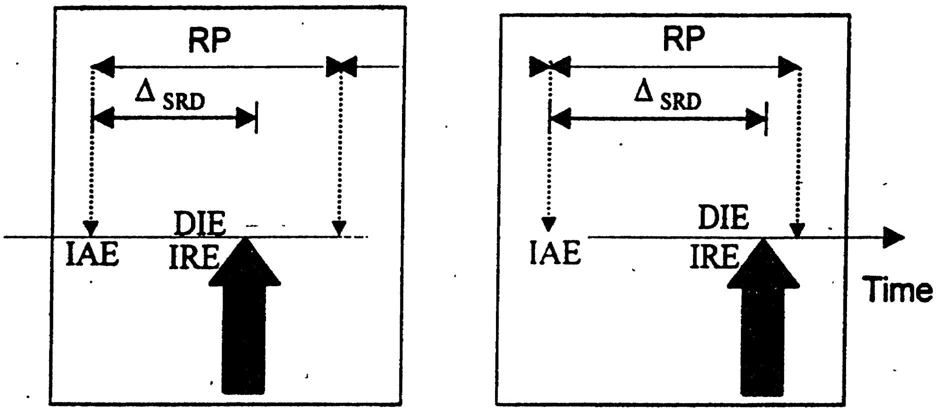
Mode 1 Information-Transfer Delay:



Mode 2 Decision-Implementation Delay:



Mode 3 Status-Review Delay:

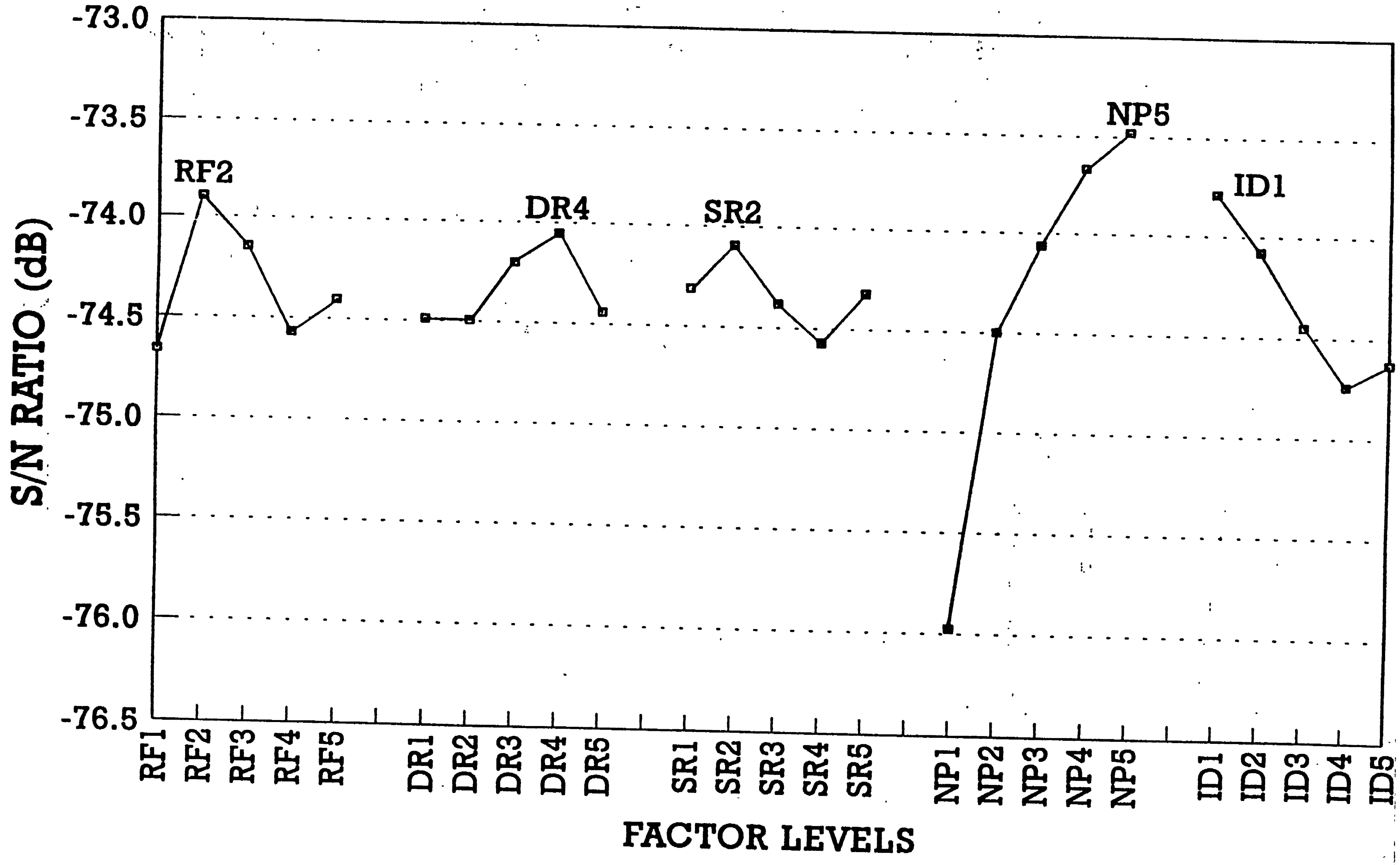


LEGEND

IRE	Information request epoch
IAE	Information arrival epoch
DIE	Decision implementation epoch
Δ_{ITD}	Magnitude of information transfer delay
Δ_{DID}	Magnitude of decision implementation delay
Δ_{SRD}	Magnitude of status review delay
RP	Review period

- Information flow from arrival epoch to decision implementation epoch
- Real-time information arrival upon request
- Status information request epoch
- Information flow from request epoch to decision implementation epoch
- Real-time decision implementation epoch
- System status information samples to database

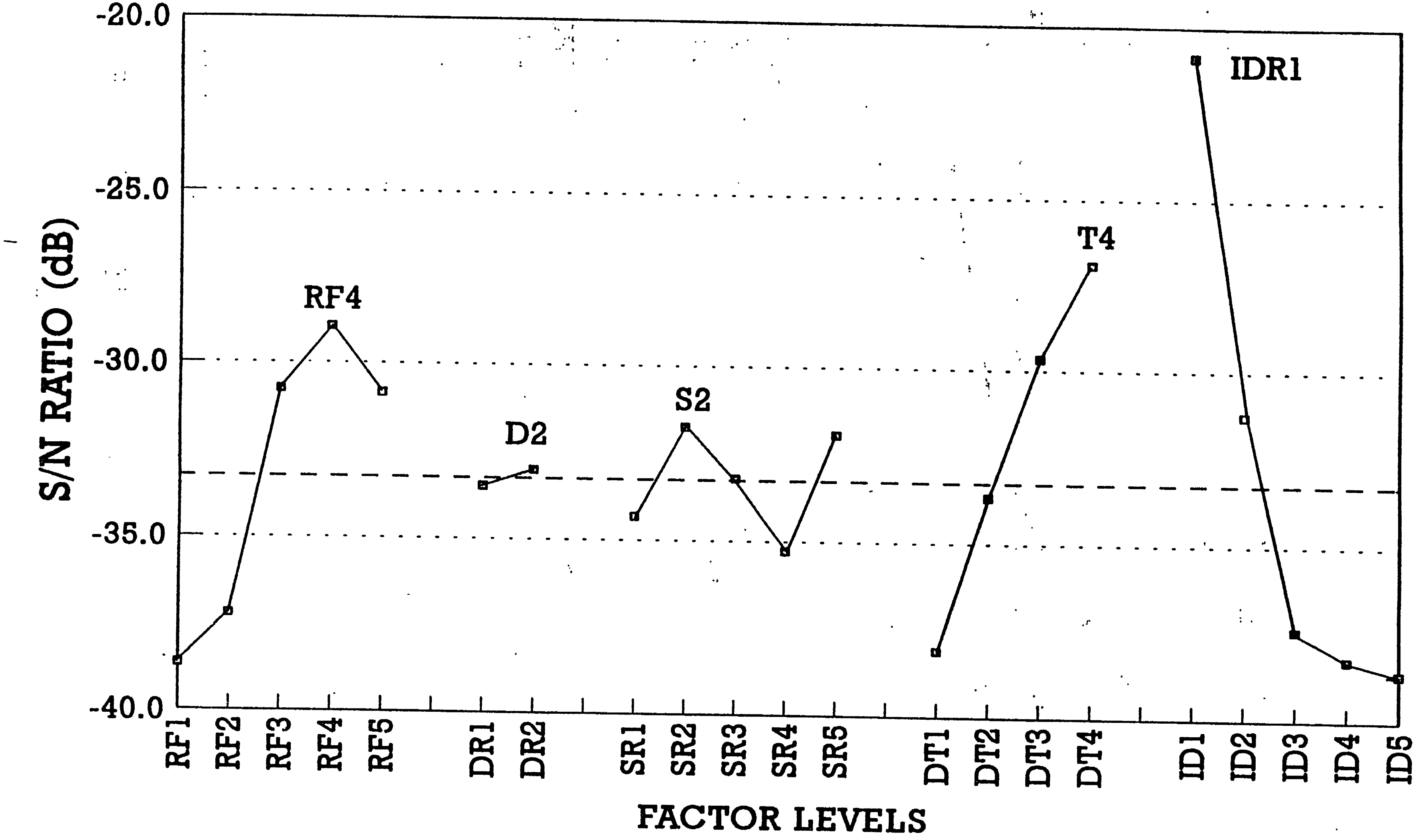
FIG.2: ANOM PLOT OF FACTOR MAIN EFFECTS
(MODE 3 INFORMATION DELAY)



Note: Optimal factor level combination is indicated on the graph

FIG.3: ANALYSIS OF MEANS PLOT OF FACTOR MAIN EFFECTS

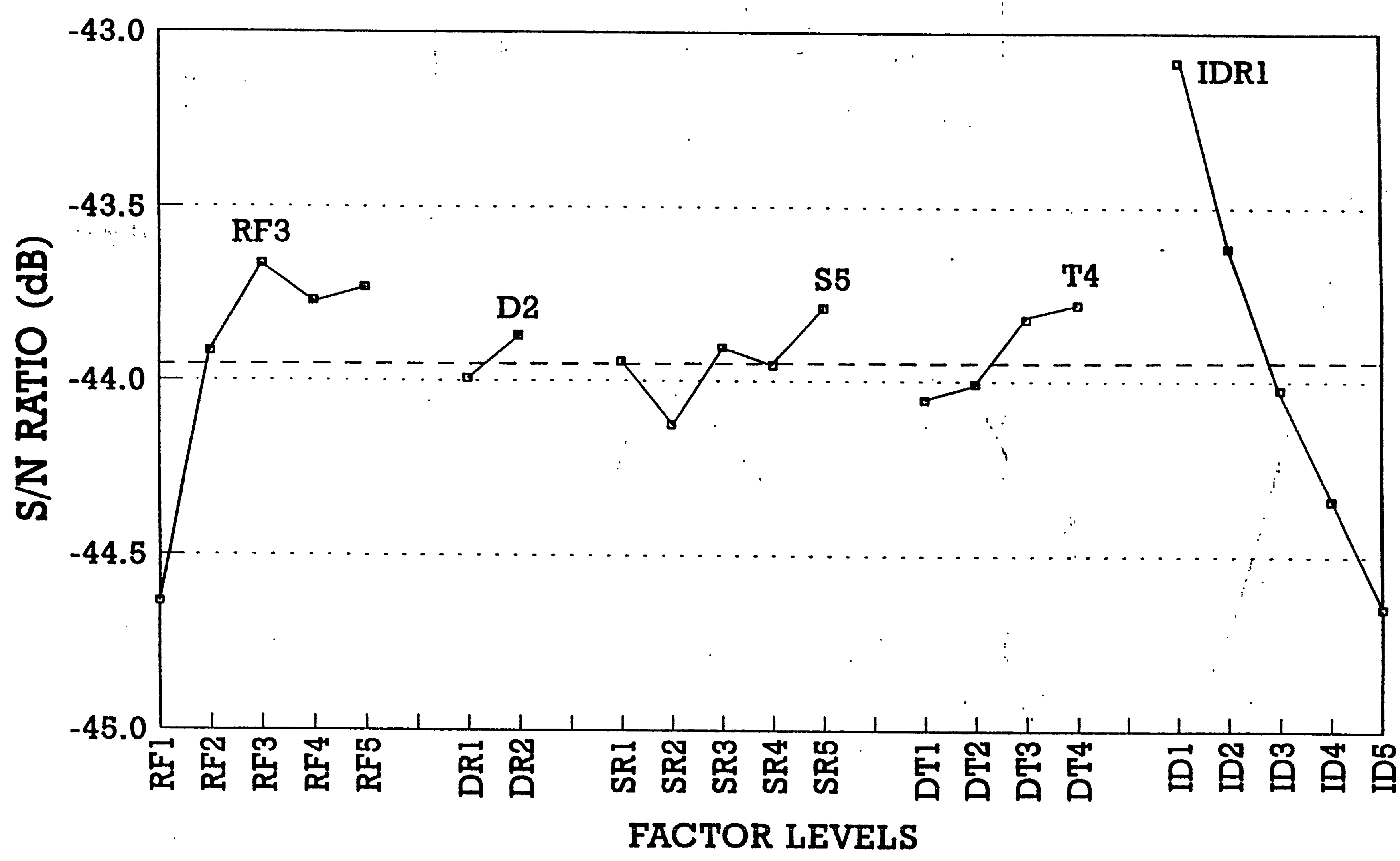
PERCENT TARDINESS (IDR = 0.0 - 2.0)



Note: Optimal factor levels indicated on the graph

FIG.4: ANALYSIS OF MEANS PLOT OF FACTOR MAIN EFFECTS

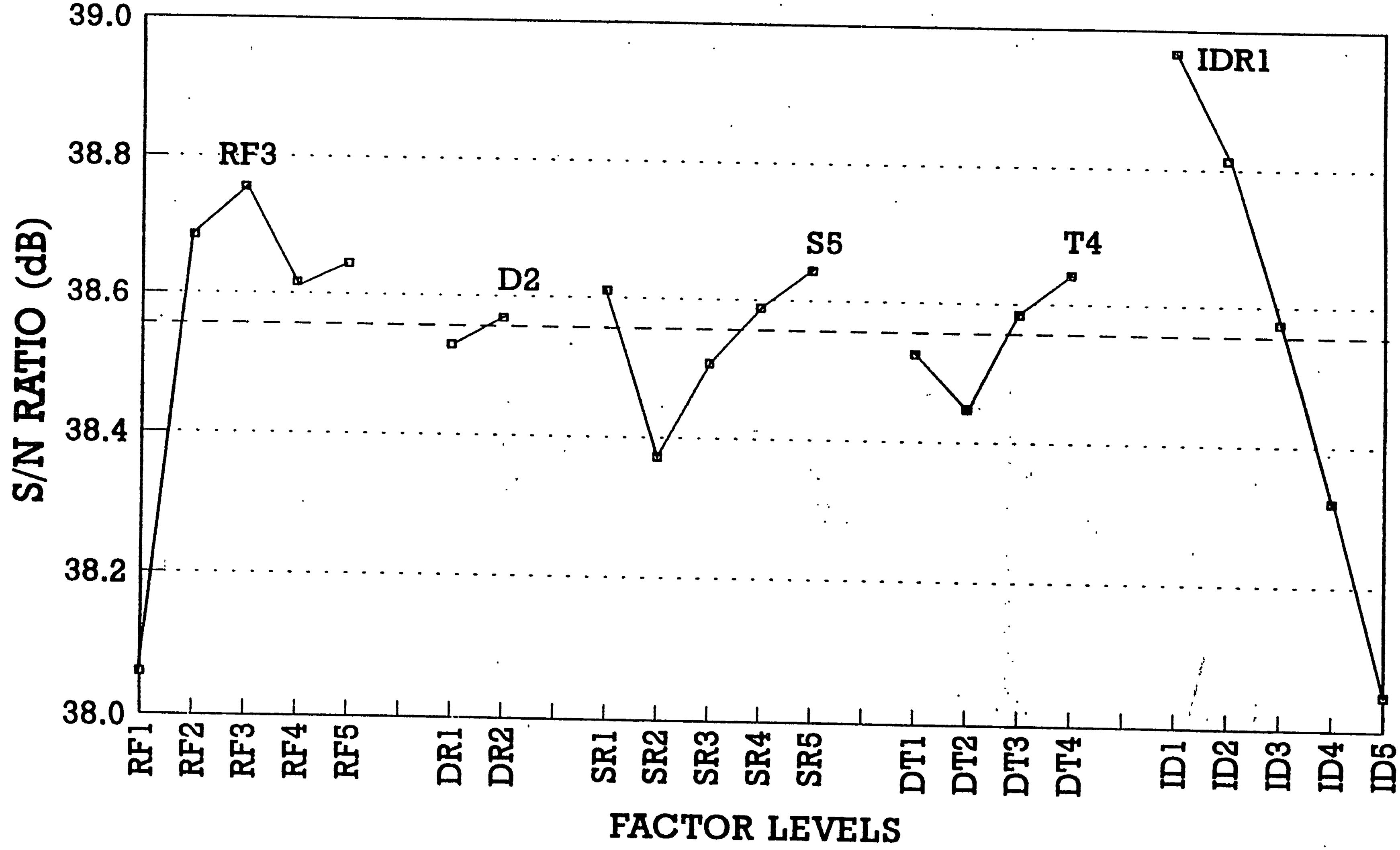
MEAN FLOWTIME (IDR = 0.0 - 2.0)



Note: Optimal factor levels indicated on the graph

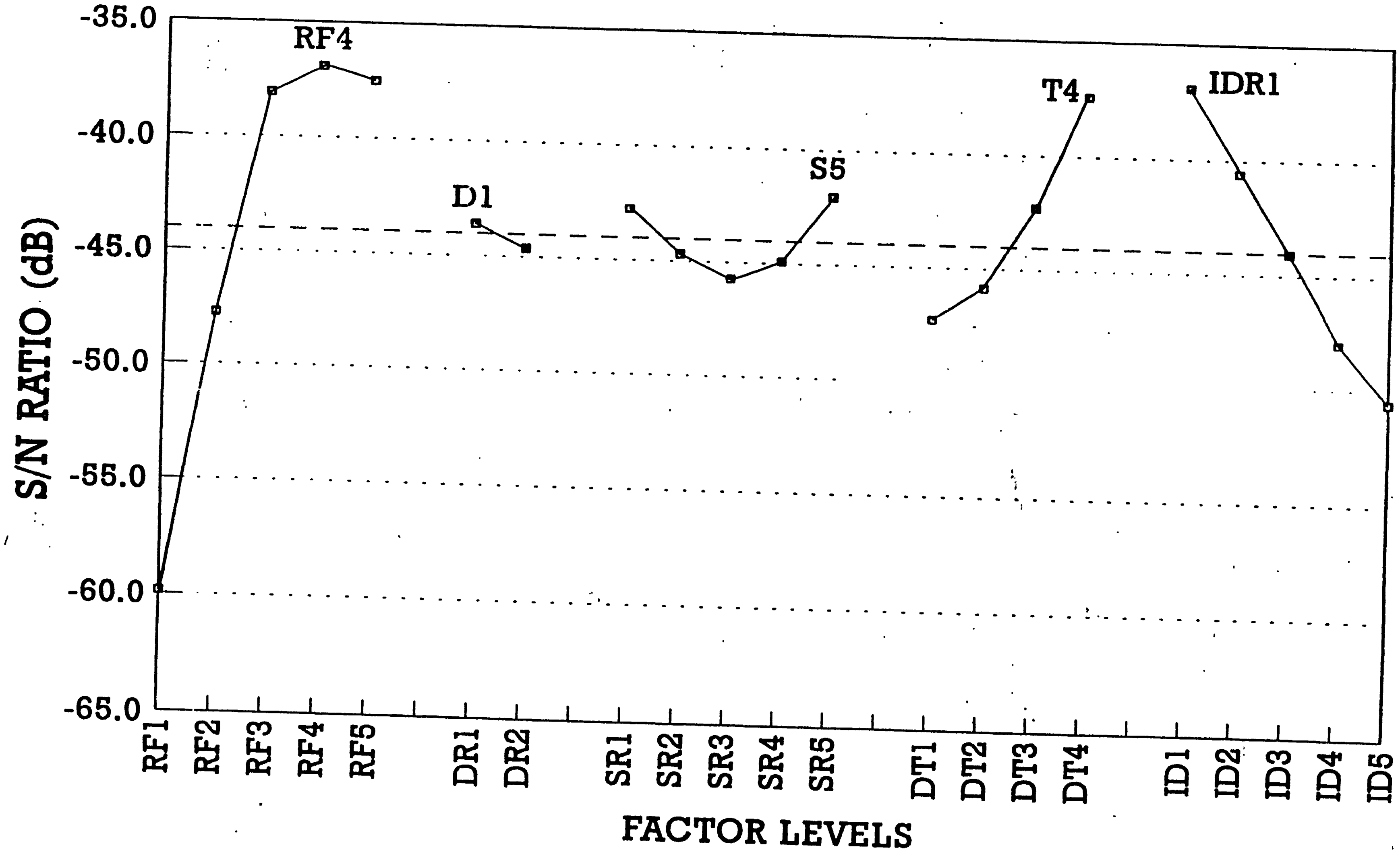
FIG.5: ANALYSIS OF MEANS PLOT OF FACTOR MAIN EFFECTS

AVERAGE MACHINE UTILIZATION (IDR = 0.0 - 2.0)



Note: Optimal factor levels indicated on the graph

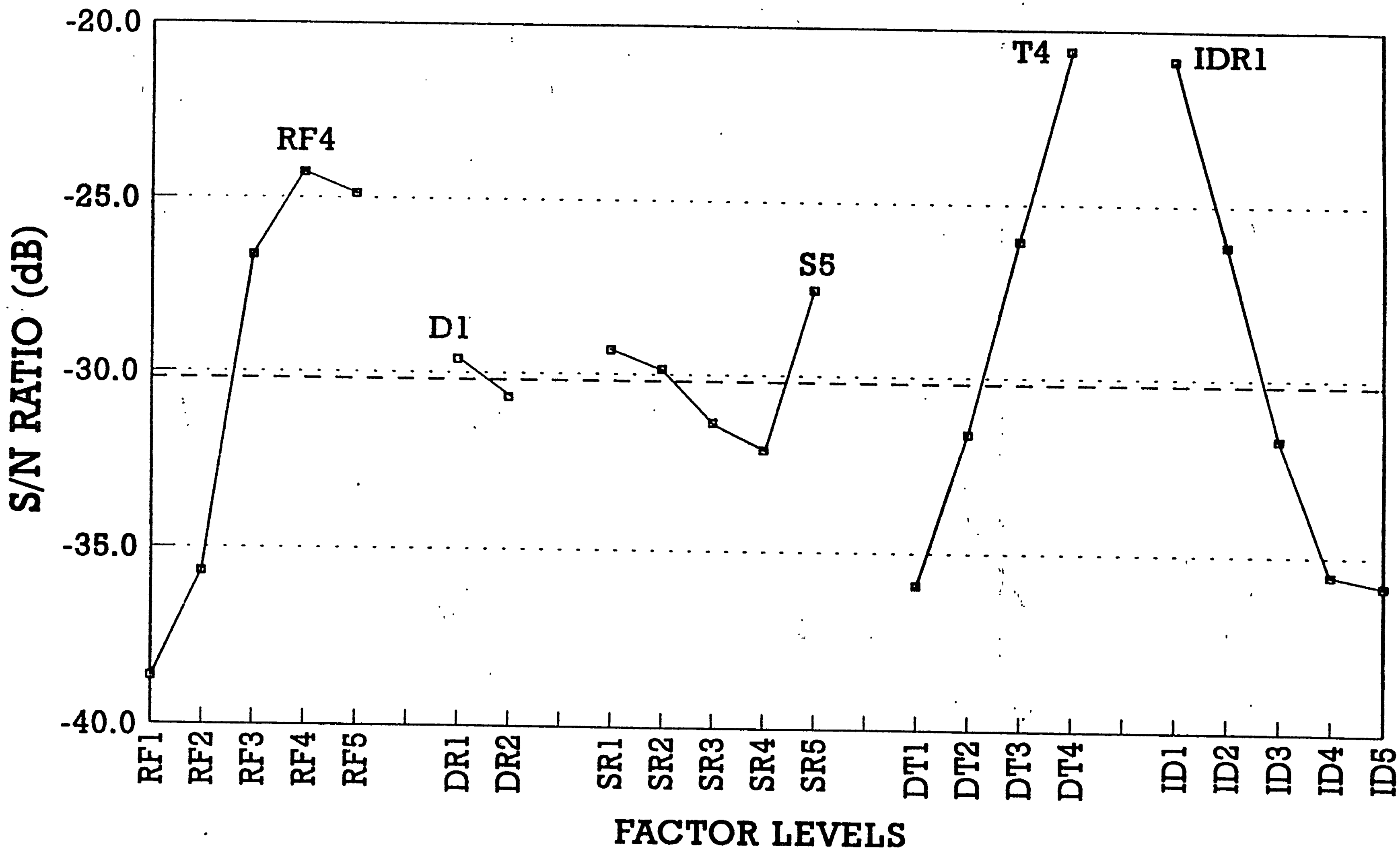
FIG.6: ANALYSIS OF MEANS PLOT OF FACTOR MAIN EFFECTS
CONDITIONAL MEAN TARDINESS (IDR = 0.0 - 1.0)



Note: Optimal factor levels indicated on the graph

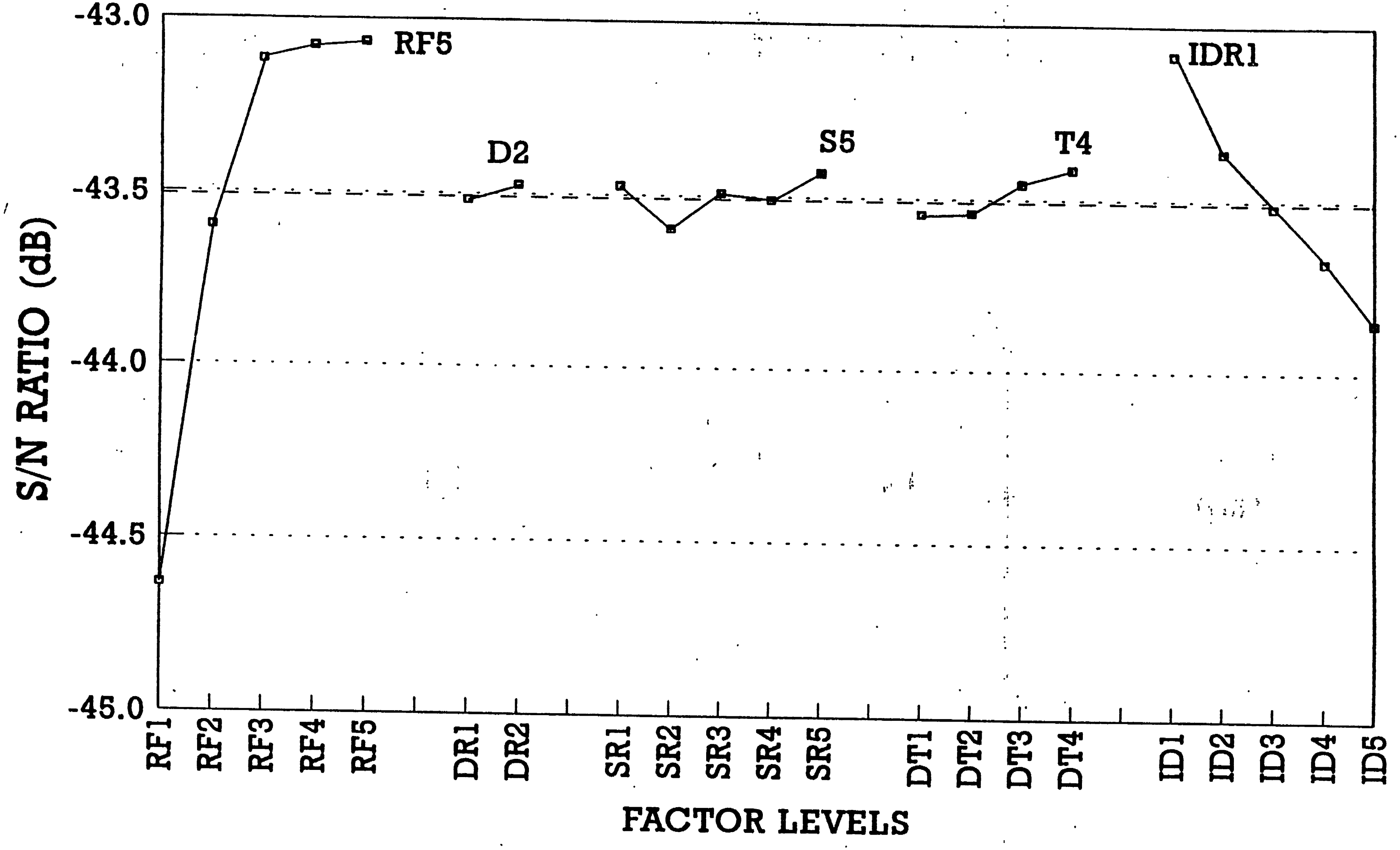
FIG.7: ANALYSIS OF MEANS PLOT OF FACTOR MAIN EFFECTS

PERCENT TARDINESS (IDR = 0.0 - 1.0)



Note: Optimal factor levels indicated on the graph

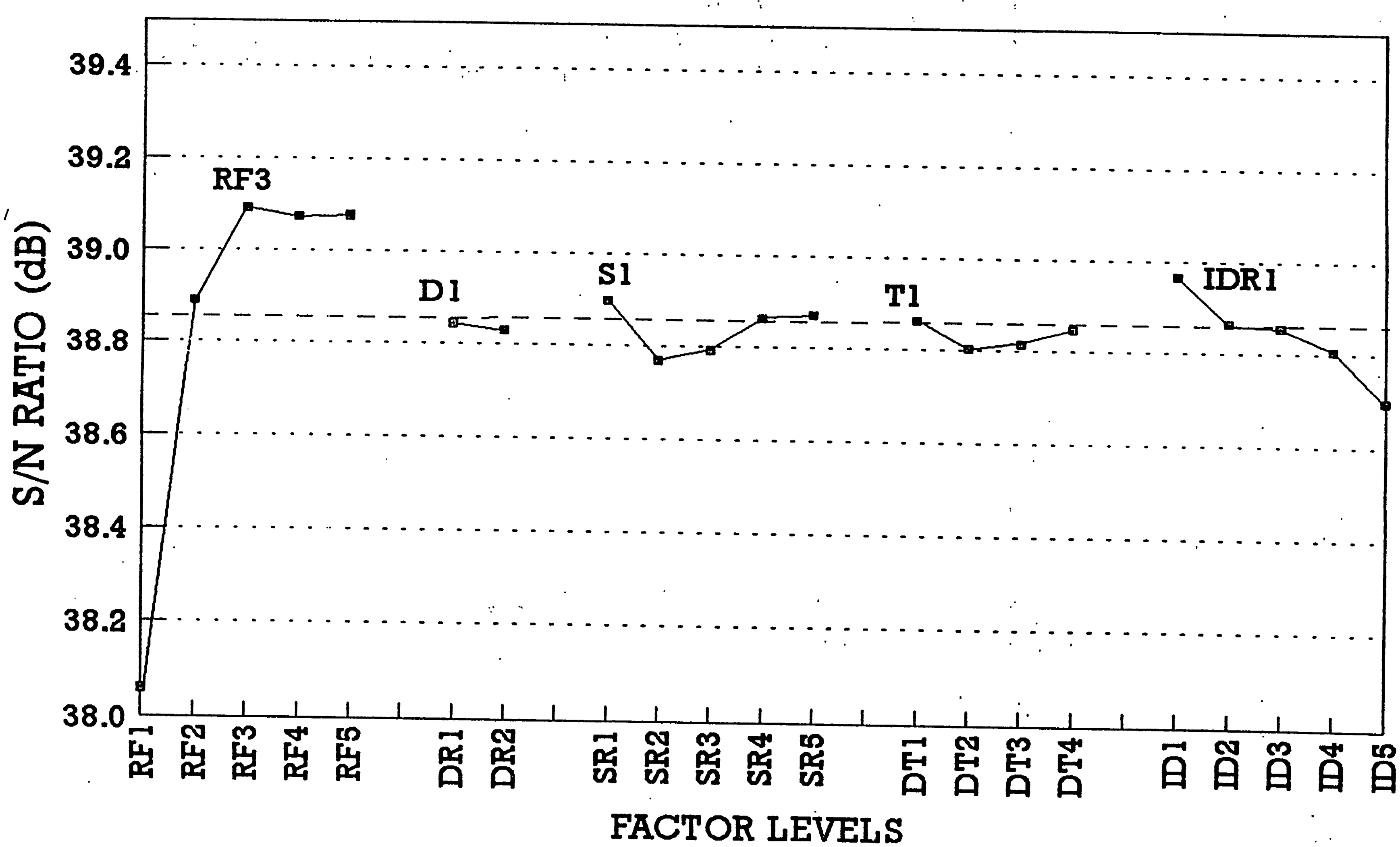
FIG.8: ANALYSIS OF MEANS PLOT OF FACTOR MAIN EFFECTS
MEAN FLOWTIME (IDR = 0.0 - 1.0)



Note: Optimal factor levels indicated on the graph

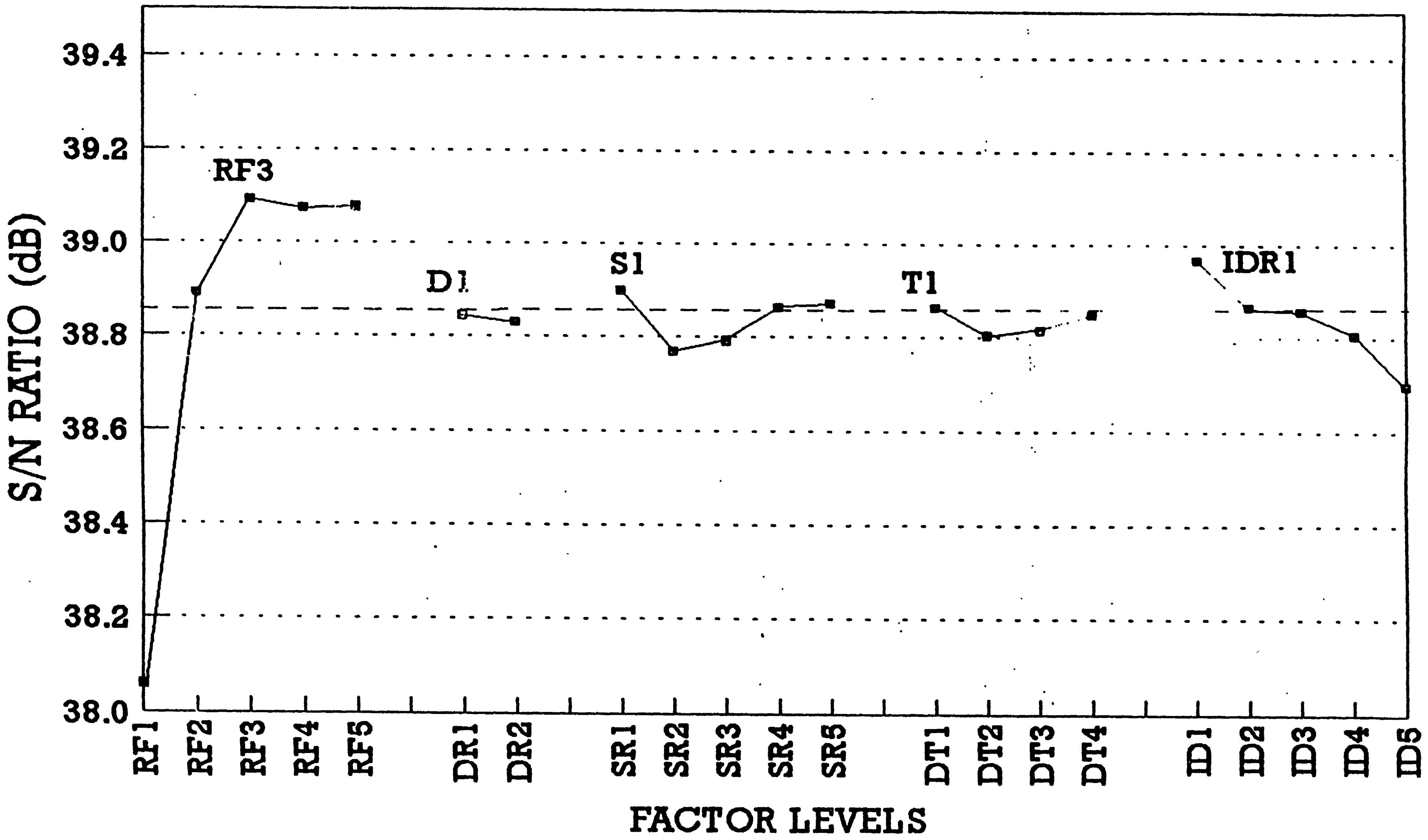
FIG.9: ANALYSIS OF MEANS PLOT OF FACTOR MAIN EFFECTS

AVERAGE MACHINE UTILIZATION



Note: Optimal factor levels indicated on the graph

... FACTOR MAIN EFFECTS
AVERAGE MACHINE UTILIZATION



Note: Optimal factor levels indicated on the graph