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Maintenance float decision models in flexible manufacturing systems—Taguchi design and regression metamodel approach

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MAINTENANCE FLOAT DECISION MODELS IN FLEXIBLE MANUFACTURING SYSTEMS - TAGUCHI DESIGN AND REGRESSION METAMODEL APPROACH

by

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ABSTRACT

MAINTENANCE FLOAT DECISION MODELS IN FLEXIBLE MANUFACTURING SYSTEMS - TAGUCHI DESIGN AND REGRESSION METAMODEL APPROACH

by

Chu-Hua Kuei

Adviser: Professor Michael N. Chanin

This paper proposes a new strategic approach to the modeling of maintenance float decisions in a Flexible Manufacturing Cell and Flexible Manufacturing System. This approach incorporates problem definition and formulation, simulation model, Taguchi experimental design, ANOVA algorithm, data analysis, regression metamodel, and mathematical programming. Taguchi experimental design is used to generate the input variables into the simulation program. The simulation results are analyzed using Taguchi's ANOVA algorithm and data analysis procedure. Input variables found significant are subsequently applied in a regression metamodel. Predictor models for the machine utilization and/or throughput are developed and their validities tested. Cost decision models are further developed to show the applicability of our models to decision situations. Currently no procedure is available for determining how to design the best simulation experiment based on the Taguchi method. Therefore this study proposes aids that have been found useful in designing these experiments.

The objectives of this study are as follows: 1) to utilize the Taguchi design in the simulation experiment, 2) to analyze the main effects and interaction effects of controllable factors on the machine utilization in the FMC with maintenance float policy and on the throughput in the FMS with maintenance float policy, 3) to examine the relationships between machine utilization and/or throughput and the number of spares parts, the number of repair persons, mean time between failure (MTBF), and mean time to repair (MTTR). 4) to predict the performance of very complex manufacturing systems, and 5) to minimize the expected total system cost per unit time subject to certain system constraints.

The use of such an approach reduces the amount of work needed in order to obtain a reliable and dependable model for maintenance float systems. It also benefits from the flexibility of simulation by not requiring some of the restricting assumptions made by analytical models. Additionally, this approach can help operation managers to make an effective and competitive decision.

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CHAPTER 1

INTRODUCTION

There is a growing interest in flexible manufacturing systems (FMSs). The preponderance of literature supports this view. FMS has grown popular over the years due to the emphasis on the modernization of American business as a means of regaining local and global competitiveness. Recent studies point towards automation and in particular FMSs as means of achieving increased productivity and therefore, improving a company's competitive edge [Singhal, 1987].

An FMS is a "computer controlled configuration of semi-independent work stations and a materials handling system (MHS) designed to efficiently manufacture more than one part number at low to medium volumes" [Young, 1988]. A typical FMS consists of the following basic components [Dupont, 1982, Yao, 1983, Kusiak, 1985, Klahorst, 1986, Groover, 1987, Fry and Smith, 1989]: 1) a group of computer numerical control (CNC) machines, 2) an automated MHS, 3) a central supervisory or host computer and several personal computers' at each machine, 4) a tool storage and retrieval system required by the CNC machines, 5) local work-in-process (WIP) storage at each machine and a central WIP storage at the system level, 6) different types of jobs - different both in physical shapes and sizes and in work requirement, and 7) loading and unloading stations.

FMS applications can be found mostly in the automotive, machine tools, aerospace/defense, and general mechanical industries worldwide [Kochan, 1986].

There are various ways to classify FMSs. One is to distinguish between an FMS and a manufacturing cell. According to Groover [1987], a distinction can be made by the number of machines in the grouping. A grouping of four or more machines is a system, and three or fewer machines constitute a cell. Groover [1987] also divided FMSs into two distinct types: 1) a Random FMS, and 2) a Dedicated FMS. A random FMS is equipped with general-purpose machines to deal with the variations in product and it is capable of processing parts in various sequences. A dedicated FMS is used to produce a much more limited variety of part configurations. Therefore, the machine sequence is identical or similar for all parts processed on the system.

Since there is some uncertainty concerning the conditions under which a manufacturing system may be termed "flexible", Browne [1984] defines eight types of flexibilities to clarify this confusion (Table 1-1). Based on those definitions, four different types of FMSs are further categorized by Browne [1984]. These four types of FMSs are a flexible machining cell

(FMC), a flexible machining system, a flexible transfer line, and a flexible transfer multi-line. The basic component of the FMC is a general purpose CNC machine tool. The flexible machining system then consists of different types of FMCs. It can have real-time, or on-line control of part production. It should allow several routes for parts with small volume production. This type of operation is highly machine flexible, process flexible, product flexible and routing flexible. In the flexible transfer line, each operation is assigned to, and performs on only one machine for all part types. For each part, there is a fixed route through the system. This type of operation is similar to the dedicated transfer line. However, the difference is that it is set up more often, and it is relatively quick. Since the flexible transfer line has less capability to deal with machine breakdowns, multi-line systems can be used to increase the routing flexibility.

There are several advantages to the use of FMSs today. These advantages were better outlined by Fry and Smith [1989] who list them as follows: "direct labor reduction, indirect labor reduction, improved utilization, flexibility, WIP inventory reduction, reduced lead time and increased throughput, reduction of scrap, reduction of set-up time and optimum balance of production." Moreover, Choobineh et al. [1986] comment that "increased levels of competition, shorter product cycles, and increased demands for customized products are some of the reasons for an emphasis on flexibility."

Kennedy [1987] indicates that if maintenance is neglected, the advantages of an FMS will erode. Therefore, development of a suitable maintenance program is crucial to an FMS. In order to justify the investment on FMSs, they will have to be in operation twenty-four hours a day for about five or six days in a week. Any malfunction of equipment could seriously influence the performance of the system [Meredith, 1989]. In addition, a well designed production system is not complete until management has taken into consideration the reliability of the system [Hottenstein, 1968].

Maintenance actions which tend to improve system reliability is classified by Pan [1984] into four broad policy categories: 1) preventive maintenance (PM), 2) corrective maintenance, 3) spare provisioning and redundancy allocation, and 4) combined preventive and corrective maintenance policies. Published work has concentrated on the spare provisioning and redundancy allocation of tools in automated manufacturing system [Vinod and Sabbagh, 1986, Pan et al., 1986]. Hottenstein [1968] also suggest five actions for solving maintenance problems in the conventional manufacturing system. They are:

1) Providing redundancy in the system by using parallel component arrangement in any stage of the system.

2) Decoupling successive stages of the production system by interstage inventory storage.

3) Utilizing a policy of PM so as to repair or replace critical components before they fail.

4) Increasing the size of repair crews so as to reduce average system downtime.

5) Maintaining inventories of spare parts so as to reduce average system downtime.

Among these actions, Gilbert [1985] noted that the first action is too expensive while the second action is not desirable in the flexible manufacturing environment. Moreover, the importance of PM is significantly reduced in automated systems. Thus, the number of repair crews and the number of standby units are the two major decision variables in an FMS environment. The combination of these two maintenance actions is known as maintenance float policy which was well defined by Chanin [1978], Madu [1985] and Georgantzas [1987].

A maintenance float policy is typically used in both manufacturing and service sectors when it is important to keep operating equipment at a high level of availability. The float is made up of standby units immediately available to replace failed units. Failed units are sent to the repair shop for repair and are placed in the standby node after repair. This type of operation is shown in Figure 1-1. Kuei [1988] presents a comprehensive review of the maintenance float models. He also presents a complete summary of the many approaches that have been used to deal with this problem. These approaches are classified as: reliability, queueing, and simulation.

In this study, we apply maintenance float policy to an FMS for the following reasons: 1) maintenance float policies will help in reducing the severity of failures, 2) they are easy to implement, and 3) the policies will not interfere with the operational status of the FMS since this system's operation is never interrupted for repair or PM.

Further, we consider two types of FMSs: 1) an FMC, and 2) an FMS. The FMC contains a CNC machine with spare parts and is supported by a repair shop. However, there is a competition from the rest of the system for the limited number of repair persons. This type of operation is shown in Figure 1-2. The FMS consists of four machines that can be grouped into two machine types. Each machine has its own spare parts and is supported by a repair shop. This mode of operation is presented in Figure 1-3. The physical layout of this hypothetical FMS is shown in Figure 1-4. This FMS manufactures two types of parts, and uses automatic guided vehicles (AGVs) to transport WIP among loading stations, machines, waiting spaces and unloading stations.

In order to make efficient maintenance operation decisions, we must understand the underlying behavior of this type of complex system. This requires information. Information can be obtained by direct experimentation on a real system or by building analytical, and simulation models. The experimentation on a real system is expensive and impractical. Moreover, it is not always easy to model maintenance float systems analytically. In many cases, the analytical models only take into account the machining resources of the system. Moreover, several limiting assumptions such as ample services as well as exponential failure distribution are often used to generate the models (Levine, 1965; Hardy and Krajewski, 1975; Madu, 1985, 1987; Beck, 1987). For instance, by assuming exponential failure and repair time, the closed form solution may be obtained by closed queuing network approach [Gordon et al. 1967]. Madu et al. [1988] found that the ample service assumption has significant impact on the system performance (e.g. machine utilization). Madu et al. [1989] also indicated that the assumption of an exponential failure distribution implies a constant failure rate. Therefore, the cases for increasing or decreasing failure rates captured by more complex failure distributions such as the gamma are not adequately modeled. Furthermore, analytical modeling of advance manufacturing systems such as FMSs is extremely difficult. The analytical models may be adequate in the planning of an FMS if the system of interest has infinite local or system buffer (or waiting) space, exponential service time, and uses simple scheduling and routing schemes such as first come first served (FCFS). But this type of operation seldom takes place in the real world. In other words, the analytical models often ignore some important aspects of the FMS such as pallets and fixtures, loading and unloading stations, central (or system) or local (or machine) buffers, AGVs, geometric locations, transfer time, dispatch rules, tool failures, machine breakdowns and maintenance actions. Therefore, simulation seems to offer the best approach to model these complex systems. However, simulation results are often specific and may not be generalized. We therefore propose a strategic approach for simulation study to optimize maintenance float systems.

The strategic approach presented in Figure 1-5 incorporates problem definition and formulation, simulation model, regression metamodel form, Taguchi experimental design, regression analysis and mathematical programming. To find an optimal or satisfactory solution to a problem, one must first know what the problem is. Therefore, problem definition and formulation is the most crucial step in a simulation analysis. Because of the degree of realism that can be included in a simulation model, using simulation as a problem-solving technique has been widely employed by practitioners and researchers. Once we have a valid simulation model, an appropriate regression metamodel form should be chosen by the experimenters. A regression metamodel is a model which expresses the input-output relationship in the form of a regression equation. Based on this metamodel form, Taguchi experimental design is used to determine the values of the input variables for the simulation program. The simulation outputs are analyzed using Taguchi's ANOVA algorithm and data analysis procedure. Taguchi design is used here because it is easy to learn and implement. These qualities make our strategic approach more useful in terms of application. In addition, the apparent cost and time savings realized from the simulation design, will extend its use among practitioners and researchers. Input variables found significant are subsequently applied in an alternative regression metamodel. Predictor models for the machine utilization and/or throughput are developed and their validity tested. Using the metamodel approach, simulation results can be generalized and reused. Finally, cost decision models are developed to show the applicability of our models to decision situations.

The use of our strategic approach, reduces the amount of work needed in order to obtain a reliable and dependable model for maintenance float systems. It also benefits from the flexibility of simulation by not requiring some of the restricting assumptions made by analytical models. The integration of metamodels with the Taguchi design also enables us to conduct "what if" type of analysis. Such sensitivity analysis is necessary in studying the model's parameters. Additionally, it saves time and cost from rerunning simulation experiments. This approach will also offer decision support and improve the effectiveness of maintenance float decisions.

The objectives of this study are as follows: 1) to utilize the Taguchi design in the simulation experiment, 2) to analyze the main effects and interaction effects of controllable factors on the machine utilization in the FMC with maintenance float policy and on the throughput in the FMS with maintenance float policy, 3) to examine the relationships between machine utilization and/or throughput and the number of spares parts, the number of repair persons, mean time between failure (MTBF), and mean time to repair (MTTR), etc.,..., 4) to predict the performance of very complex manufacturing systems, and 5) to minimize the expected total system cost per unit time subject to certain system constraints.

Our approach is significantly different from existing approaches because:

1) a sequential approach is taken so that the experimenter can learn while the experiment proceeds. This learning process, is intended to reduce the time it takes to conduct the experiment.

2) Taguchi design is used so that necessary information for

decision making can be obtained in less time and with less effort.

3) simulation results are interpreted and generalized by metamodel techniques.

4) mathematical programming is applied in conjunction with the experimental analysis, in order to find satisfactory solutions to maintenance float systems.

As a result, a combination of simulation, experimental design, regression metamodel, and mathematical programming may assist operation managers in making timely and accurate decisions. It should be noted that, the system response is assumed to be linear over the range of the factor levels we investigated because there are only two levels for each factor in the initial experiment. The validated metamodel can only provide good estimates within the ranges of controllable factors studies by the experimenter. Moreover, the combination of standby units and repairpersons obtained are not necessarily optimum because the model is based on simulation. However, the model yields satisfactory solution to this problem.

The financial implications of this study to operations management in the FMS environment are obvious. Maintaining large units of standby units and large number of repairpersons will tie up capital at high opportunity costs. On the other hand, too few standby units and repairpersons will result in the high cost of downtime.

This paper is organized in the following manner. In the following chapter we present a review of maintenance issues in FMSs, maintenance float policy, simulation in manufacturing, regression metamodel, and experimental design and Taguchi method. A strategic approach for modeling maintenance float system is presented in chapter three. In chapter four, we discuss the flexible manufacturing cell's problem definition and formulation, simulation model, the Taguchi method, multiple regression analysis and decision models. Chapter five illustrates the application of this strategic approach on an FMS. Conclusions, major findings and management implications and directions for future research are made in the last chapter.

CHAPTER 2

LITERATURE REVIEW

2.1 Maintenance Issues in a Flexible Manufacturing System

Recently, installing advanced manufacturing technology (AMT) and in particular FMS is used by many organizations to increase the competitiveness in the local and global markets. However, as noted by Voss [1988], most organizations believe that they have successfully implemented AMT only when the operation is working reliably and there is little down-time, and/or the new AMT has a high utilization rate. Therefore, proper maintenance management is more critical than ever before.

Most recently, several papers have discussed the maintenance issues in FMSs. Hora [1987] indicates that in the past, downtime was accepted by many American companies because its impact on manufacturing cost was negligible. This was due to the economic climate that allowed management to tolerate inefficiency. However, the high interest rates and increasing global competitiveness have changed the economic climate. Now, there is a growing emphasis on improving manufacturing capability as a means of improving productivity and profitability. Proper maintenance management and planning are seen by many as desirable to attain these goals. Claire [1988] discusses the necessity of proper maintenance management to support a highly integrated manufacturing operation. Since the equipment (e.g. different types of machine) in this type of operation depends on each other, an equipment breakdowns are more critical than ever before. Gilbert [1985] indicates that increased automation and reduced WIP inventory in factory have become popular as a means of increasing productivity. However, automation will result in less frequency of preventive maintenance, while reduced WIP inventory will uncover maintenance problems that have previously been hidden. Meredith [1987] describes the maintenance problems experienced by three firms using FMSs. One firm (START) was in the process of implementing a system, the other (MID) had been using an FMS for a few years, and the third (END) was looking at rebuilding its system. The maintenance problems START and MID faced concerned the vendor's specifications for the equipment. He comments that "early in the implementation stage, one of START's robot carts was almost always broken down, another was almost always in operation, and the third exhibited almost exactly the failure rates specified by the vendor....In spite of MID's extensive predesign simulation of their stacker crane FMS, they experienced major problems with it because of a seemingly minor assumption concerning the vendor's specifications for the crane....The lesson here is that naive assumptions concerning the format of the problem can be disastrous in practice." To keep END's FMS in shape, it has devoted extra maintenance effort to the hardware because parts wear out. Ottinger [1987] reported that there are five levels of spare parts provisions for robot system. On the first level, one may elect to have no spare parts on hand. The second level is to have some of spare parts recommended by robot vendor. The third level is to have all of the spare parts recommended by the vendor. The fourth level is similar to the third level, but provides a better measure. The fifth level uses identical spare robot. Without spare parts, he indicates that expected downtime should be 24 hours to allow for air freight of needed parts from the vendor. Ottinger [1987] also notes that PM for more sophisticated robots can be as simple as checking hydraulic oil, cleaning controller tape heads, regreasing ball screws, changing oil filters and checking for mechanical or cable wear.

Since a large number of components are interconnected in a highly complex fashion, an FMS could be difficult to maintain. Consequently, maintenance personnel need assistance in dealing with the complex cognitive problems which may arise in troubleshooting the FMS. Rogers et al. [1986] describe a procedure for developing an expert system to solve these problems. Simulation is utilized to study the random behavior of the system for a given failure time distribution. Villa [1988] also reports an expert system for tool monitoring and maintenance in automated machining processes. This expert system can recognize a guaranteed-reliability maintenance intervention each time the tool cutter decay exceeds some prespecified level. Singhal et al. (1987) indicate that FMSs represent a special class of automated manufacturing systems. Furthermore, they note that FMSs have been widely studied because they embody many of the problems of automated manufacturing systems.

Kennedy [1987] discusses five issues that are of concern in maintaining FMSs:

(1) How much self-diagnostic equipment is justified for an FMS?

(2) How much PM should be performed?

(3) How should downtime costs be calculated?

(4) How much maintenance should be done in-house, and how much by outside contractors?

(5) What spare parts should be stocked, in what quantities?

Based on our discussions of the simple maintenance float systems in the previous sections, it is clear that we are interested in the fifth issue. Kennedy [1987] also points out that the solution to these issues is twofold. First, data must be collected to define the failure models of FMSs so that these models can be classified by the increasing or decreasing nature of their failure rates. Second, models must be developed to convert failure data from the shop floor into output useful to managers. The fifth issue can be resolved by the development and application of models aimed at minimizing the total carrying and downtime costs associated with a given FMS.

By using closed queueing network theory, Vinod and John [1986] investigate a failure prone FMS with a two-stage repair facility. A cost model which searches for optimal repair capacities subject to preset availability requirements of the resources is presented.

Most recently, practitioners as well as researchers are realizing the importance of tools failure, and maintenance problems in the FMS. For instance, Vinod and Sabbagh [1986] indicate that a critical aspect which affects the performance of a manufacturing system is the availability of tools at the right time to process work pieces. As a result, the optimal allocation of spare tool is an important design issue. By assuming exponential failure time, Vinod and Sabbagh [1986] study the trade offs involved between stocking spares of multiple tool types and the cost of operating the repair facility. Kusiak [1986] also considers tool spare management problems. He discussed advantages and disadvantages of four basic tool storage policies, whereby standby tools are stored either in a tool magazine or in a remote tool storage system or both. The problem of machine breakdowns due to tool breakage is also considered by Gaalman et al. [1987]. They conduct a simulation study to investigate the possibility of reducing the investment in tools by sharing the tools among the machines via an automated tool transporting vehicle. The major tooling issues have been classified by Gray et al. [1989] into three levels: tool, single machine, and system - based on the scope of the decision involved. In addition to a comprehensive review on current research at each level, Gray et al. [1989] also provide a list of tool decision problems at each level. The effective capacities of facilities is often hampered by tool breakdown or wear and tear. Therefore, Gray et al. [1989] indicated that maintaining the availability of the required tools of each type is very important in improving the system's (e.g. FMCs, flow lines and FMSs) performance.

From this discussion, we notice that mathematical formulations as well as solution procedures for maintenance float problems in an FMS are seldom addressed in the literature [Mainmon, 1988]. As a result, much work remains in this area.

2.2 Maintenance Float Policy

A maintenance float system is a system with a fixed number of machines in operation. These machines use a type of part (e.g. tool) which is subject to failure. The operating machines are supported by a repair shop and a number of backup parts (e.g. spare tools). The need to maintain standby parts and repairpersons is to minimize system downtime. When a part in operation breaks down, it is replaced by a unit in standby status if one exists. The failed unit goes into the repair shop for repair, and returns back after repair to standby status. At each given time, a fixed number of operational units should be maintained. Units are assumed to be completely rejuvenated after each repair. This mode of operation is presented in Figure 1-1.

One of the earliest attempts in determining the number of standby units a system needs is presented by Levine [1965]. By assuming exponential failure time, he presents the analytical results of maintenance float factors. A maintenance float factor is the fraction of an operating center's population that has failed in the long run (i.e. the system's operation is at steady state). Using this float factor, the optimum number of standby units can be calculated. His model was extended to the cases of Weibull [Lowe and Lewis 1983], gamma [Madu, 1985], and triangular [Georgantzas, 1987] failure distributions for equipment failure times.

Early queueing models are presented by Koenigsberg [1958,1960]. He considers a two stage cyclic queue and studied the effects of standby units on the efficiency of the system such as the mean number of units at stage i, the mean length of the waiting line at stage i, the utilization of the stage i, and so on. Madu [1988a, 1988b] uses Buzen algorithm [1973] and develops maintenance float models for a one repair center case and subsequently for the two repair centers case with load independent servers. Using cost analysis and a finite source queueing model, Hilliard [1976] solved the maintenance float problem for both an identical component independent system and an identical component serial system. Gross et al. [1983] used a closed queueing network approach and optimization algorithm to find the optimum combination of the number of standby units and the number of repair persons in a base repair center and a depot repair center. They applied Gordon and Newell's [1967] approach (who showed that the number of units at each node of a closed queueing network is a product form) and the Lawler-Bell optimization algorithm to find the optimum combination of standby units and repair persons in the base and depot repair centers. In all these papers, the researchers assume that exponential distribution apply at each of the nodes of the network. These models become difficult to use when the failures and repairs are differentiated.

Sahu et al. [1970] simulated the engines of a fleet of aircraft using actual data of failure rate and service rate. They modeled service stations in series. The objective of their study was to find the optimum number of spare units so as to balance the cost of maintaining spare inventory with the cost of down time. Using a simulation approach, Hardy and Krajewski [1975] considered multiple maintenance policies such as PM, and maintenance float in a truck depot. The aim of their study was to find a satisfactory maintenance policy. Due to a request by the maintenance department for the operation research group in the Portuguese National Airline, Johnson and Fernandes [1978] reported the relationship between the number of spare engines with regular scheduled maintenance and the number of days predicted by the simulation model when there are no engines in the store. Rueda et al. [1985] also reported their simulation of a transit bus system which found the optimum fleet size, and the quantity of spares units provided for each bus component. Banerjee and Flynn [1987] report a simulation study of maintenance policies for a group technology shop. Madu et al. [1989] discuss the effects of the coefficient of variation (CV) on maintenance float policy. Using simulation experimental results and statistical tests, they conclude that the average equipment and server utilization are more sensitive to CV changes when an increasing failure rate is realized, and less sensitive under a decreasing failure rate. Moreover, the average waiting time to repair was observed to be very sensitive to CV changes when a decreasing failure rate is realized. Madu et al. [1988] also compared the float levels obtained from analytical models to experimental simulation. They report that if there are waiting lines in the repair shop, the float levels will significantly differ under the exponential failure case. This result is, however, expected.

In the analytical model, ample service is assumed, while in the simulation study, a finite number of repair persons is assumed. The more repair persons we have, the less waiting time we shall expect when units fail. In the former case, we have enough repair persons to handle any failed units, while the failed units most of the time must wait in the latter case. They also defined a system reliability ratio, r, which is equal to MTTR/MTBF. Furthermore, they used different r, namely, .25, .5, .75 and 1, and obtained the utilization of operating units (p), and the total average waiting time of units undergoing repair (W). Their conclusion is that: when r is small, p is high and W is small. Recently, Madu and Chanin [1989] used fractional factorial designs to generate metamodels from the simulation results for the measures of performance such as the equipment utilization of the maintenance float system. Georgantzas and Chanin [1989] examine the effects of the maintenance department capability and redundancy options on the availability of the operations facility. Their simulation model was conducted by assuming the failure and repair times follow an Erlang-2 distribution. The study's main purpose is to investigate what is appropriate in the establishment of a maintenance float policy for operations systems from which a high level of operations availability is demanded. Kuei et al. [1990] also illustrate the application of a combination of simulation model, Taguchi experimental design, and metamodels on a maintenance float problem.

In this study, our focus on more complex manufacturing systems and the application of the Taguchi designs, differentiates our study from those of others.

2.3 Simulation in Manufacturing

Suri [1985] notes that the main models used to evaluate FMS performance can be divided into five classes: static allocation models, queueing network models, simulation models, perturbation analysis, and Petri nets. Presently, simulation is perhaps the most widely used computer-based performance evaluation tool for FMSs [Suri, 1985].

When using a simulation approach, it is not necessary to build, disrupt the operation of, or destroy a real system. Furthermore, as Ignall et al. [1978] remark, "the standard use of simulation is direct: to answer a specific question or to obtain a description of the behavior of a system as some of its parameters are changed." Therefore, simulation is frequently used to analyze manufacturing systems. Haider et al. [1986] report that 59% of simulation applications are in the area of manufacturing systems. Moreover, as noted by Law et al. [1989], "this has been caused by the greater complexity of automated systems, reduced computing costs brought about by microcomputers and engineering workstations, improvements in simulation software which have reduced model development time, and the availability of graphical animation which has resulted in greater understanding and use of simulation by engineering managers." They also report that there are presently, more than twenty-five simulation packages with strong orientation toward manufacturing problems. Most of these packages were introduced within the last five years.

There also has been a dramatic increase in the use of simulation for the design/planning and the scheduling and control of FMSs during the past few years. The design/planning of an FMS includes the design of work stations, MHS, waiting space, system configuration, and the allocation of the production task among the work stations [Yao, 1983]. The scheduling and control problems include decisions on the production rate of each product type, the loading of the machines and the time and sequence to release the jobs into the system [Yao, 1983]. The design, planning, scheduling and control of FMSs has received substantial attention in recent years due to high initial investment cost of such systems as well as the unprecedented mixture of success and horror stories of FMS implementations [Kiran et al., 1989]. Stecke [1986] also defines and describes FMS's design, planning, scheduling, and control problems in details. She also indicates that a policy to handle machine tool and other breakdowns should be determined during the design phase. It is then implemented during the control phase of an FMS.

The increased need for the use of simulation has been recognized by case studies reported in the literature. Redmond [1983], presents a simulation study to assess FMS configuration issues and to comprehensively understand the dynamics of an FMS system. The simulation model was able to establish system throughput and utilization of the machines, material handling devices and load/unload stations. Akella et al [1984] used a detailed simulation of an automated printed circuit card assembly line at the IBM Corporation plant at Tucson, Arizona, to study the effects of ways to dispatch parts into system. Carrie [1986] evaluated a Scottish engineering company that invested 7 million British pounds on FMS for the manufacturing of complex castings. This study evaluated the sensitivity of the FMS operating performance to variations in part mix, operation times, and machining methods. Godziela [1986] reports on how to improve an FMC design in Garrett Turbine Engine Company by using SLAM simulation model. Mills [1986] also used simulation in the design of a cellular manufacturing facility for the McDonnell Douglas Helicopter Company. Wang [1986] developed a PCModel to design an automated guided vehicle (AGV) system in one of Intel's assembly plants in Arizona. The simulation is used to identify the optimal quantity of material which should be loaded on the AGV. Chisman [1987], developed a simulation model to study, identify, and correct production problems in an FMS. Gaalman et al. [1987] conduct a simulation study for the Dutch truck manufacturer DFA to investigate the possibility of tool sharing in an FMS. In their study, tool breakages were assumed to follow a Poisson process. The system performance is measured by the fraction of time that machines must wait for a tool. The inputs are the process plan, tool lives, tool transport and handling time, and the tool mix. Bookbinder and Kotwa [1987] estimated the minimum number of AGVs required to meet the minimum targeted output for the General Motors of Canada's Oshawa, Ontario automobile body-framing assembly plant. Knoner [1987] report a simulation study in the Siemens factory at Augsburg, FRG. The simulation model was developed as a tool for system design and optimization. The model predicts throughput and flow times for the various printed board assemblies types, station utilization, buffer contents and the behavior of the transportation systems. Brown [1989] also reported a simulation case study conducted in IBM. IBM planned to have an advanced manufacturing system to produce printed circuit boards (PCBs), which are used in almost all the IBM's products from mainframes to PCs. This advanced manufacturing system has to be flexible enough to produce the various types of PCBs needed, and adapt to product changeovers quickly. The design and analysis team of IBM used SLAM II to conduct a simulation study. This study, provided solutions to the following questions: number and types of equipment required, number and types of material handling and storage devices needed, desired equipment layout, buffer requirements, desired part volumes and mixes, alternative material routings, and operating policy alternatives and their implications. Tatikonda and Crosheck

[1989] used Lotus 1-2-3, MANUPLAN II, SIMAN and CINEMA to evaluate the performance of a recently installed FMS in Ohmeda manufacturing plant of the B.O.C. Group, Inc. Fry et al. [1989] conduct a simulation study to investigate the procedures used to allocate tooling between the various resources and the procedures used to schedule the processing of parts. This model evaluates the operational procedures before and after FMS installation in FMC Corporation. Chisman [1989] uses simulation modeling to evaluate the proposal, design and implementation of a new flexible printed circuit board (PCB) line of the Apple Computer plant in Cork, Ireland. Kiran et al. [1989] also reported their use of simulation for evaluating alternatives in the design and planning phases of a proposed FMS in General Dynamics-Pomona Division.

Case studies of simulation applications in FMSs are presented in Table 2-1.

2.4 Regression Metamodel

The simulation results are often situation specific. It is not easy to relate simulation input to output in many cases. Hunter and Naylor [1970], Kleijnen [1987], Kelton [1988] and Friedman [1984, 1988, 1989] pointed out the need for metamodels to aid in the interpretation and generalization of simulation results.

Gardenier [1990] defined a metamodel as "models of simulation models - which express the input-output relationship in the form of a regression equation". The advantages of using metamodel were discussed by Friedman [1989]. Among these are, "model simplification; enhanced exploration, optimization and interpretation of the model; the unravelling of a model's dynamics in order to gain a better understanding of the system's behavior; generalization to models of other systems of the same type; the ability to test many hypotheses regarding the system without performing additional runs; ease in answering inverse questions, e.g. given a particular value for a response variable, what input factor level is needed?".

The use of a metamodel in post-simulation analysis has been steadily increasing (see Table 2-2). Blanning [1975] applied a single factor regression analysis on an inventory problem of a warehouse. Weeks and Fryer [1977] derived a functional relationships between five system performance measures such as mean job flow time, mean job lateness, mean job earliness, mean job due-date and mean labor transfer and three decision variables such as the labor assignment, the dispatching rule and the due-date assignment. Kleijnen [1979] established a 2^{6-2} fractional factorial experimental design and used multiple regression to examine the relationships between handling capacity and queue length, and between storage capacity and yearly throughput for the Europe Container Terminus company. Stecke [1982] also illustrates how to use simulation to create a regression model for deciding the number of machines to assign to an operator in the machine interference problem. Friedman [1984] used the metamodel technique to analyze the simulation results for M/M/1 queuing systems. Wang [1986] also used multiple regression analysis to construct a functional relationship between system performance (i.e. throughput) and three controllable factors such as the mean demand rate, the number of carts and the different FMS configurations. Alholou et al. [1986] also developed metamodels for the performance of multiprocessor interconnection networks. Diesch [1987] also reported a study to determine a relationship between machine center breakdowns, lathe cell breakdowns, material handling system breakdowns and system effectivity in an automated flexible manufacturing system. Marks [1987] used a single factor regression analysis to examine the relationships between the throughput of an automated serial robot system and certain constituent variables. Hira and Pandey [1987] also used single factor regression analysis on a manual flow line simulation model. By using the least squares method, Chow [1987] constructed a metamodel for the throughput and the coefficient of variation of process times in a sequential production lines system. The multiple regression analysis technique was applied by Cheng [1987] to a simulation study of MRP capacity planning. Most recently, Kleijnen et al. [1988] established a 2^{4-1} fractional factorial design and applied multiple regression analysis on an FMS. A two-stage modeling approach proceeds empirically by first building a simulation model of the flexible assembly system and then performing regression analysis on the data. Similar experimental design is followed by Winters [1988]. Madu et al. [1989] used 2^{5-1} and 3^{5-1} fractional factorial design, regression analysis and mathematical programming to analyze maintenance float systems. Kuei et al. [1990] applied Taguchi's experimental design, ANOVA, regression analysis and mathematical programming to the maintenance float problem. Friedmen [1988, 1989] used this technique to analyze an M/M/S queuing system, a time-shared CPU system, and an inventory control system. Porta Nova and Wilson [1989] also constructed a metamodel for a queuing network system. Lin [1989] also applied this technique to analyze an automated flow line. Shang and Tadikamalla [1989] applied a least squares regression method to an automated printed circuit board assembly line and concluded that system output can be explained and predicted by system variables. Shaikh and Althouse [1989] also used multiple linear regression analysis for comparing communication network routing algorithms. The use of regression metamodel in manufacturing has been extensively discussed by Madu [1990]. Depending upon the number of parameters to be estimated, and the structure of the metamodel consisting of linear and/or interaction terms, Gardenier [1990] introduced PRE-PRIM, an integrated set of statistical tools and computerized algorithms, to calculate the required number of simulation runs. Her paper concentrated on the uses of statistical experimental design procedures in reducing the data collection demands, and in improving the reliability of results obtained in computer simulation. Sridharan and Berry [1990] investigated the impact of adjustments in the design parameters of master production schedule (MPS) freezing methods on two performance measures: MPS lot-size cost and stability. The structure relationships between performance measures and several of the MPS design parameters are also reported.

A summary of major applications of metamodel is shown in Table 2-2.

2.5 Experimental Design and Taguchi Method

In the initial stage of many experiments, a large number of factors may have to be tested simultaneously. In such experiments, a large number of runs will be required in order to consider all the possible combinations of the different levels specified for the controllable factors (i.e a complete factorial design). For example, when an experiment consists of only 10 factors, each at two levels, the number of factor combinations is 2^{10}. Thus, a total of 1024 design points will be required for the experiment. Furthermore, if the designs were replicated ten times in order to achieve the desired level of precision in the estimate, then we would have to make 10,240 separate simulation runs. Box et al. [1978] indicated that these designs (i.e. factorial designs at two levels) are of importance for a number of reasons: 1) they can indicate major trends and so determine a promising direction for further experimentation, 2) they form the basis for two-level fractional factorial designs, 3) these designs and the corresponding fractional designs may be used as building blocks so that the degree of complexity of the finally constructed design can match the sophistification of the problem, and 4) the interpretation of the result is easy. Dey [1985] also pointed out that complete factorial experiments are too expensive and impracticable in most situations. It is therefore not necessary to carry out such large experiments especially when the interest is to estimate only lower order effects. Under this situation, higher order effects are assumed insignificant. The economy of space and material in such situations could be achieved by considering only a fraction of a complete factorial design (i.e. a fractional design). However, in using a fractional design, we loss some information that may otherwise, be available if a complete factorial design is used. As noted by Kelton [1986], in carrying out a fractional rather than a full design, we give up the ability to estimate higher-order interactions and receive in return a more modest requirement in terms of the number of runs. Therefore, how to select an appropriate fractional design by which useful information can be obtained with a reasonable degree of precision from less than a full experiment of a factorial design is an important issue.

Davies [1956], Anderson [1974], Daniel [1976], Box et al. [1978], Hicks [1980], Raktoe et al. [1981], Montgomery [1984], Dey [1985] and Petersen [1985] have discussed factorial and fractional factorial designs extensively. These experimental designs have found widespread application in agriculture and quality control studies [Margolin et al., 1976, Phadke, 1989a, Ryan, 1989].

Hunter et al. [1970], Kleijnen [1975, 1987], Shannon [1975], Fishman [1978], Law et al. [1982], Kelton [1986, 1988], Francis [1987] and Hoover and Perry [1989] also discuss complete and fractional factorial designs that are specifically applicable to simulation experiments. A summary of major applications of complete and fractional factorial designs is presented in Table 2-2.

Apart from these standard techniques, Genichi Taguchi has proposed comprehensive experimental design procedures to deal with quality control problems. These procedures were initially applied in Japan's manufacturing system. The main purpose of Taguchi design is to identify the setting of product and process parameters that will reduce performance variation. Many Japanese companies have experienced success with Taguchi's strategy for off-line quality control [Kacker, 1986]. Because Taguchi's method is easy to use, his approach has gained wide applicability in Japan. However, it was not until the mid-1980s that the United States became aware of Taguchi's approach [Ross, 1988].

Pignatiello [1988] distinguished two different aspects of the Taguchi method: the Taguchi strategy and the Taguchi tactics. The former is the conceptual framework for planning a product or process design experiment while the latter is a collection of specific methods and techniques such as the Taguchi design and signal-to-noise ratios suggested by Taguchi and Wu [1980]. The present study emphasizes the use of Taguchi design to model a maintenance float system.

Lin [1989] noted that there are two major characteristics of the Taguchi type design: 1) the experimental design, and 2) the process to find the optimum level of each controllable factor. In the Taguchi experimental design, main effects and almost all the possible combinations of the two-factor interactions of controllable factors are considered in the design of an experiment. In the process to find the optimum level of each controllable factor, the effects of each controllable factor and their two-factor interactions can be tested by the use of ANOVA as suggested by Taguchi and Wu [1980]. Thus the optimum combination levels and their contributions can be found. The Taguchi experimental design approach is very efficient due to the following reasons: 1) the statistical techniques are very simple, 2) the number of experiments can be reduced, 3) the significant controllable factors can easily be identified, 4) it is easy to conduct an experiment through the use of linear graphs (see Figure 2-1, 2-2, 2-3, and 2-4), and 5) it is easy to find the optimum design of a system for decision makers.

Because of these advantages, Taguchi's experimental designs have found widespread applications in both Japan and Taiwan. For instance, Taguchi and Wu [1980] reported that in 1976, 2700 experiments conducted in Japan used orthogonal tables. In 1966, Professor Yu-In Wu, one of the authors of the english version of Taguchi's method [1980], introduced Taguchi methodology to Taiwan. Since then, this method has gained wide acceptance in several industries. For example, mechanical, electrical, chemical, petroleum, sugar, latex, assembly and manufacturing industries in Taiwan continue to use Taguchi's method [Wu, 1976]. Recent, applications of Taguchi's Methods in the United States and in the United Kingdom are documented in Bendell [1988] and Dehnad [1989].

Sullivan [1987] reports that Professor Yu-In Wu introduced the Taguchi method to Ford Inc., U.S.A. in April 1983. Other U.S. firms such as General Motors, Chrysler, General Electric, Goodyear, Xerox, AT&T, Texas Instruments, and the International Technology Institute (ITI) have been very successful in applying this method in shortening the product development cycle, improving quality, and reducing costs.

Barker [1986] applied L_{27} orthogonal array in order to find a system to prevent breakage of a small plastic part used in the carburetor of a lawn mower engine. Byrne and Taguchi [1987] also used this approach to find a method to economically assemble an elastomeric connector to a nylon tube that would deliver the requisite pull-off performance to be fit for use in automotive engine components. Schmidt et al.

[1989] also reported that Shipley company's R&D scientists and operations engineers applied Taguchi experimental design successfully for new product development. Shipley company supplies photoresist to the microelectronics industry for use in making computer chips. After realizing that a new generation of photoresist was needed, a design team was formed at Shipley company. This team was to respond to change as fast as possible. Therefore, Taguchi L_8 orthogonal array was used. Finally, it took seven months to conceptualize and introduce the new product - Megaposit S9400 Photoresist into the marketplace. Prior to the use of Taguchi's design, this project normally took four years. Phadke [1989a] used L_{18} design for the quality control problem in the integrated circuit fabrication process. Furthermore, he applied L_{36} design to the circuit design problem at AT&T. Phadke [1989b] also reported that a computer simulation model was used for the optimization problem of a differential operational amplifier circuit, which is commonly used in telecommunications. The optimization objective was to minimize the offset voltage. The L_{36} array was also used to simultaneously study the five control factors that the design team identified. Katz and Phadke [1989] applied L_{18}, L_{27}, and L_{36} designs on the manufacturing process of microchips in AT&T. They comment on the use of Taguchi design as follows: "the results reported by the Taguchi design program are significantly better than what was happening before. It is not necessary to be the best - it is more important to be near the best."

In the United Kingdom, the application of Taguchi's methodology to optimize the performance of load control software for system X was reported by Dentskevich and Appleton [1988]. In their experiment, L_{16} and L_{18} orthogonal arrays are used. Bandurek and Wilson [1988] also applied L_{16} to improve the production yield of a magnetic card reader. Wilson et al. [1988] used L_8 design to achieve the minimum variability about an optimum hardness of cart seat cushions. In order to show the management that the present production level of transducer, a high quality telephone receiver/transmitter, was already optimum, Madsen [1988] applied L_{27} design. A summary of major applications of Taguchi design can be found in Table 2-3.

Most recently, Gunter [1989] comments on the use of experiment designs as follows: "there is controversy among adherents of various approaches to the application of design of experiments. especially between the advocates of the Taguchi methods vs. those of standard methods. Controversy in science is normal and usually healthy. Unfortunately, much of the present debate seems to have degenerated to the level of argument about which soap powder sells better. This is an argument in which I definitely do not want to get involved. ... I would like to focus on the need to do something, rather than stand around and do nothing while waiting for the smoke to clear." Hunter [1985] also comments on the usefulness of various experimental designs: "The key to understanding the usefulness of one experimental design over another rests in the linkages between the designs and the models (e.g. the first or second order models) chosen to describe the response under study."

A summary of major contributors in the areas of maintenance issues in FMSs, maintenance float policy, simulation in munufacturing, regression metomodel, experimental design, and Taguchi method is presented in Figure 2-3. Since it is not easy to develop analytical models for an FMC and an FMS with maintenance float policy, we therefore proposed a novel strategic approach for simulation studies to optimize these complex systems. The need for this study emerged from the review of the developments and limitations in the above areas.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Generalization of Simulation Results

Simulation results are often specific and may not be generalized. Kleijnen [1974, 1975, 1981, 1987] presents a regression metamodel to yield a close approximation to the simulation results. A detailed description of Kleijnen's method will be discussed here. Assuming a valid simulation model is available, Kleijnen [1981, 1987] proposed a procedure for regression metamodeling. We summarize his procedure from the flow chart he presented.

1) Select a regression model form.
2) Design the experiment using appropriate factorial or fractional factorial matrix.
3) Make simulation runs based on the experimental design matrix.
4) Estimate regression coefficient β.
5) Validate the regression model. If rejected, go to step 1; Else, include validation runs.
6) Reestimate coefficient β.
7) Test significant of coefficient βs. If there is any nonsignificant coefficient β, set this β=0 and go to step 6; Else, make a conclusion.

This approach, starts by postulating a regression model like equation 3-2 or 3-3. Based on the regression model, the minimum number of simulation runs and the factors levels for each run can be chosen. Three approaches to the design of experiments have been extensively discussed by Kleijnen [1987]: one factor at a time, full factorial design and 2^{k-p} fractional factorial design. If there are too many factors under study, Kleijnen [1987, p.323] suggested using group-screening designs. In group screening design, individual factors can be aggregated into groups of factors. If a group turns out not to be significant, then we may conclude that all its members are not important.

After selecting an appropriate experimental design matrix, simulation runs for each design point with appropriate replications are conducted. Regression coefficients (βs) are estimated. At this moment, it is important to statistically test whether the first step's assumption is realistic. One statistical test suggested by Kleijnen [1979, 1987] is as follows. Generate some new observations y from the simulation model. Use a t-statistic to compare these observation y to the predicted value y' based on the regression metamodel estimated from the old observations. If the assumption is not reasonable, he suggested three alternatives such as add higher order interactions (e.g. three-factor interactions) in the regression model, look for transformation, or reduce the experimental area (i.e. reduce the range of factors). Among these alternatives, adding higher order interactions are difficult to interpret intuitively and, it increases the number of simulation runs. If analytical results for a specific problem (e.g. M/M/S) are available, these results may suggest a direction of transformation to a better metamodel. For instance, in a M/M/S case, we may use a logarithmic transformation [Friedman, 1988]:

$$\ln W = \ln\alpha + \beta_1 \ln\lambda_i - \beta_2 \ln\mu_i - \beta_3 \ln(S_i) + \ln e_i$$

where ln W with respect to the inputs is given by the hypothesized multiplicative model:

$$W = \frac{\alpha(\lambda_i)^{\beta 1} e_i}{(\mu_i)^{\beta 2}(S_i)^{\beta 3}}$$

Friedman (1988) indicates that W is dependent on λ/μ*S. W is the expected residence time in the system; λ is the mean arrival rate following the Poisson process; μ is the mean service rate following the exponential distribution; S is the number of identical service channels. In the absence of theoretical indications of the form of the relationships, scatter diagrams and/or residuals plot may be employed to indicate appropriate models. Based on the scatter diagrams several models employing x_i^2, logarithmic and reciprocal transformations can be tested. For instance, if a term involving x_1^2 is needed, then the plot of residuals against x_1 would show systematic curvature as opposed to the random scatter that is typical of good model specification [Chatterjee and Price, 1977, p.61, Atkinson, 1985, p.9]. Other linearizable functions with corresponding transformations when curvature is observed in the scatter diagram of y against x can be found in Chatterjee [1977, p.29]. If all else fails, Kleijnen [1987] suggests reducing the experimental domain. The aim of these alternatives ways should always be to make the approximating metamodel as simple as possible.

If the assumption in step 1 is reasonable, then the estimates of the model coefficients β are made more accurate by adding the new observations and reestimating the new coefficient β. The final step is to test the significance of the coefficients β (i.e. significantly different from zero). If there is any nonsignificant coefficient (β), set this β=0 and reestimate all the coefficients. Once this has been done, conclusions can be drawn.

Our approach is an extension of Kleijnen's work. However, the use of the Taguchi design and cost model, differentiates our approach from his.

3.2 The Use of Taguchi Design

Based on our previous discussions and Table 2-2, three experimental designs are considered in this study: a complete factorial design, fractional factorial design and Taguchi design.
Five criteria frequently used in the literature [Kleijnen, 1975, Kleijnen et al., 1979] are applied here to compare these three experimental designs. These comparison are presented in Table 3-1.

1) Small number of runs.

The total number of design points in the complete factorial is the product of the number of levels for each factor. For instance, 2^5 design (with this design, there are five factors, and each factor at two levels) requires 2*2*2*2*2=32 design points. If we assume that the higher-order interactions (e.g. two-factor interactions, three-factor interactions,...and so on) with which the main effects are confounded are zero or quite small, fractional factorial design can be used. For instance, if it is assumed that three-factor, four-factor, and five-factor interactions are insignificant, only 2^{5-1} design points need to be considered. A discussion of the methods for constructing this type of fractional factorial design is given in Box, et al., [1978].

Taguchi and Wu [1980] suggest the use of a L_{16} orthogonal experimental design (or array) to accommodate factors with two levels. In the orthogonal array, every pair of columns in the array, all combinations of levels occur equal number of times. Because of this balanced arrangement, one factor does not influence the estimate of the effect of another factor and vice versa [Ross, 1988]. The L_{16} array specifies that sixteen experimental runs be conducted and used in order to find the best combinations of the 2^5 design. As noted by Byrne et al. [1987], this can be done since the design is orthogonal, a property that permits the effect of each factor to be separated out. If all the higher-order interactions such as two-factor interactions can be neglected, the number of runs needed can be reduced dramatically. A comparison of the number of runs required by both the Taguchi orthogonal array and a complete factorial design is shown in Table 3-2. Table 3-3 presents a comparison of the number of runs required by both the simplest version of Taguchi orthogonal array and a fractional factorial design with different resolutions. The term "resolution" is used in the experimental design literature to express what can be estimated from a particular fractional factorial design. Box et al. [1978] give a detailed discussion of this concept. From Table 3-2 and 3-3, it is observed that greater savings on the number of simulation runs are possible with the use of larger orthogonal arrays or fractional factorial designs. A major part of Taguchi's idea is that some interactions can often be safely neglected based on prior knowledge of a particular problem and quick industrial experiment responses. Moreover, one of his explicit assumptions is that higher order interactions such as three-factor interactions, four-factor interactions,..., and so on have no significant effect on experiments in manufacturing industries. Therefore, both fractional factorial design and Taguchi design need smaller number of runs compared to that of a complete factorial design.

2) Ease of Implementation.

A unique feature of Taguchi design is the use of linear graphs. Discussions on the use of these linear graphs and their relationships to orthogonal array tables are presented in Taguchi and Wu [1980]. Most recently, Lewandowski and Lindeke [1989] present a program for the preparation of orthogonal arrays for use in Taguchi design experiments. This program generates experimental design matrices for two-level factor designs such as L_8, L_{16} and L_{32}, three-level factor designs such as L_9 and L_{27}, mixed factor level designs such as L_{18}, L_{36} and L_{54}, and multiple levels designs. The major input requirements are: 1) the general design structure, 2) the total number of factors and their names, and 3) the total number of interactions and their names. With these inputs, a suitable design is generated by the program.

Fractional factorial designs are not difficult to generate once the experimenter knows the design generators. However, graphical techniques such as Taguchi's linear graph can easily be understood and implemented by practitioners as well as researchers having only a limited knowledge of statistics and experimental design. The implementation of a complete factorial design is also very easy because the total number of design points in need is simply the product of the number of levels for each factor.

3) Flexibility of the design.

Taguchi and Wu [1980] show how to extend two or three-level designs to four, eight, and nine levels designs. For instance, in order to create a four-level design from a two-level system, three columns have to be sacrificed. These three columns consist of any desired two columns and the column that corresponds to their interaction. Consequently, four different levels can be assigned to the four combinations 11, 12, 21, and 22 formed from levels 1 and 2 of any two of the three columns. This technique is referred to as the "multiple levels design". Following similar logic, eight-level design can also be conducted. If only seven levels are required, the experimenter can repeat one of the levels. Therefore, the eighth level of a particular factor is a duplicate of one of the actual seven levels. Usually, this will be the factor that the experimenter considers the most important. This approach, is referred to as the "dummy level technique". Moreover, mixed factor level designs such as L_{18}, L_{36} and L_{54} and linear graphs are also available in Taguchi [1977]. When all the two-factor interactions can be assumed very small, L_{18} can be used when one two-level factor and seven three-level factors are considered in the experiment; L_{36} can be applied when eleven two-level factors and twelve three-factors are considered in the experiment; L_{54} can be used when one two-level factor and twenty five three-factors are realized. In Box et al. [1978] or other experimental design textbooks, the most common designs are 2^k, 2^{k-p}, 3^k, and 3^{k-p}.

Generally, Taguchi design is more flexible when compared to standard experimental designs. A complete factorial design is also very flexible. Experimenters can apply any level they want for each factor. But the consequence is that a large number of experimental runs, will be required.

4) Desired confounding pattern.

Applying Taguchi's design methods could be quite risky if experimenters do not realize the confounding pattern of higher order interactions in their design. For example, the L_{16} orthogonal array we used in chapter four is the same as 2_V^{5-1}

fractional factorial design discussed by Box et al. [1978]. This is also obvious from the way we arrange factors and two-factor interactions on the orthogonal array's columns. 2_V^{5-1} fractional factorial design is a resolution V experiment. The resolution power indicates the clarity of which individual factors and interactions may be seen (or evaluated) in an experiment [Ross, 1988]. Suppose we have five factors: A, B, C, D, and E which are assigned to columns one, two, four, eight, and fifteen, respectively (see Table 4-1). Two-factor interactions can be assigned to the remaining columns based on the suitable linear graph (see Figure 2-1). This is the most complex version of L_{16} design. one of the design generators for this particular case is -ABCDE. Once the design generator is given, the alias structure can easily be obtained by taking the generalized interactions of the relevant effect with each of the components of the design generator. For instance, if the design generator is I=-ABCDE and then the alias structure of A is -BCDE, which is a generalized interaction of A and -BCDE, the alias relationships are as follows:

A = -BCDE; B = -ACDE; C = -ABDE; D = -ABCE; E = -ABCD;

AB = -CDE; AC = -BDE; AD = -BCE; AE = -BCD; BC = -ADE;

BD = -ACE; BE = -ACD; CD = -ABE; CE = -ABD; DE = -ABC;

In view of the aliasing of effects among themselves in a Taguchi fractional factorial set up, assumptions regarding the absence of certain effects have to be made for getting unbiased estimates of other effects. For example, in the example quoted above, A can be estimated under the assumption that the four-factor interaction -BCDE is absent and so on. Also, AB can be estimated under the assumption that the three-factor interaction -CDE is zero or very small and so on. If the simplest version of L_{16} design is used (i.e. fifteen two-level factors experiment), all the higher order interactions are then assumed to be zero or very small.

Two-level and three-level fractional factorial designs were discussed by Box et al. [1978], and Montgomery [1984], respectively. Box et al. [1978] also provide a comprehensive list of design generators for two-level fractional factorial design with three to eleven factors.

Thus, desired confounding patterns can be realized in both Taguchi design and standard fractional factorial experimental designs. Obviously, knowledge of the underlying confounding pattern plays a crucial role in applying the Taguchi design as well as the standard fractional factorial experimental design.

5) Ease of analysis

Both Taguchi design as well as standard fractional factorial design are easy to analyze. Taguchi algorithm for constructing the associated ANOVA table can be applied to two-level, three-level, and multiple-level designs. Using a personal computer (PC), it just takes few seconds to identify the significant factors and/or two-factor interactions, and construct the associated ANOVA table. In the simulation experiment, an experimenter may obtain an experimental response without replication at each design point. In this situation, the Taguchi algorithm for constructing the ANOVA table is also applied and it is very easy to use (see Section 3.3). The 2^k and 2^{k-p} designs are also easy to analyze [Box et al. 1978, Hunter, 1985]. Yates algorithm can be employed to estimate the factorial effects.

Based on the above analysis, this author believes that Taguchi design is more appropriate for use in our study of maintenance float systems. However, Taguchi experiments arise from quality control problems and are not unique to simulation (see Table 2-4). Therefore, a suitable guideline is needed to apply Taguchi design in simulation study. This essential issue is discussed in section 3.3.

3.3 The Strategic Approach

The strategic framework presented in Figure 1-5 provides an organized and scientific way to assist decision makers in understanding the underlying complexities of maintenance float simulation models. At first, an operation problem must be defined and formulated. Second, a simulation model should be developed for the given system. Third, an appropriate metamodel structure should be proposed. Fourth, Taguchi experimental design, the analysis of variance (ANOVA) algorithm and the analysis of data are used to test the type of relationships between the independent and dependent variables. For example, the main and interaction effects of the independent variables on the dependent variable were investigated via Taguchi experimental design. This helps to explore and understand the complex relationships between the variables. Fifth, regression metamodels are developed based on the significance of these relationships. The metamodels, offer simple approximations to the dependent variable which in this paper is the average machine utilization (EU) or throughput (TH). Finally, the decision models developed are implemented in a cost structure to search for the "optimum" number of standby units and repair channels subject to certain constraints. The combination of standby units and repair channels obtained are not necessarily optimum since the model is based on simulation output. However, the model yields satisfactory solution to this problem.

So, our approach consists of the following steps:

Step 1. Problem Definition and Formulation

This is probably the most important step in our approach. Questions to be answered are:

-What is the problem?

-Which performance measures are to be used?

-Which factors are needed, and which higher order interactions are to be expected?

-What are the objective functions and constraints?

Several methods such as brainstorming, flowcharting, dialectical debate and cause-effect diagrams (e.g. fish bone diagram) can be used to determine the problem definition and formulation.

Step 2. Simulation Model

. Model construction

Three alternatives are available when selecting an appropriate language for FMS simulation study [Carrie 1986]: 1) write your own program in a general purpose language such as FORTRAN, 2) use a simulation package or language such as

GPSS, and 3) use an FMS simulator. A detailed list of world views and language features against which languages can be judged for modelling and simulating manufacturing systems has been given by Ekere and Hannam [1989]. The key features of world views are ease of systems conceptualization, naturalness of system representation, suitability for manufacturing applications, model readability and self-documentation, and ease of translation into code. The evaluation of language features includes model characterization and programming, model development, experimenting and reporting, and commercial and technical support. They indicate that cost is a very significant factor in the choice of software.

The choice of programming language pervades all aspects of model construction. General purpose languages tend to leave the analyst largely to his own devices, providing little assistance in constructing a logically correct program to represent the model. Simulation languages can facilitate the coding of the computer program, and also possess features that ease the debugging task [Hoover and Perry, 1989]. An FMS simulator can convert data into a simulation model and automatically runs the simulation program. Standard outputs as well as graphic presentations are generated. Model development is significantly simplified by this approach.

. Model verification and validation

The term verification involves examining the actual computer code to insure that it models the proper concepts, whereas the term validation is concerned about proving that the model is an adequate representation of reality. Therefore, validation can only be approached, but never achieved [Francis, 1987, Banks, 1990].

Before the simulation production runs are conducted, two decisions must be made: the number of replications and the run length.

Since there is considerable variability from replication to replication, if we stop with just a single run of the simulation, we would be misled about the system's expected response [Kelton, 1986]. As a result, an appropriate number of replications must be chosen.

One way to check for steady-state behavior is to conduct a very long simulation run. Certain number of sets of outputs with a smaller interval are chosen with this long run. The simple decision rule examines the output value from one interval set and compares it with all output values from succeeding interval sets. If the particular output value is either larger or smaller than all remaining output values in the long run, it is said to be part of a transient state. If the particular output value is neither the largest nor the smallest of the remaining output values in the long run, it is presumed to be part of the steady-state output. This heuristic procedure is similar to that of Solomon [1983]. This heuristic procedure is applied to the FMC case as well as the FMS case to detect the presence of transients.

Chrissis and Gecan [1986] suggested another way to check for steady-state behavior. The method is stated as follows. At first, a set of replications have to be divided into two subsets. The replications in the first subset are run for some number of time units. The second subset of replications are run for slightly longer periods. By performing a t-test, if there is no significant different between the results of these two subsets, an estimator for a system performance can be constructed using all replications in the original set. Otherwise, a new subset of replications has to be carried out for longer periods. A t-test is then performed on the two most recent samples. This process goes on until steady state behavior can be realized. Other heuristic procedures are discussed by Solomon [1983].

Sargent [1988] describes various validation techniques such as 1) animation, 2) comparison to other models, 3) Fixed values, 4) face validity, 5) parameter variability, 6) predictive validation, 7) traces, and 8) historical data validation. When using animation, the model's operational behavior is displayed graphically as the model moves through time. Using the second technique, an analytical or approximation models can be constructed with necessary assumptions. Simulation results then can be compared with closed-form analytic predictions. The fixed values technique is used when hand calculated values are possible to obtain. Face validity is used when experts to a specific problem are available. Parameter variability is used to investigate the output on the change of input values. Predictive validation is used when the actual system outputs are available. When using trace technique, researchers have to trace through the whole model to check if the model's logic is correct and if the necessary accuracy is obtained. If historical data are available, simulation model can be validated by historical data.

Step 3. Metamodel Form

Suppose we denote the system performance measure such as machine utilization as y and the k independent or controllable factors as x_j (j=1,...K, where K is the number of factors), we have

$$y=f(x_1,\ldots,x_k,e) \tag{3-1}$$

where f(.) is specified by the simulation model and e is the error term. Friedman [1988] further indicated that one metamodel frequently postulated in simulation analysis is the general linear model (or regression model) of experimental design because regression model has the great advantage of being a familiar technique. As noted by Schmidt and Meile [1989], one may argue that many system responses are not truly linear, and often they are not. But within a narrow design space, the linear approximation of a nonlinear response can result in a very fruitful description of the optimum space. Moreover, in many situations, even the model is not linear, it can be easily transformed to a linear model by a logarithmic transformation.

If it could be assumed that the simulation model yields a system performance y equal to the additive effects of the inputs x_j (j=1,...K, where K is the number of factors), then it may be represented as:

$$Y_i=\beta_0 + \sum_{j=1}^{K} \beta_j x_{ij} + e_i, \quad i=1,\ldots,n \tag{3-2}$$

where Y_i is the value of system performance in the i-th observation (or replication); x_{ij} is the value of the j-th input factors in the i-th observation; β_j is the coefficients of the factor j and e_i is the error term (i.e. the experimental error) and β_0 is the grand mean.

If we assume that the simulation input factors may interact, then the following model is proposed:

$$Y_i=\beta_0 + \sum_{j=1}^{K} \beta_j x_{ij} + \sum_{j<k} \sum_{k=2}^{K} \beta_{jk} x_{ij} x_{ik} + (\ldots) + e_i, \quad i=1,\ldots,n \qquad (3\text{-}3)$$

Here the coefficient β_{jk} denotes interaction between the factors j and k and the term (...) in equation 3-3 suggests that higher-order models (e.g. including three-factor interactions) are possible.

Based on the proposed metamodel, an appropriate factorial or fractional factorial design is selected. Simulation outputs were then generated according to the experimental design matrix.

<u>Step 4</u>. Taguchi Method

. Setting appropriate levels.

It is seldom clear just what values should be used to test for each factor. Therefore, prior knowledge of the system itself is important. For instance, in a two-level factorial design, Kelton [1988] suggested choosing the levels to be extreme in some sense, which needs the judgement by someone familiar with the actual system being simulated. Another suggestion is to use prior information from published papers about similar systems (see Table 2-3) to set the appropriate levels.

. Design the experiment according to an appropriate orthogonal array and linear graph.

As noted by Kelton [1986], a carefully designed course of simulation experimentation sets the stage for an appropriate and effective analysis of the output from these simulations. Therefore, a suitable Taguchi design for a specific problem must be chosen with caution. To design these experiments efficiently, we need a set of tables and simple procedures to construct orthogonal designs with minimum effort. Orthogonal arrays and their linear graphs developed by Taguchi [1977] satisfy this need very well [Phadke, 1989a]. Based on the number of factors and levels of interest and the assumptions of high order effects, an appropriate orthogonal array can be selected. By referring to linear graph, each factor and their interactions can be assigned to the appropriate columns in the orthogonal array (see Table 4-2 and 5-2).

In the initial stage of experiment, we recommend considering all possible two-factor interactions. The cost to the experimenter is more runs. However, the experimenter can benefit from gaining some knowledge and gathering useful evidence.

. Make simulation runs for each experimental design point. At each design point, an appropriate replication (i.e. using different random number seeds) should be chosen.

Since simulation results are random events, a single run at any design point would be meaningless. Therefore, appropriate replications should be conducted. The average of the system responses result from different random number seeds is considered as the output at this particular design point.

Note that the interaction conditions can not be controlled when conducting an experiment because they are dependent upon the main factor levels. Only the analysis is concerned with the interaction columns.

. Evaluate the main effects and two-factor interactions by Taguchi algorithm.

After simulation outputs are realized, it takes a LOTUS program only a few seconds to analyze the data and determine which of the factors are significant and whether any interacted (i.e. construct the associated ANOVA table) using the Taguchi algorithm. ANOVA is a statistically based decision tool for detecting any differences in average performance of groups of items tested [Ross, 1988]. The major purpose of the ANOVA table is to separate the total variation of the observations into accountable sources, such as factors influences, and experimental error. To complete the ANOVA calculations, one other component must be considered, that being the degrees of freedom (d.f.). A degree of freedom in a statistical sense is associated with each piece of information that is estimated from the data. Another way to think of the idea of degrees of freedom is to allow 1 degree of freedom for each independent comparison that can be made in the data [Ross, 1988]. For instance, level one of factor A compared to level two of factor A has 1 d.f. The following steps are taken in order to obtain the ANOVA for two-level design.

1) Calculate the sum of simulation results related to level one of each factor and record the results in column one of the ANOVA table.
2) Calculate the sum of simulation results related to level two of each factor and record the results in column two of the ANOVA table.
3) Calculate $[(\text{column } 1 - \text{column } 2)^2/N]$. N is the number of runs.
4) Calculate the sum of all error messages (or experimental errors). There are two sources of error messages. One possibility is to use unassigned columns in the orthogonal array to represent an estimate of error variation. Another possibility depends on some smaller column effects relative to others. These smaller effects are used as estimates of the error variance [Taguchi and

Wu, 1980, Ross, 1988].

5) Determine the degrees of freedom. The d.f. for each factor is the number of levels minus one. The d.f. for an interaction is the product of the interacting factor's d.f. [Ross, 1988].

6) Calculate the mean square for each factor.

7) Calculate the F value.

. Choose additional runs if necessary.

Experimental design is, in general, a learning and a sequential process. As noted by Box et al. [1978], the preliminary experimental design and result may be used as building blocks for further analysis. In this study, we assume that the system response is approximately linear over the range of the factor levels chosen because there are only two levels for each factor in the initial experiment [Montgomery, 1984]. Kuei et al. [1990] provide a proposition about choosing additional runs for further analysis (i.e. follow-up experiment) on realized experimental results from a series of simulation experiments:

Proposition: If any factor is highly significant (e.g. its mean square is too high compared to other factors), then it may be necessary to change this factor's level from two (or three) levels to a higher number of levels in the experimental design.

. Interpret the result

The main effect of a factor should be individually interpreted only if there is no evidence that the factor interacts with other factors [Box, et al. 1978]. When there is evidence of one or more such interaction effects, the interacting factors should be considered jointly. Taguchi and Wu [1980] also suggest the following procedure for data analysis and estimation:

1) Calculate the total of the system response by the factor and its level.
2) Divide the total by the number of observations for this factor and its level. This is the estimation of the effect of this factor at this level.
3) Calculate the range of error for these values (i.e. the estimations) by the F distribution. The statistic used is

   $\pm \sqrt{(F_{v1,v2},\alpha, *(V_e/n_e))}$

   where, $_{v1}$ is the d.f. for numerator, $_{v2}$ is the d.f. for denominator, α is the risk, V_e is the value of the error variance used for verification of factors' significance in the ANOVA. n_e is the mean number of observations for one particular factor and its level.

Furthermore, graphical presentation used to supplement the ANOVA table is strongly recommended by Taguchi and Wu [1980], Box et al. [1978], Hicks [1982], Montgomery [1984] and Ryan [1989].

The main objectives of these steps are: 1) reduce the number of runs in an experiment, 2) factorial search to reduce number of factors, and 3) select likely candidates for regression analysis.

Step 5. Regression Analysis and Metamodel Validation

The regression analysis will be made only if the ANOVA shows a significant difference in the system performance due to levels of some factors and we wish to go further and see how system performance may be related to those independent factors [Hicks, 1982]. For example, we may ask: How does system performance vary with some significant independent factors? Can one find a functional relationship between system performance and some significant independent factors that might enable one to predict system performance from those factors.

In our strategic approach, given that the ANOVA table has been constructed, factors found to be statistically significant are further used to build a regression model. This is the Pareto principle [Gitlow et al. 1989]. The idea of the Pareto principle is to select few factors which have the largest impacts on the system's response. Kuei et al. [1990] also provide a proposition about this idea from the experience of a series of simulation experiments:

Proposition: If any independent factor is significant in the ANOVA of the Taguchi experimental design, it should be considered as an independent variable in the regression model.

At this stage, we utilize Kleijnen's regression metamodeling procedure from step 4 to step 7 to develop an appropriate metamodel. Least-squares technique is used to fit equations to data. The least-squares method is used to [Daniel and Wood, 1971]: "find the values of the constants in the chosen equation that minimize the sum of the squared deviations of the observed values from those predicted by the equation". After an equation is obtained, a study of the residuals is a necessary step to check if the equation is a "good" fit or not.

Regression analyses are used here to investigate 1) the appropriateness of functional forms, 2) relations among independent variables, and 3) normality of residuals.

Step 6. Decision Models

Once a metamodel is validated, we can use this model to predict the system performance for selected values of influencing factors within the range this model is constructed. Furthermore, this metamodel can be applied in a cost structure to determine the optimum strategies for complex operations management problems.

Hoover and Perry [1989], and Shanthikumar and Sargent [1983] also indicate that one of the problem solving techniques for complex systems involves the combined use of simulation and analytic modeling. The simulation model is used as a subordinate to the analytical model. Hoover and Perry [1989] consider four approaches to the optimization problem with several system performances: 1) independent optimization of all system performances, 2) optimization of a selected system performance while constraining the remaining system performances, 3) optimization of a linear function of the system performances, and 4) optimization through goal programming algorithms. In this study, only the first approach is used. The solution procedures depend on which approach one selects.

Recently, Gunter [1990] noted that: "In reality, there is no such thing as a true optimum. We are proceeding empirically here. That is, we depend on data. As always, we see through a glass darkly: the models (e.g., equations) that we derive and solve to optimize are only useful approximations at best. Thus, the optima we derive might be better described as regions of desirable performance. Design of experiments can be used to find and approximately map these regions."

The objective of this section is to describe a step by step procedure for determining the best solution to the complex operation problems with the minimum expected experimental costs. A well designed simulation study is not complete until experimenters have taken into account all the steps we discussed.

CHAPTER 4

MAINTENANCE FLOAT MODELING FOR A FLEXIBLE MANUFACTURING CELL

4.1 Problem definition and Formulation

Suppose operation managers are interested in the utilization of one major machine (e.g. a CNC machine) in the system. This machine can perform only one function (e.g. milling or drilling). The major component of this machine is the tool. However, this tool is subject to failure. When the tool fails, this machine stops. The failed tool will be sent to the repair shop. In the repair shop, this failed tool may or may not be repaired immediately because the rest of the system compete for the limited number of repair persons. After repair, the repaired tool is sent back to the machine for operational purposes. Operation managers may consider applying maintenance float policy to this particular machine. If that is the case, once a tool in operation breaks down, it will be replaced by a unit in standby status if one exits. Therefore, the machine can operate by using a standby tool as a substitute for the failed tool. The failed tool goes into the repair shop for repair and returns back after repair to standby status. A complete illustration of this process appears in Figure 1-2.

Some of the primary assumptions of this system may be summarized as follows:

1) The tool is renewable.

2) The repaired tool is assumed to be as good as new.

3) The switchover time is negligible.

4) When the tools are loaded in the standby state, they never lose their operational ability. In technical term, they are Known as "cold standbys".

5) There is only one type of repair needed.

6) Tools considered are independent and identical.

7) Tools fail time and repair time follow the exponential distribution.

Moreover, the operation managers note that there are m types of tools with different mean time between failures (MTBFs) and mean time to repairs (MTTRs) available in the market. They want to know the type and the number of standby tools to maintain as well as the number of repair persons they should hire for a specified service level at a minimum system cost.

From the problem definition, we can build the following model to search for the optimum solutions. Although the combination obtained through this approach is not necessarily optimum due to our dependence on simulation outputs, we shall henceforth refer to these satisfactory solutions as optimum. Let

C_i: cost of type i tool; per unit time.

C_s: operation cost of repair persons; per unit time.

m_i: the index of type i tool. If we use the type i tool, then it equals to 1; otherwise, 0.

R: a prespecified service level.

C_{lp}: lost production cost; per unit time.

EU: the expected value of machine utilization.

S: the number of repair persons.

F_i: the number of standby units of type i.

Assuming only one type of tool can be used in the system, we obtain:

$$\min \sum_{i=1}^{m} m_i(F_i+1)C_i + S*C_s + (1-EU)C_{lp} \tag{4-1}$$

$$\text{S.T. } EU \geq R \qquad i=1,2,\ldots,m \tag{4-2}$$

$$EU = f(S,\ F,\ MTBF,\ MTTR) \tag{4-3}$$

$$\sum_{i=1}^{m} m_i = 1 \tag{4-4}$$

$$m_i = 0 \text{ or } 1 \tag{4-5}$$

$$S,\ F_i \geq 1 \text{ and are integers, } i=1,2,\ldots,m$$

The first term in equation 4-1 is the total cost of tools, the second term is the total operation cost of repair persons and the third term is the lost production cost. The inequality of equation 4-2 ensures that the average utilization of operation tools is not less than the required level in the long run. The functional relationships between machine utilization (EU) and certain factors (i.e. the number of repairmen, the number of standby units, mean time between failure and mean time to repair) is determined from section 4.3. Furthermore, equation 4-4 and 4-5 implies that only one type of tool can be used in the system.

Finally, the operation managers are also interested in questions such as "what if the failure rate of tools available in the market follows either Erlang-2 or Gamma distribution?". As a result, three cases are discussed in the next chapter. In case 1, the failure rate is generated from exponential distribution; while in case 2, the failure rate follows the Erlang-2 distribution with shape parameter 2 and scale parameter 1 and the Gamma failure distribution with shape parameter equals to 0.5 and scale parameter equals to 1 is discussed in case 3.

4.2 Simulation Model

There are two major parts in the simulation model. The first part consists of a FMC with supply of tools and the second part represents competition from the remainder of the shop for the limited repair persons. The model is similar to that of Schriber (1974).

In both parts of the model, tool failure and repair times are generated from an exponential distribution for case one problem. A transaction is used to simulate a tool while the machine itself is simulated with a facility. When a tool fails, it is replaced by a standby if one exists. Meanwhile, the failed tool is sent to the repair shop. When the repair is completed, the repaired tool returns back to the standby node. The repair persons are simulated with a storage. The failed tool goes into repair after it captures one of the repair persons. However, each failed tool competes with other failed items which come from the rest of the system for the limited number of repair persons.

Pilot experiments with a simulation run length varying from 10,400 time units to 249,600 time units showed that this model reached steady state after 124,800 time units. This steady state behavior is presented in Figure 4-1. Thus a run length of 124,800 time units was chosen for these experiments.

Also from our previous experience and pilot study, five replications would result in a reasonable estimation for machine utilization.

4.3 Metamodel Form

In this study, we assume that the simulation input factors may interact, thus the following model is proposed:

$$EU = \beta_0 + \sum_{j=1}^{4} \beta_j x_j + \sum_{j<k} \sum_{k=2}^{4} \beta_{jk}\, x_j\, x_k, \tag{4-6}$$

Here, EU is the system performance measure - equipment utilization; β_0 is the grand mean; β_j is the coefficients of the factor j; x_j is the value of the j-th input factors; and the coefficient β_{jk} denotes interaction between the factors j and k.

In this chapter, we considered all the possible two-factor interactions when constructing the metamodel. The cost to this approach is more runs. However, operations managers and industrial practitioners may benefit from our finding. For example, the experience and results obtained from this study can help to reduce the number of runs needed when conducting a similar experiment in practice.

4.4 Taguchi Method

From the problem description, four factors affect this single machine's operation and their levels are as follows:

1) S: the number of repairmen (1 and 3),
2) F: the number of standby units (1 and 3),
3) MTBF: mean time between failure (12 and 24),
4) MTTR: mean time to repair (5 and 10).

The knowledge and experience of a particular system is needed in order to select appropriate levels for these factors. This expertise, in our example, can be developed through simulation experiments. For instance, given the MTBF and MTTR (these information may come from vendors of tool companies), the upper bounds of S and F can be determined by pilot simulation runs. Beyond certain upper bounds, the system performance are the same.

Here, we are interested in the relationship between the dependent variable machine utilization (i.e. EU), and all the independent variables - S, F, MTBF and MTTR. Based on a $L_{16}(2^{15})$ orthogonal array (see Table 4-1), we obtained an experimental design table (see Table 4-2). The different columns in this table represent the effect of independent variables, the interaction effect of two independent variables, and the error messages (or experimental error), respectively. Note that we allocated five error messages to five unassigned columns (i.e. we did not assign any factor and two-factor interaction on these five columns) in Table 4-2. As a result, we have five more degrees of freedom to estimate the error variation. This will increase the sensitivity of the experiment to detect small changes in the system performance measures due to small change in the factor's levels. This technique is crucial when we have only one repetition at each design point. The systematic assignment of the levels to the four factors are presented in Table 4-3. The corresponding linear graph for this experiment can be found in Figure 2-1. The corresponding values of EU were obtained after sixteen simulation runs with five replications (see Table 4-3). The ANOVA algorithm suggested by Taguchi and Wu [1980] was applied on the realized values of EU and the selected input values for the independent variables.

The ANOVA table (see Table 4-4) shows that MTBF, F, S, MTTR and MTBF*S are significant at $\alpha = 0.001$, whiled S*MTTR are significant at $\alpha = 0.05$. Since the sum of square (SS) value of MTBF*F, F*S, MTBF*MTTR AND F*MTTR are quite low, thus, the joint effects of these variables yield error messages (see Section 3.3 step 3). Therefore nine error messages are presented in this table. As a rule of thumb, Taguchi and Wu [1980] and Ross [1988] suggest that the degrees of freedom of the pooled error should be about half of the total degrees of freedom.

Table 4-4 suggests that the F, the interaction S*MTBF, and the interaction S*MTTR require interpretation. Thus, a data analysis was performed by the standard procedure given in Taguchi and Wu [1980]. The results are plotted in Figure 4-3, 4-4 and 4-5. Graphs such as these are frequently vary useful in interpreting significant interactions and in reporting results to non-statistically trained management [Montgomery 1984]. The following tentative conclusions are apparent from the plots:

- Higher number of floats (F) gives improved EU (Figure 4-3).
- The effects of the number of repair persons (S) and MTBF can not be interpreted separately because of the large S*MTBF interaction. The interaction evidently arises from a difference in sensitivity to MTBF change for the two levels of S, with lower level of S the MTBF effect is 0.212 on EU, but with higher level of S it is 0.041 (Figure 4-4).
- The interaction effect of S and MTTR is also large. With lower level of S the MTTR effect is 0.154 on EU, but with higher level of S it is 0.0415 (Figure 4-5).

4.5 Regression Analysis and Model Validation

Based on the ANOVA results, an alternative regression metamodel is proposed.

$$EU = a_0 + a_1*MTBF + a_2*F + a_3*S + a_4*MTTR + a_5*MTBF*S + a_6*S*MTTR \quad (4\text{-}7)$$

Based upon the data obtained from our simulation (see Table 4-3), the regression function is as follows:

$$EU = 0.410875 + 0.02479167*MTBF + 0.04475*F + 0.152875*S - 0.04205*MTTR - 0.007125*S*MTBF + 0.01125*S*MTTR \quad (4\text{-}8)$$

The R^2 of 0.971163 and the model F value of 50.52 indicate high associativity of independent factors and two interactions with EU. All significant levels are very high (see Table 4-5). Moreover, residual analysis indicates that the residuals of this model are normally distributed because they contain no obvious pattern. In order to evaluate and test this equation, four simulation runs were conducted in order to validate the metamodel. The average percentage deviation (i.e. this is the average over four experiments of the following measurement: [metamodel-simulation]/simulation; [.] is the absolute value) is 1.9%. In other words, EU values obtained via the metamodel are sufficiently close to EU values obtained from the simulation model. This indicates that the metamodel can be useful for prediction purposes. Figure 4-2 compares the EUs obtained by the simulation model to the EUs predicted using the metamodel.

These equation provide good estimates for MTBF ϵ [12,24], F ϵ [1,3], S ϵ [1,3] and MTTR ϵ [5,10]. ([] denotes the interval of one controllable factor) Thus, this formula can be used to predict the EU within the range considered in this section.

4.6 Decision Models

Since the aim of this study is to find the optimal combination of standby units and repair persons, the regression metamodel obtained through the Taguchi experimental design is applied in a cost structure to determine this "optimum" combination.

Suppose we have m types of tools with different MTBFs and MTTRs and one type of repair persons, and a specific service level is needed, we can build a cost model to search for the best type and the optimum number of tools and the optimum number of repair persons. For the sake of completeness, we duplicate the same cost formulation from section 4.1. Moreover, a metamodel with estimated coefficients is also presented here. The cost model is stated as follows:

$$\min \quad \sum_{i=1}^{m} m_i(F_i+1)C_i + S*C_s + (1-EU)C_{lp} \qquad (4\text{-}9)$$

$$\text{S.T.} \quad EU \geq R \qquad i=1,2,\ldots,m \qquad (4\text{-}10)$$

$$EU = 0.410875 + 0.02479167*\Sigma m_i*MTBF_i + 0.04475*\Sigma m_i*F_i + 0.152875*S - 0.04205*\Sigma m_i MTTR_i - 0.007125*S*\Sigma m_i*MTBF_i + 0.01125*S*\Sigma m_i*MTTR_i \qquad (4\text{-}11)$$

$$\sum_{i=1}^{m} m_i = 1 \qquad (4\text{-}12)$$

$$m_i = 0 \text{ or } 1 \qquad (4\text{-}13)$$

S, $F_i \geq 1$ and are integers, $i=1,2,\ldots,m$

To obtain the optimum value of F and S, we would search for all the possible values of MTBF, MTTR, F, and S that satisfy the constraint on EU. This will result in smaller search space for the optimum combination of F and S (see Table 4-6). Moreover, since the F and S are finite numbers, the computation effort is reduced. Therefore, a matrix of total costs for feasible combination of F and S can easily be generated. We shall illustrate this solution procedure for determining optimum F and S in the following example.

Numerical example

Suppose we have three types of tools and one type of repair persons. Their data are as follows:

$C_1 = 200$, $C_2 = 450$, $C_3 = 500$

$C_s = 100$,

$MTTR_1 = 5$, $MTTR_2 = 7$, $MTTR_3 = 9$

$MTBF_1 = 14$, $MTBF_2 = 18$, $MTBF_3 = 22$

C_{lp}: 2,000

R: 0.85

Therefore, we obtain:

$$\text{Min} \quad \{200m_1*(F_1+1) + 450m_2*(F_2+1) + 500m_3*(F_3+1)\} + 100*S + 2000*(1-EU) \tag{4-14}$$

$$\text{S.T.} \quad R \geq 0.85 \tag{4-15}$$

$$EU = 0.410875 + 0.02479167*(m_1*14+m_2*18+m_3*22) + 0.04475*(m_1*F_1+m_2*F_2+m_3*F_3) + 0.152875*S - 0.04205*(m_1*5+m_2*7+m_3*9) - 0.007125*S*(m_1*14+m_2*18+m_3*22) + 0.01125*S*(m_1*5+m_2*7+m_3*9) \tag{4-16}$$

F, S $\geq$ 1 and are integers

We can separate this problem into three subproblems, then compare the solutions of these three subproblems and choose the best of them. Here, we just illustrate how to solve one of these subproblems, namely, type one tool case.

$$\text{Min} \quad 200*(F+1) + 100*S + 2000*(1-EU) \tag{4-17}$$

$$\text{S.T.} \quad EU \geq 0.85 \tag{4-18}$$

$$EU = 0.5477074 + 0.04475*F + 0.152875*S - 0.09975*S + 0.05625*S = 0.5477074 + 0.04475*F + 0.109375*S \tag{4-19}$$

F, S $\geq$ 1 and are all integers

From Table 4-6, the minimum cost \$858.83 is obtained when using one standby unit and three repair persons. According to this process, we can find the optimum solution for the other subproblems (i.e. type 2 tool and type 3 tool cases). By comparing these three solutions, we can find the optimum solution for this example.

Variations in the above formulation, such as various skills repair persons may also be considered. Suppose we have m types of tools with different MTBFs and n types of repair persons with various skills, and a specific service level is needed. To determine the best type and the optimum number of tools and repair persons, the objective function may be mathematically stated as follows:

$$\min \quad \sum_{i=1}^{m} m_i(F_i+1)C_i + \sum_{j=1}^{n} n_j S_j{*}C_{sj} + (1-EU)C_{lp} \qquad (4\text{-}20)$$

Suppose that we have n types of repair persons with various skills and one type of tool, and a specific service level is needed. To determine the best type and the optimum number of repair persons and the optimum number of tools, the objective function for this problem can be stated as follows:

$$\min \quad (F+1)C + \sum_{j=1}^{n} n_j S_j{*}C_{sj} + (1-EU)C_{lp} \qquad (4\text{-}21)$$

4.7 Erlang-2 Failure Distribution Case

The systematic assignment of the levels to the four factors for the Eralng-2 case (i.e. with shape parameter 2 and scale parameter 1) is still the same as those for the exponential case (see Table 4-7). The only difference is that the MTBF is from 24 to 48. The corresponding values of EU were obtained after sixteen simulation runs with five replications (see Table 4-7).

The ANOVA table (see Table 4-8) Shows that MTBF, S, MTTR, MTBF*MTTR, and MTBF*S are significant at $\alpha = 0.001$, whiled F are significant at $\alpha = 0.05$. Since the sum of square (SS) value of MTBF*F, F*S, F*MTTR AND S*MTTR are quite low, thus, the joint effects of these variables yield error messages. Therefore nine error messages are presented in this table.

Based on the ANOVA results, a simple additive regression metamodel is proposed.

$$EU = a_0 + a_1*MTBF + a_2*F + a_3*S + a_4*MTTR + a_5*MTBF*S + a_6*MTBF*MTTR \qquad (4-22)$$

This yields an R^2=0.997055. All significant levels of MTBF, F, S, MTTR, MTBF*S, and MTBF*MTTR are very high (see Table 4-9). Moreover, residual analysis indicates that the residuals appear to be randomly distributed (i.e., e = NID $(0,\delta^2)$. Therefore, the metamodel of this Erlang-2 case is:

$$EU = 0.608025 + 0.0045875*MTBF + 0.0067125*F + 0.11215*S - 0.02872*MTTR - 0.00126354*MTBF*S + 0.00032208*MTBF*MTTR \quad (4\text{-}23)$$

This particular metamodel is, however, applicable only in the following intervals:

MTBF $\in$ [24,48], F $\in$ [1,3], S $\in$ [1,3] and MTTR $\in$ [5,10].

This model suggests: 1) Factors MTBF, F, S, and joint effect of MTBF and MTTR have beneficial effects on the EU, 2) Factor MTTR has a nonbeneficial effect on the EU, and 3) There is a trade-off between MTBF and S as shown by the negative coefficient. This model can be used to predict the EU for selecting values of MTBF, F, S, and MTTR as long as they are within their respecting operating ranges. In addition, this metamodel can be integrated in a cost structure to assist the decision maker in determining the maintenance float poicy that will satisfy a specified service level.

4.8 Gamma Failure Distribution Case

The systematic assignment of the levels to the four factors for the Gamma failure distribution with shape parameter equals to 0.5 and scale parameter equals to 1 is still the same as those for the exponential case (see Table 4-10). The only difference is that the MTBF is from 6 to 12 and the MTTR is from 2 to 5. The corresponding values of EU were obtained after sixteen simulation runs with five replications (see Table 4-10).

The ANOVA table (see Table 4-11) Shows that MTBF, S, MTTR, MTBF*MTTR, and MTBF*S are significant at α = 0.001, while F is significant at α = 0.05. Since the sum of squares (SS) values for MTBF*F, F*S, F*MTTR AND S*MTTR are quite low, thus, the joint effects of these variables yield error messages. Therefore nine error messages are presented in this table.

Based on the ANOVA results, an alternative regression metamodel is proposed.

$$EU = a_0 + a_1*MTBF + a_2*F + a_3*S + a_4*MTTR + a_5*MTBF*S + a_6*MTBF*MTTR \qquad (4-24)$$

This model also fits very well (i.e. R^2=0.998442). Table 4-9 shows that the parameter estimates of all the independent factors - MTBF, F, S, and MTTR are significant in determining EU at α = 0.001. Furthermore, significant levels of MTBF*S, and MTBF*MTTR are very high (see Table 4-9). In addition, residual analysis indicates that the residuals appear to be randomly distributed (i.e., e = NID $(0,\delta^2)$. The equation obtained for the gamma failure distribution provides good estimates when MTBF falls in the interval 6 and 12 hours. The input values for the other independent variables remain the same. Hence, the metamodel for the gamma case is:

$$EU = 0.4659833 + 0.0182389*MTBF + 0.007875*F + 0.1417*S - 0.0750667*MTTR - 0.00365833*MTBF*S + 0.00295556*MTBF*MTTR \tag{4-25}$$

This metamodel helps to better understand the relationships between EU and the independent factors and some of their interactions. Finally, a cost model can be constructed to show the applicability of this metamodel to a specific decision situation.

4.9 Results and Discussions

The three cases presented show that:

1) The effect of factor S is very predominant.
2) Factors MTBF, and F have beneficial effects on the EU.
3) Factor MTTR has a nonbeneficial effect on the EU.
4) The joint effect of factors MTBF and S has a nonbeneficial effect on the EU.
5) In the exponential case, the joint effect of factors S and MTTR has a beneficial effect on the EU while in Erlang-2 and Gamma cases, the joint effect of factors MTBF and MTTR has a beneficial effect on the EU.

As we discussed in section 2.5, prior knowledge and experience can help to reduce the number of runs needed when conducting an experiment. In chapters four and five, we considered all the possible two-factor interactions when designing the experiment. The cost to this study is more runs. However, operations managers and industrial practitioners may benefit from our finding. For example, a list of factors and interactions might include F, S, MTBF, MTTR, S*MTBF, and S*MTTR for the FMC with exponential failure distribution in practice. As a result, L_8 design with eight runs may be considered under similar circumstances. Based on the $L_8(2^7)$ orthogonal array (see Table 4-13), we recommend an experimental design for use (see Table 4-14). The corresponding linear graph is shown in Figure 4-6. Again, the unassigned columns in the L_8 (i.e. column 7) represent an estimate of error variation. Following the same scheme, experimental designs for Erlang-2 and Gamma cases are arranged (see Table 4-15). The corresponding linear graph is shown in Figure 4-7.

Furthermore, Having determined that the regression metamodel is acceptable, the next step is to use the metamodel to investigate the effects of change of factors on the system performance. By using regression metamodel one can detect opportunities to improve the performance of the system without rerunning the simulation. However, it should be pointed out that these results are limited to the range considered in this chapter. Although in these particular cases the range of applicability is extremely limited, in similar or very different environments, analogous equations can easily be developed.

CHAPTER 5

MAINTENANCE FLOAT MODELING FOR A FLEXIBLE MANUFACTURING SYSTEM

5.1 Problem definition and Formulation

The FMS chosen here for modeling in our strategic approach is depicted in Figure 1-4. This hypothetical FMS is similar to that of Schriber (1985). However, we relaxed some of the assumptions. For example, the assumption that the machine never breaks down, is relaxed. A maintenance float policy is applied to this unreliable FMS. We also did not model pallets and fixtures as done by Schriber [1985].

There are two type A dedicated machines (i.e. each machine performs only one type of operation), two type B dedicated machines, and four waiting spaces in the system. This system is used to manufacture parts of types one and two. Each part type has its own dedicated loading station and its own dedicated unloading station. Parts of type 1 visit machines of type A with machining time requirement of 15 minutes. Parts of type 2 visit machines of types B and A, in that order, with machining time requirements of 20 and 10 minutes, respectively. 42.86 percent of the parts manufactured are of type 1 and the other 57.14 percent are of type 2. Only seven parts are admitted to the system at any given time to avoid a deadlock phenomenon. A deadlock phenomenon is a situation in which no part in the system can move. This could happen, if all waiting spaces and machines are occupied by parts. Therefore, some researchers suggest that the maximum number of parts admitted to the system should be one less than the sum of the number of machines and the number of waiting spaces [Co and Wysk 1986, Schriber and Stecke 1987]. When a part leaves the system, another part is allowed to go into the system. Admittance in to the system is based on the part type sequence plan. For instance, the part type sequence plan could be 1, 2, 1, 2, 1, 2, 2. This part type sequence plan is considered as one of the factors that operation managers are interested in.

Parts move from point to point in the system according to Schriber's (1985) procedure. Parts of type 1 that have just entered the system wait in their own loading station until both a cart and a type A machine become available to it. The part then claims the closest idle cart and the closest idle type A machine. The cart travels to the part type 1's loading station, picks up the part, and transports it to the machine. At the completion of this service, the cart then becomes idle, and remains at that machine location until it is again needed. When an operation on a part is performed, this part then waits at the machine until a cart and part type 1's unloading station becomes available. The part then claims the closest idle cart, travels to its own unloading station, and leaves the system. At the same time, a signal is sent to allow a new part to enter into the system. The cart again becomes idle and stays at the unloading station. The only difference between parts of type 1 and type 2 processes is that when the first operation is performed on the parts of type 2, the part then waits at the machine (i.e. type B machine) until a cart and either a waiting space or a type A machine becomes available to it. The parts then proceed to an appropriate location (i.e. either to the waiting space or the machine of correct type). If the part is moved to the waiting space, the part will stay there until both a cart and a type A machine become available to it.

Machine availability implies that the machine is not loaded (i.e. it does not manufacture any part) and is in an operational condition. It is assumed that these machines use tool that is subject to random failures. The operating machines are supported by a repair shop and a number of backup parts (e.g. spare tools). When a part in operation breaks down, it is replaced by a unit in standby status if one exists. The failed unit goes into the repair shop for repair and returns back after repair to standby status. This mode of operation is presented in Figure 1-3.

Certain assumptions have been made about the operation of this hypothetical FMS.

1) AGV breakdowns do not occur.
2) There is no traffic congestion.
3) Shortest processing time is used in the system to dispatch parts to machines.
4) Travel times in the system are fixed (e.g. set at one minute per segment traversed. For instance, machine A and machine B are one segment apart, machine B at location four and waiting space at location six are two segment apart).
5) Units are assumed to be completely rejuvenated after each repair.
6) The failure rates are identical in all type A machines and follow the exponential distribution.
7) The failure rates are identical in all type B machines and follow the exponential distribution.
8) Each machine requires only one tool to process a job.

Other assumptions are the same as those in Section 4.1.

To determine the optimal levels of spare tools of different types and the capacity of the repair facility, the problem may be mathematically stated as follows:

$$\text{Min} \quad C_s*S + \sum_{i=1}^{Na} C_{FAi}*FAi*m_i + \sum_{j=1}^{Nb} C_{FBj}*FBj*m_j \tag{5-1}$$

$$S.T.\ TH_i \geq (\text{Desired Throughput})_i, \quad i=1,2 \tag{5-2}$$

$$TH_i = f(S, Fa, Fb, Ma, Mb, MTTR, PS) \tag{5-3}$$

$$\sum_{i=1}^{Na} m_i = 1 \tag{5-4}$$

$$m_i = 0 \text{ or } 1 \tag{5-5}$$

$$\sum_{j=1}^{Nb} m_j = 1 \tag{5-6}$$

$$m_j = 0 \text{ or } 1 \tag{5-7}$$

S, Fa and Fb $\geq$ 1 and are all integers

C_{FAi}: cost of type i tool for machine A; per unit time.

C_{FBj}: cost of type j tool for machine B; per unit time.

C_s: operation cost of repairman; per unit time.

m_i: the index of type i tool for machine A. If we use the type i tool, then it equals to 1; otherwise, 0.

m_j: the index of type j tool for machine B. If we use the type i tool, then it equals to 1; otherwise, 0.

S: the number of repair persons

FA_i: the number of standby units of type i tool for machine A.

FB_j: the number of standby units of type j tool for machine B.

TH_i: throughput of product i.

Ma: MTBF for machine A.

Mb: MTBF for machine B.

Fa: the number of standby units for machine A.

Fb: the number of standby units for machine B.

MTTR: mean time to repair.

PS: the part sequence.

The above problem is difficult to solve because the constraints in the formulation can not be expressed explicitly in terms of the defined factors. These constraints can only be evaluated when values for the factors are specified. We will therefore use our strategic approach to deal with this optimization problem.

The objective function can be revised by including the profit terms on the throughput of part type 1 and part type 2 if operations managers are interested in the profit maximization problem. This gives rise to the new objective function:

$$\text{Max} \quad (P1*TH1 + P1*TH2) - (C_s*S + \sum_{i=1}^{Na} C_{FAi}*FAi*m_i + \sum_{j=1}^{Nb} C_{FBj}*FBj*m_j) \tag{5-8}$$

where,

P1: profit for product 1.

P2: profit for product 2.

TH1: throughput of product 1.

TH2: throughput of product 2.

Variations in the above formulation, such as only one type of repair person and tool may also be considered. These problems may be mathematically stated as follows:

$$\text{Min} \quad C_s*S + C_{FA}*FA + C_{FB}*FB \tag{5-9}$$

or

$$\text{Max} \quad (P1*TH1 + P1*TH2) - (C_s*S + C_{FA}*FA + C_{FB}*FB + Na*Oa + Nb*Ob) \tag{5-10}$$

s.t.

$$C_s*S + C_{FA}*FA + C_{FB}*FB \leq \text{Budget} \tag{5-11}$$

$$TH_i \geq (\text{Desired Throughput})_i, \quad i=1,2 \tag{5-12}$$

$$TH_i = f(S, Fa, Fb, Ma, Mb, MTTR, PS) \tag{5-13}$$

S, Fa and Fb $\geq$ 1 and are all integers

where,

Na: Number of machine type a.

Nb: Number of machine type b.

Oa: Machine a's operating cost.

Ob: Machine b's operating cost.

5.2 Simulation Model

The listing of a GPSS model for an FMS with maintenance float policy is shown in Appendix A-2. There are eight model segments in this program: 1) introduction of parts into the system, 2) the movement of type 1 parts, 3) the movement of type 2 parts, 4) the selection of the nearest cart, 5) the selection of the nearest waiting space, 6) the selection of the nearest type A machine, 7) the selection of the nearest type B machine, and 8) the machine breakdowns, repair and return process.

A transaction is used to simulate a part from model segments 1 to 7. A particular part will go through the system based on the logic described in previous section. In the last model segment, a transaction which represents tool failure is generated from an exponential distribution. When a tool fails, it is replaced by a standby if one exists. Meanwhile, the failed tool is sent to the repair shop. When repair is completed, the repaired tool returns back to the standby node.

Pilot experiments with a simulation run length varying from 1 week to 40 weeks showed that this model reached steady state after 30 weeks. So that a run length of 35 weeks was chosen for these experiments. Our previous experiences with similar models, and pilot study, suggest that five replications would result in a reasonable estimation for throughput of part type 1 and 2.

5.3 Metamodel Form

In this study, we assume that the simulation input factors may interact, thus the following model is proposed:

$$TH = \beta_0 + \sum_{j=1}^{6} \beta_j x_j + \beta_7 x_7 + \sum_{j<k} \sum_{k=2}^{6} \beta_{jk}\, x_j\, x_k + \beta_{4,7}\, x_4\, x_7, \tag{5-14}$$

Here, TH is the system performance measure - throughput; β_0 is the grand mean; β_j is the coefficients of the factor j; x_j is the value of the j-th input factors (i.e. x_1: MTBF of Machine A; x_2: MTBF of machine B; x_3: the number of repair persons; x_4: MTTR; x_5: the number of standby units for machine A; x_6: the number of standby units for machine B; x_7: part sequence.); and the coefficient β_{jk} denotes interaction between the factors j and k.

In the next section, whether this model is adequate or not can be tested by ANOVA procedure. If the output is insensitive to certain input factors and two-factor interactions then those factors and two-factor interactions can be eliminated from the proposed metamodel. This will then lead to an alternative version of model.

5.4 Taguchi Method

From the problem description, seven factors affect this FMS's operation and their levels are as follows:

1) S: the number of repairmen (1 and 4),
2) Fa: the number of standby units for machine A (2 and 5),
3) Fb: the number of standby units for machine B (2 and 5),
4) Ma: mean time between failure of machine A (120 and 240),
5) Mb: mean time between failure of machine B (100 and 200),

6) MTTR: mean time to repair (40 and 80),
7) PS: part sequence (1,2,1,2,1,2,2 and 1,1,1,2,2,2,2)

Here, we are interested in the relationship between dependent variables which are throughput of part type 1 and part type 2 (i.e. TH1 and TH2) and all the independent variables - S, Fa, Fb, Ma, Mb, MTTR and PS. Based on a $L_{32}(2^{31})$ orthogonal array (see Table 5-1) and a linear graph (see Figure 2-2), we obtained an experimental design table (see Table 5-2). Note that all the possible two-factor interactions except for the PS are considered in this experiment because we assume PS may have joint effect with MTTR only,. Note also that we allocated eight error messages to eight unassigned columns in Table 5-2. As a result, we have eight more degrees of freedom to estimate the error variation. As we mentioned in the previous chapter, this will increase the sensitivity of the experiment to detect small changes in the system's performance measures due to small changes in factor's levels. This technique is crucial when we have only one repetition at each design point. The systematic assignment of the levels to the seven factors are presented in Table 5-3. The corresponding values of TH1 and TH2 were obtained after thirty-two simulation runs (see Table 5-3). The ANOVA algorithm suggested by Taguchi and Wu [1980] was applied on the realized values of TH1 and TH2 and the selected input values for the independent variables.

The ANOVA table (see Table 5-4) shows that Mb, MTTR, Fa, Fb, and S are significant at $\alpha = 0.001$, while Ma and Ma*Fa are significant at $\alpha = 0.05$. Since the sum of squares (SS) values for Ma*Mb, Ma*MTTR, S*Fa, Ma*S, Mb*Fa, Ma*Fb, Mb*Fb, MTTR*Fb, MTTR*PS, and Fa*Fb are quite low, thus, the joint effects of these variables can be considered as error messages (see Section 3.3 step 3). Therefore, eighteen error messages are presented in this table and the total degrees of freedom of the pooled error is about half of the total degrees of freedom.

Table 5-4 suggests that the MTTR, S, Fb, Mb, and the interaction Ma*Fa require interpretation. Thus, a data analysis was performed by the standard procedure given in Taguchi and Wu [1980]. The results are plotted in Figure 5-2, 5-3, 5-4, 5-5 and 5-6. The following tentative conclusions are apparent from the plots:

- Lower level of MTTR is better than the higher level of MTTR.
- Higher number of repair persons (S) gives improved TH1.
- Higher number of floats for machine B (Fb) gives improved TH1.
- Higeher level of Mean Time Between Failure (MTBF) results in a large improvement on TH1.
- The effects of the number of floats for machine A (Fa) and MTBF for machine A (Ma) can not be interpreted separately because of the large Ma*Fa interaction. The interaction evidently arises from a difference in sensitivity to Ma change for the two levels of Fa, with lower level of Fa the Ma effect is 4.899995 on TH1, but with higher level of Fa it is -0.093005.

These conclusions are valid for this particular FMS.

5.5 Regression Analysis and Metamodel Validation

Based on the updated knowledge about the relationship between the factors, and their effects on the throughput from the ANOVA results, two alternative regression metamodels are proposed.

$$TH1 = a_0 + a_1*Ma + a_2*Mb + a_3*S + a_4*MTTR + a_5*Fa + a_6*Fb + a_7*Ma*Fa \quad (5\text{-}15)$$

$$TH2 = a_0 + a_1*Ma + a_2*Mb + a_3*S + a_4*MTTR + a_5*Fa + a_6*Fb + a_7*Ma*Fa \quad (5\text{-}16)$$

These models fit the data very well (i.e. R^2=0.844106 and R^2=0.84301, respectively). All significance levels are very high (see Table 5-5 and Table 5-6). Furthermore, residual analysis indicates that the residuals appear to be randomly distributed (i.e. e = 0). These equations provide good estimates for Ma ϵ [120,240], Mb ϵ [100,200], S ϵ [1,4] , Fa ϵ [2,5], Fb ϵ [2,5] and MTTR ϵ [40,80]. In order to evaluate, test and validate these equations, nine simulation runs that were not used in the experimental design were carried out. The relative prediction errors (i.e. [metamodel-simulation]/simulation, [.] denotes the absolute term) of the metamodels are examined by comparing the metamodels' predictions of TH1 and TH2 to those obtained from the simulation (see Table 5-7 and 5-8). All relative errors are below 23% and in half the cases are well below 10%. The average percentage deviation over these nine experiments for TH1 and TH2 are 10.5% and 12.74%, respectively. Thus, the following metamodels are obtained.

$$TH1 = -10.59875 + 0.0701*Ma + 0.0511225*Mb - 0.13941875*MTTR + 2.32441667*S + 3.2715*Fa + 1.13516667*Fb - 0.01463333*Ma*Fa \quad (5-17)$$

$$TH2 = -14.11502083 + 0.09317743*Ma + 0.06808813*Mb - 0.18522031*MTTR + 3.08864583*S + 4.337*Fa + 1.4981875*Fb - 0.0193559*Ma*Fa \quad (5-18)$$

From the ANOVA table (see Table 5-4), the mean square of S is quite high compared to those of other factors. Based on the proposition 2 [Kuei et al., 1990], further analysis on this highly significant factor is recommended. Further analysis is conducted using a L_{16} orthogonal array (see Table 5-9) and the corresponding linear graph (see Figure 2-3). In this design, level of S is assumed to vary from 1 to 4 and columns 2, 4 and 6 are used to represent the level of S. Consequently, additional simulation runs are conducted. These new observations can be found in Table 5-10.

Combining the results from the L_{16} and the L_{32}

experimental designs, the following regression models are obtained for TH1 (see Table 5-11).

$$TH1 = -9.10038684 + 0.06075322*Ma + 0.05442733*Mb - 0.14792255*MTTR + 2.21494581*S + 3.05363939*Fa + 1.04025014*Fb - 0.0115154*Ma*Fa \quad (5-19)$$

This model fits well (i.e. $R^2 = 0.802985$). The residual plot shows residuals tend to fall within a horizontal band centered around 0, displaying no systematic tendencies to be positive and negative.

The accuracy of the prediction can be improved by this new metamodel. The low relative prediction errors are realized when the predictions of this new metamodel are compared to simulation results (see Table 5-12). Figure 5-7 compares the TH1 obtained by the simulation model to the TH1 predicted using the metamodel with L_{32} design and the metamodel with L_{32} and L_{16} designs. The average percentage deviation over the nine experiments for validating simulation metamodel is 8.485%. It is suggested that the proposition we recommend is very useful for prediction purposes.

These models suggest: 1) Factors Ma, Mb, Fa, Fb, and S have beneficial effects on the TH1 and TH2, 2) Factor MTTR has a nonbeneficial effect on the TH1 and TH2, and 3) There is a trade-off between Ma and Fa as shown by the negative coefficient. This model can be used to predict the TH1 and TH2 for selecting values of Ma, Mb, Fa, Fb, S, and MTTR as long as they are within their respecting operating ranges. In addition, this metamodel can be integrated in a cost structure to assist the decision maker in determining the maintenance float policy that will satisfy a specified service level.

5.6 Decision Models

Since the aim of this study is to find the optimal combination of standby units and repair persons, the regression metamodels obtained through previous sections are applied in a cost structure to determine this "optimum" combination. The optimization model presented in section 5.1 is restated here.

$$\text{Min} \quad C_s*S + \sum_{i=1}^{Na} C_{FAi}*FAi*m_i + \sum_{j=1}^{Nb} C_{FBj}*FBj*m_j \tag{5-20}$$

$$\text{S.T.} \quad TH_i \geq (\text{Desired Throughput})_i, \qquad i=1,2 \tag{5-21}$$

$$\begin{aligned} TH1 = {} & -10.59875 + 0.0701*Ma + 0.0511225*Mb - \\ & 013941875*MTTR + 2.32441667*S + 3.2715*Fa + \\ & 1.13516667*Fb - 0.01463333*Ma*Fa \end{aligned} \tag{5-22}$$

$$\begin{aligned} TH2 = {} & -14.11502083 + 0.09317743*Ma + 0.06808813*Mb - \\ & 0.18522031*MTTR + 3.08864583*S + 4.337*Fa + \\ & 1.4981875*Fb - 0.0193559*Ma*Fa \end{aligned} \tag{5-23}$$

$$\sum_{i=1}^{Na} m_i = 1 \tag{5-24}$$

$$m_i = 0 \text{ or } 1 \tag{5-25}$$

$$\sum_{j=1}^{Nb} m_j = 1 \tag{5-26}$$

$$m_j = 0 \text{ or } 1 \tag{5-27}$$

S, Fa and Fb $\geq$ 1 and are all integers

C_{FAi}: cost of type i tool for machine A; per unit time.

C_{FBj}: cost of type j tool for machine B; per unit time.

C_s: operation cost of repairman; per unit time.

m_i: the index of type i tool for machine A. If we use the type i tool, then it equals to 1; otherwise, 0.

m_j: the index of type j tool for machine B. If we use the type i tool, then it equals to 1; otherwise, 0.

S: the number of repair persons

FA_i: the number of standby units of type i tool for machine A.

FB_j: the number of standby units of type j tool for machine B.

TH_i: throughput of product i.

Ma: MTBF for machine A.

Mb: MTBF for machine B.

Fa: the number of standby units for machine A.

Fb: the number of standby units for machine B.

MTTR: mean time to repair.

A computer program written in FORTRAN is developed by the author for this cost model (see Appendix A-4). The program, searches through a three dimensional cost surface (i.e. costs of repair persons, cost of floats for machine A, and cost of float for machine B) for the optimum solution. On reaching the optimum, the optimum policy as well as the throughput are generated. The computer program can help operations managers to make an effective decision on maintenance float problems. Figure 5-8 illustrates the optimization algorithm used.

Suppose that we have a maintenance float problem where MTBF for machine A = 120, MTBF for machine B = 100, MTTR = 40, $S \le 3$, F for machine A ≤ 5, F for machine B ≤ 5, the throughput level for type 1 is at least 15, and the throughput level for type 2 is at least 17. The costs are given as C_S = \$100/hr, C_{Fa} = \$90/hr and C_{Fb} = \$90/hr. By using this search program, it is realized that the optimum number of repair persons = 3, the optimum number of standby units for machine A = 5, and the optimum number of standby units for machine B = 3. Furthermore, TH1 = 15.368, TH2 = 20.37 and the total cost per hour is \$1020.

5.7 Results and Discussions

The present case shows that:

1) The effect of factor S is very predominant.
2) Factors Ma, Mb, Fa, Fb and S have proportionally positive effects on the TH1 and TH2.
3) Factor MTTR has a negative effect on the TH1 and TH2.
4) The joint effect of factor Ma and Fa has a negative effect on the TH1 and TH2.

These findings help to better understand the independent factors effects on the throughput of our FMS. To aid in maintenance float decision making for the FMS case, an regression metamodel is constructed (e.g. equations 5-22 and 5-23), based on post-simulation analysis. These metamodels are also integrated in a cost structure to assist the decision maker in determining the maintenance float policy that will satisfy a required throughput level. Again, these results are limited to the range considered in this chapter. Furthermore, operations managers and industrial practitioners may benefit from our finding. For example, a list of factors and interactions might include Fa, Fb, S, Ma, Mb, MTTR, and Ma*Fa for the FMS with exponential failure distribution in practice. As a result, L_{16} design with sixteen runs may be considered under similar circumstances (see Figure 2-3).

CHAPTER 6

CONCLUSIONS, MAJOR FINDINGS AND IMPLICATIONS, RECOMMENDATIONS AND FUTURE RESEARCH

6.1 Conclusions

This paper proposes a new strategic approach to the modeling of maintenance float decisions in a FMC and FMS. This need emerged out of our review of the literature on the areas of maintenance issues in an FMS, maintenance float policy, simulation in manufacturing, regression metamodel, experimental designs, and Taguch design. Our review uncovered the lack of strategic approach in the modeling of FMC and FMS. Procedures to overcome such limitations are therefore presented.

Physical production systems such as FMC and FMS are subject to breakdown. In order to maintain and improve the reliability of such advanced production systems, and consequently increase competitiveness, improve quality, and flexibility, certain maintenance actions must be taken. In this study we consider advanced manufacturing systems with two major maintenance actions: standby units provision and repair crews. These maintenance actions - maintenance float policy - are intended to reduce the severity of failures and improve the reliability of the system. The use of a maintenance float policy ensures that the advanced manufacturing system operates without interruption. In addition, they are easy to implement.

Due to some of the restricting assumptions often made by analytic models, they are of limited use in terms of practical applications. Simulation is therefore, a preferred alternative to solve complex advanced manufacturing system problems. However, the design, analysis and interpretation of simulation experiments generally require a good statistics background. This has often inhibited the application of simulation. In spite of these limitations, a simple but yet effective technique is required to enhance the use of simulation models. The Taguchi method offers a simple and an effective approach to apply simulation to real life problems.

Thus, Taguchi's method is applied in this study, in developing a strategic approach to maintenance float decision-making for the FMC and the FMS. This approach uses the Taguchi design in the simulation development stage and also in post-simulation analysis. From this experimental design, appropriate predictor models are developed for dependent variables of interest. These models are often referred to as metamodels. These models are subsequently utilized in a cost model to determine the optimum maintenance float policy that will satisfy a specified service level.

Some of the advantages of the strategic approach proposed here are: (1) It provides timely and accurate decisions to the decision maker. This enhances the decision maker's ability to respond to his dynamic market conditions. (2) It reduces the cost of running simulation. These saving are very crucial to American businesses in order to improve their productivity and competitiveness. (3) Even though these metamodels may be limited by the narrow ranges specified for the controllable variables, however, the growing application of simulation to manufacturing problems and the shift towards the development of PC simulation programs will lead to the development of custom made models. Due to the ease in using Taguchi's design, practitioners will be able to develop efficient models that accurately reflect their problem situations. (4) To reiterate, the metamodels provide accurate results within the specified ranges for the controllable variables. For example, the relative prediction error was found to be within 5 % for the FMC and within 10% for the FMS. This is a strong advantage over the analytic methods that impose limiting constraints since such constraints are unnecessary with the use of simulation. Furthermore, it should be pointed out that in some problems, analytical solutions may not be feasible. Thus, the extension of simulation results to the development of metamodels offers general solutions within the defined boundaries. This is also more superior to the use of simulation alone.

Finally, like the experimental design of products and production processes in the manufacturing industries, simulation experiments should be planned and executed in an organized and scientific manner so as to ensure economically feasible and satisfactory solutions. This paper describes such a strategic approach for the maintenance float decision models. After a simulated model is verified (or debugged) and validated, the use of this strategic approach can be thought of as being composed of three parts: design, analysis, and decision. In the design phase, Taguchi experimental design is used to generate the input variables into the simulation program. In the analysis phase, outputs are analyzed using Taguchi's ANOVA procedure. Input variables found significant are subsequently applied in a regression model. Predictor models for EU are developed and their validity tested. In the decision phase, cost oriented decision models are further developed to show the applicability of our model to decision situations. Thus, the design, analysis and decision phases of a simulation study must be done hand in hand.

6.2 Major Findings and Implications

Essentially, simulation models provide specific results to a particular problem. They are not easily generalized, and there are often problems in determining the optimum input values. In this study, we overcome some of these limitations by first identifying the appropriate input values for the major independent (controllable) variables. Secondly, we extend the applicability of the simulation results by defining meaningful boundaries. However, the definition of boundaries for the variables of interest depends on the user or operations manager and his knowledge of the problem. Thirdly, we construct metamodels for the dependent variables. The construction of metamodels may often require a large number of simulation runs especially when techniques such as full factorial designs are followed. This becomes cumbersomme and unnecessarily tedious when large number of factors are to be considered as independent variables. Although fractional designs offer more economical approach, researchers have seldom utilized them. This is mainly due to the high risks associated with their use. However, Taguchi's design approach is conceptually sound, easy to learn, and implement. Moreover, Taguchi has developed a family of fractional factorial designs that reqire minimal technical sophistication on the part of the user. Despite the fact that this technique is very useful, applications have concentrated in the quality control area. We have explored in details the Taguchi design approach and have demonstrated that it can be effectively applied to advanced production systems. To further enhance its application since it is relatively new, we have proposed a step-by-step approach in chapter 3 to assist operations managers in reaching more pragmatic decisions.

In summary, our approach consists of the following steps.

<u>Step 1</u> Problem Definition and Formulation

<u>Step 2</u> Simulation Model

- Model construction
- Model verification and validation

<u>Step 3</u> Metamodel

<u>Step 4</u> Taguchi Method

- Setting appropriate levels.
- Design the experiment according to an appropriate orthogonal array and linear graph.
- Make simulation runs for each experimental design point. At each design point, an appropriate replication (i.e. using different random number seeds) should be chosen.
- Evaluate the main effects and two-factor interactions by Taguchi algorithm.
- Choose additional runs if necessary.
- Interpret the result

<u>Step 5</u> Regression Analysis and Metamodel Validation

<u>Step 6</u> Decision Models

Furthermore, we compare three experimental designs that are most often used in the literature. This is discussed in chapter 3. Taguchi design is found to be the most appropriate for this research in terms of the small number of runs, ease of implementation, flexibility of the design, desired confounding pattern, and ease of analysis.

As we discussed in chapter 3, the total design points in the full factorial is the product of the number of levels for each factor. For instance, 2^3 design (with this design, there are 3 factors, and each factor at two levels) requires 2*2*2=8 design points. When only a few factors are to be investigated, a full factorial design is acceptable. When large number of factors are to be considered, operations managers and industrial practitioners need efficient (i.e. economical) test strategies such as fractional factorial designs. The following table shows a comparison of number of runs needed for 2-level designs with different resolutions. Resolution indicates the clarity of which individual factors and interactions may be seen (evaluated) in an experiment (Ross, 1988).

A comparison of number of runs needed for 2-level designs with different resolutions

Number of Factors	Orthogonal Array			Fractional Factorial Design			Full Factorial Design
	Resolution levels			Resolution levels			
	III	IV	V	III	IV	V	
3	L_4	-	-	4	-	-	8
4	-	L_8	-	-	8	-	16
5-7	L_8	-	-	8	-	-	32-128
5	-	-	L_{16}	-	-	16	32
6-8	-	L_{16}	-	-	16	-	64-256
9-15*	L_{16}	-	-	16	-	-	512-32768
6	-	-	L_{32}	-	-	-	64
7-16*	-	L_{32}	-	-	32	-	128-65536
17*-31*	L_{32}	-	-	-	-	-	$131072-2.1474*10^9$

* : the highest number of factors of Fractional Factorial Designs in Box et al. [1987] is 11.

- : not available

It is observed that greater savings on the numbere of simulation runs are possible with the use of larger orthogonal arrays (e.g. L_{16}, L_{32}) or fractional factorial designs.

A major part of Taguchi's concept is that some higher-order interactions can often be safely ignored based on prior knowledge of a particular problem. Therefore, the fractional factorial design is sufficient to conduct the experiment. The graphical techniques such as Taguchi's linear graph can easily be understood and implemented by practitioners having only a limited knowledge of statistics and experimental design. In Box et al. [1978] or other experimental design textbooks, the most common designs are 2^k, 2^{k-p}, 3^k, and 3^{k-p}. However, Taguchi's design can easily be extended to four, eight, and nine levels design. Moreover, mixed factor level designs and their linear graphs are also available. Finally, Taguchi's algorithm for constructing the ANOVA table is very easy to use. Thus, Taguchi methods of design are often superior to the Box and Hunter's factional factorial designs.

In many situations, operations managers' objective is to conduct "what if" analysis on the system performaces of interest. Their chances of successfully doing so will be increased if they can identify the controllable factors that affect the system performances, and the extent to which the system performances are dependent upon each factor. The use of ANOVA enables the operations manager to assess the degree of significance of each of the controllable factors. Thus, the operations manager can focus on the most important factors. As illustrated in the Tables 4-2, 4-14, 4-15, 5-2, and 5-9, the "error message" as the heading for some columns indicates that not every degree of freedom will be used for estimating effects. In other words, they can be used to estimate the error variance. In addition, Taguuchi approach makes it possible to pool the less significant terms as the error variance. Taguchi recommends that almost half of the degrees of freedom 'small' sources should be used for the estimation of the error variance. The underlying principle is that a factor found significant after this is done, is indeed significant.

Thus, the use of Taguchi design as illustrated in chapter 4 and 5, facilitates the construction of metamodel by requiring only limited simulation runs. Based on the metamodel form, L_{16} design is used in the chapter 4. This design is the one that have been used the most often in industry [Ryan, 1989]. In addition, the resultant design has resolution V. With resolution V design, both main effects and two-factor factors can be estimated. Based on the proposed metamodel form, L_{32} design is selected in the chapter 5.

For the FMC (exponential case) presented in chapter 4, we found that MTBF, F, S, MTTR, MTBF*S and S*R are the significant factors that influence EU. In the Erlang-2 case and the gamma case with shape parameter 0.5 and scale parameter 1, the significant factors are: MTBF, F, S, MTTR, MTBF*S, and MTBF*MTTR. In chapter 5, for the FMS case, we found that the significant factors that influence the TH are Ma, Mb, MTTR, S, Fa, Fb and Ma*Fa. Moreover, the part type sequence plan shows no effect on the TH in this particular FMS.

We have created metamodels in chapters 4 and 5, using the data that was obtained from the experimental runs of the simulation. For the FMC, it is observed that MTBF, F, and S have direct linear relationships with EU while MTTR and S*MTBF have inverse linear relationships with EU. Furthermore, S*MTTR and MTBF*MTTR have direct linear relationships with EU in the exponential, and the Erlang-2 and gamma cases, respectively. Similar conclusions are also derived for the FMS case. For example, Ma, Mb, S, Fa, and Fb have direct linear relationships with TH while MTTR and Ma*Fa have inverse linear relationships with TH. These findings suggest that maintenance float policy does have positive impact on the FMC and the FMS. The prediction equation could also be used for descriptive purposes. With $a_2 = 0.04475$, in Eq. (4-8), we can state that, on the average, there is approximately a increase of 0.04475 on EU for every additional standby unit used.

Chapter 5 further illustrates the need to conduct a follow-up experiment for highly significant factors. To summarize what we have learned, it would be judicious to first use a two-level design with a large number of factors (we considered seven factors in the initial stage) for the purpose of screening out factors that seem not to be significant. A follow-up experiment could then be conducted. This requires that more levels be created for such factors in order to increase the prediction power of the metamodel. In addition, a search program for optimum solutions of maintenance float policy is developed in this chapter. A numerical example is also presented.

As an FMS goes through its life cycle, maintenance problems become critical. To keep these FMSs in operational status, appropriate maintenance decisions should be made in every stage of the FMSs' life cycle. Through the use of the strategic approach introduced here, quality decisions can be made in a relatively short time period. Furthermore, sensitivity analysis can also be carried out on the regression metamodels. Thus, information on how the throughput varies with changes in any of the controllable factors is easily obtained. For example, variations in the vendor's specifications are easily estimated using the models. In addition, these models are quite useful at the early stages of FMSs. They can be used for evaluation and/or implementation purposes.

This study may serve as a guide or a reference source for operations managers and industrial practitioners involved in the design and planning of advanced manufacturing systems. As a strategic weapon, the effective management of time is equivalent to cost reduction, improved productivity, improved quality, increased flexibility, and even increased innovation.

Japanese companies such as Nippon Denso, a Toyota affiliate, have long used Taguchi's method to improve their competitiveness. Their enhanced competitiveness is as a result of drastic savings in experimental time, reduced cost of product development, and quality improvement. Western operations managers and industrial practitioners can also improve their productivity, and enhance their competitive position if they use Taguchi' method. And Taguchi's method is the heart of what our strategic approach is.

In our opinion, the present research has made the following contributions to existing body of knowledge.

1. A new strategic approach has been developed to deal with decision making in maintenance float models.
2 Regression maintenance float metamodels have been constructed to aid in the interpretation and generalization of maintenance float simulation models.
3. Taguchi design has been applied and integrated successfully in the FMC and FMS simulation experiments.
4. ANOVA technique has been used to identify the main

effects and interaction effects of controllable factors on the machine utilization in the FMC and on the throughput in the FMS.

5. In addition, the development of this methodology allows us to predict the performance of very complex manufacturing systems and to minimize the expected total system cost per unit time.

6.3 Future Research

There are many potential extensions of the research presented in this paper.

1. A useful extension would be to apply this approach to other advanced manufacturing systems such as automated transfer lines, robot system, AGV system, flexible transfer multi-line systems, automated assembly systems, automated storage systems and automated inspection systems.
2. A flexible manufacturing cell and FMS can be directly extended to multiple components failure problems. Therefore, multiple types of spares are needed to maintain the system's operation.
3. Tool sharing system will also affect the optimal allocation of spares. If a centralized tool sharing system is available, all the spare tools will be kept in the central tool crib and are sent to a particular machine location when needed. The trade-off between this tool storage policy and the number of optimal spare tools is also an interesting topic to study.
4. Our approach can also be applied to other operations management areas such as quality control, inventory control, and scheduling problems.
5. Finally, an investigation of the impacts of different maintenance actions such as the buffer size, preventive

maintenance, repair service, and maintenance float on the advanced manufacturing systems which are subject to failure is also a direction for future research.

Figure 1 - 1 Maintenance Float System

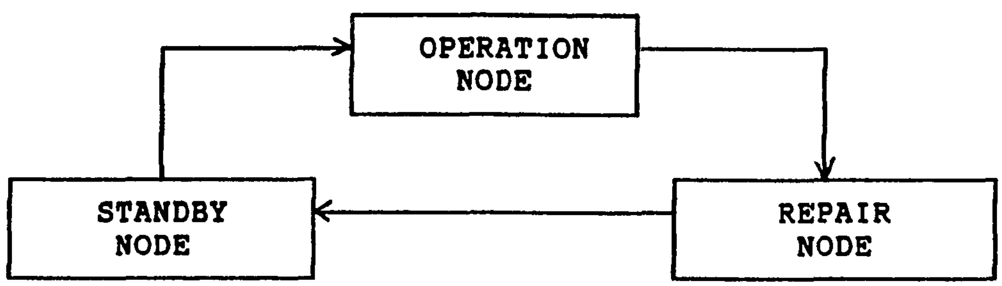


FIGURE 1 - 2 Flexible Manufacturing Cell with Tool Failures

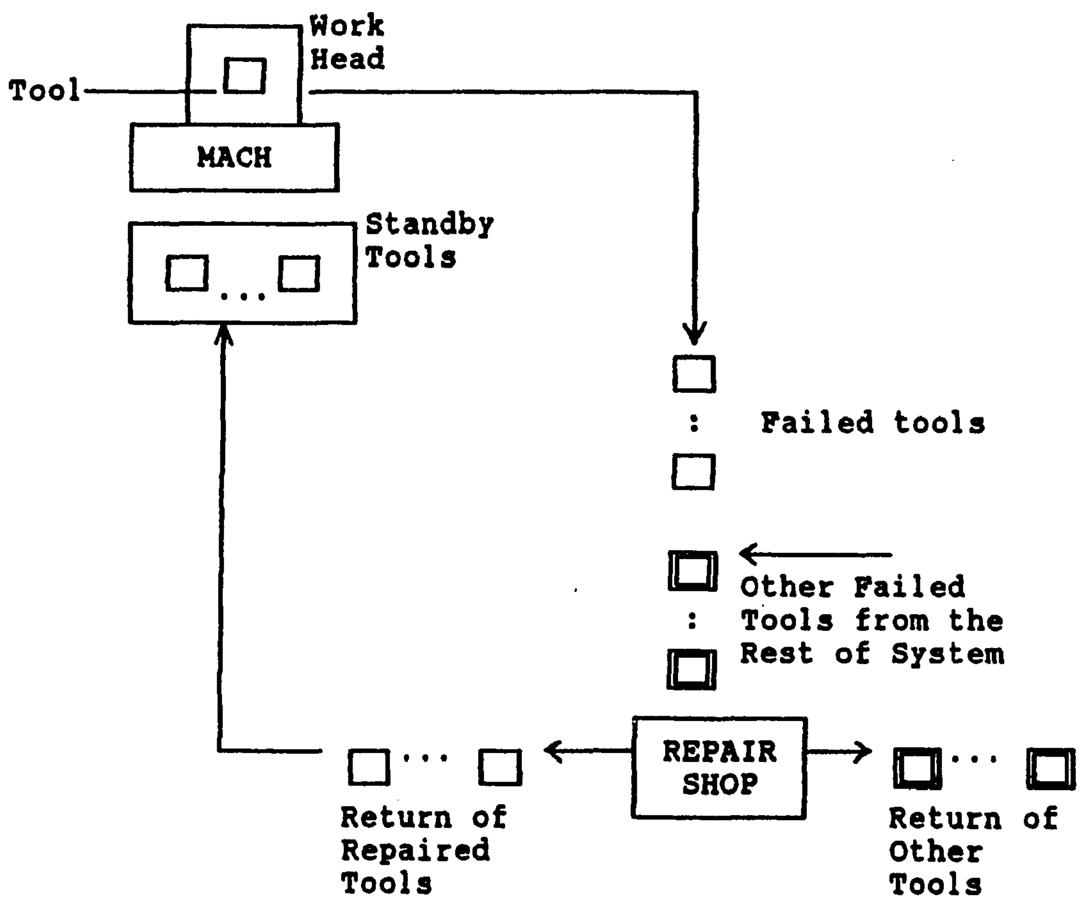


FIGURE 1 - 3 Maintenance Float Policy for an FMS

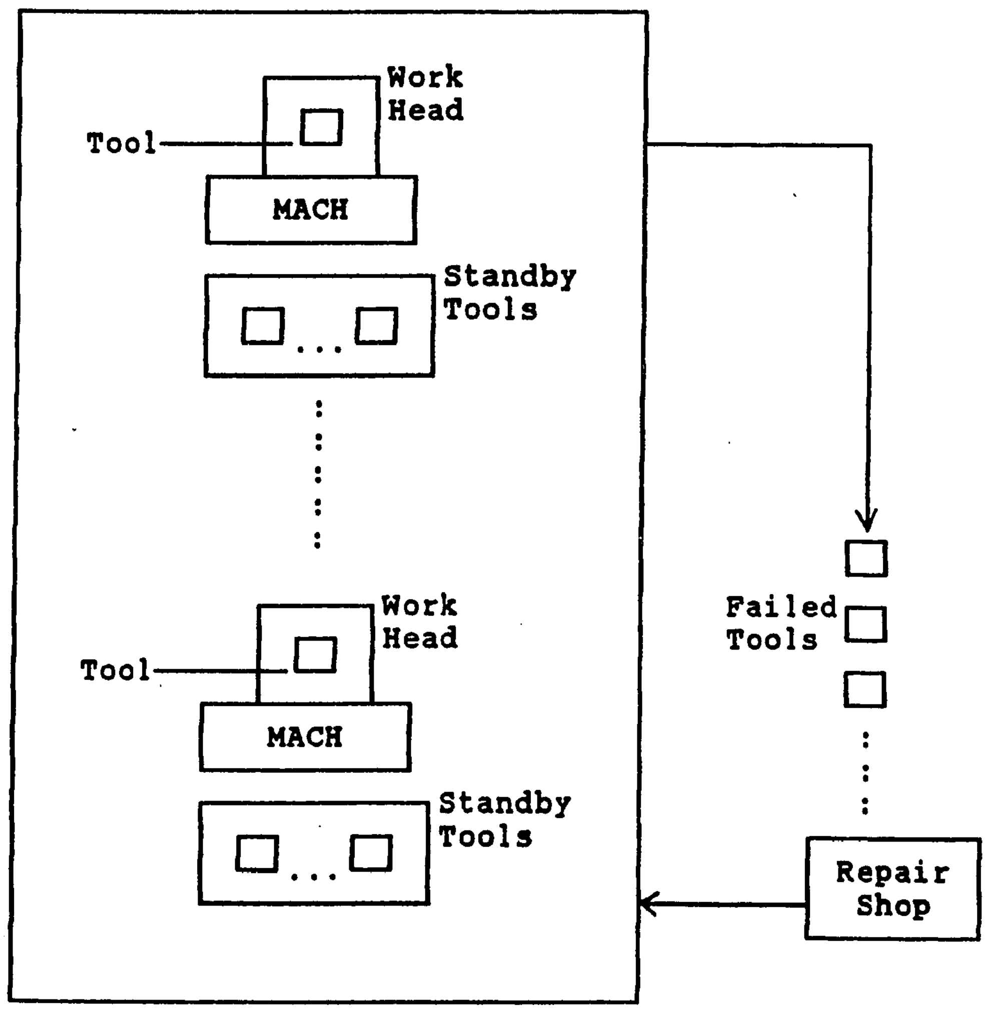


FIGURE 1 - 4 Physical Layout of the Hypothetical FMS

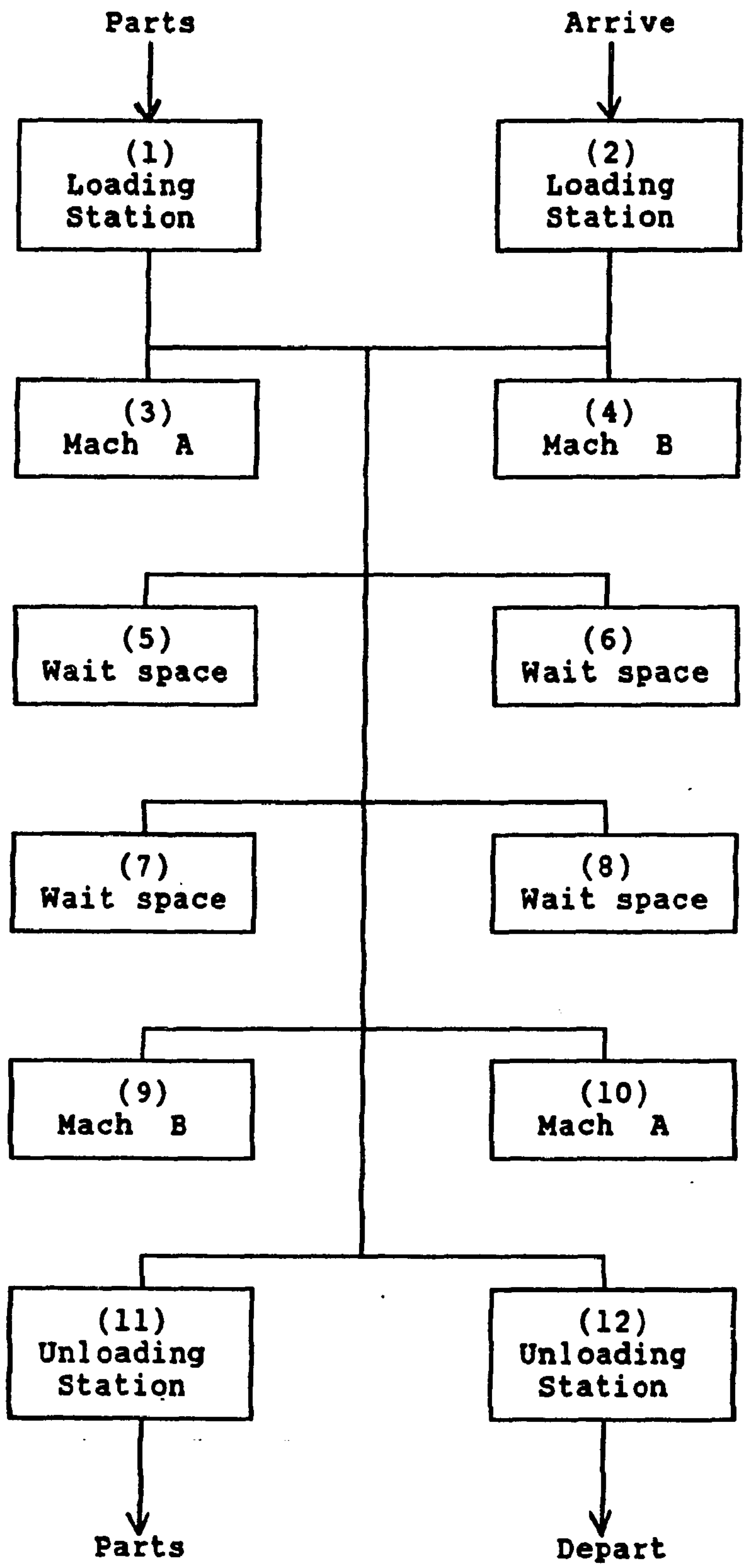


Figure 1 - 5 A Strategic Approach for the Maintenance Float Decision Models

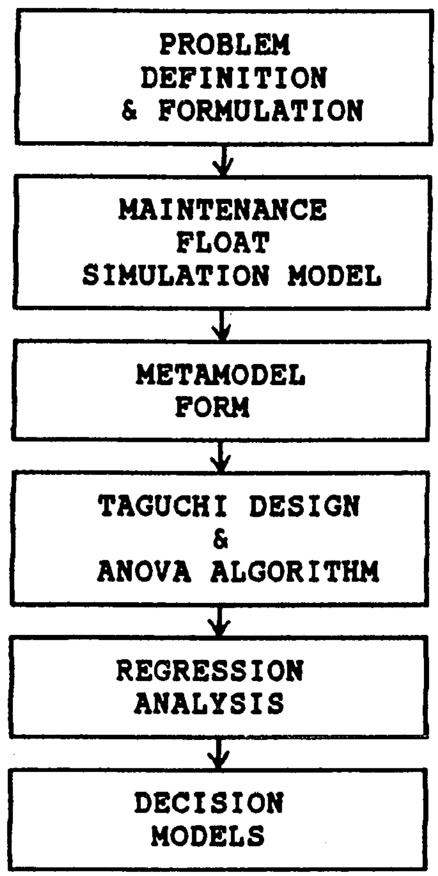
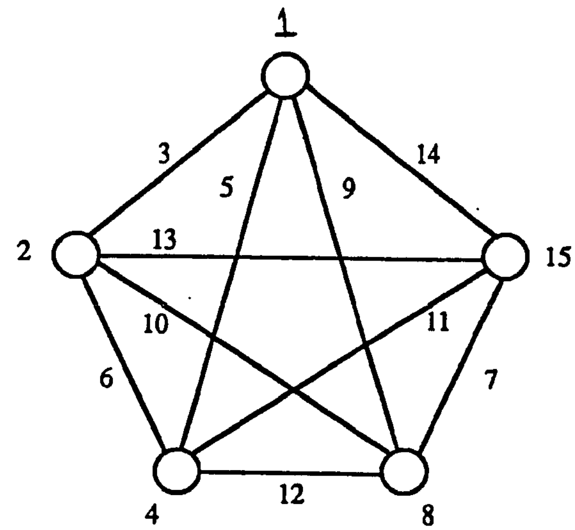
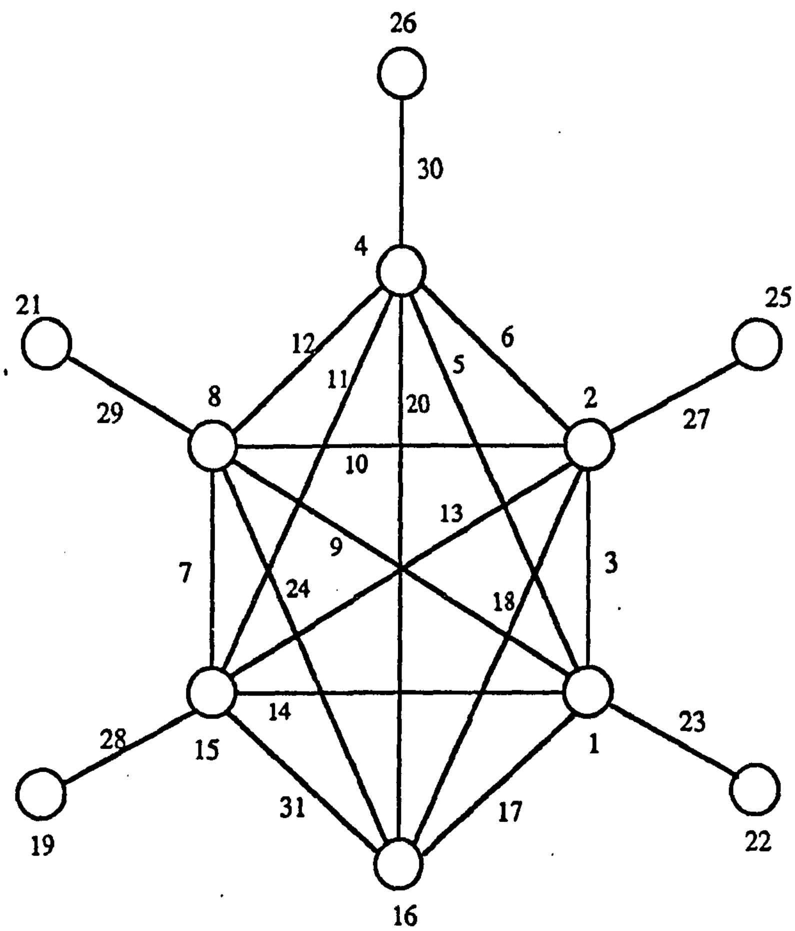


Figure 2-1 Linear Graph of L_{16} (2^{15}) orthogonal arrary



Source: Taguchi and Wu (1980)

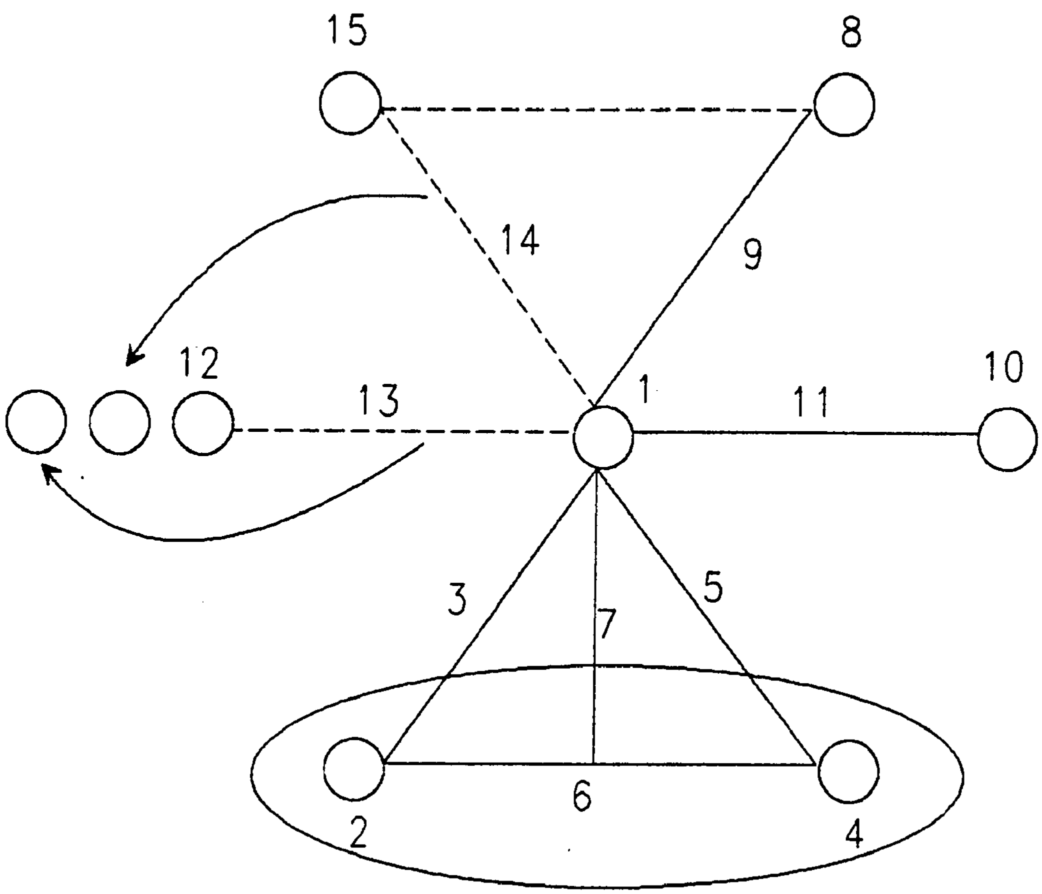
Figure 2-2 Linear Graph of L_{32} (2^{31}) Orthogonal Array



Source: Taguchi and Wu (1980)

Figure 2–3 Linear Graph of

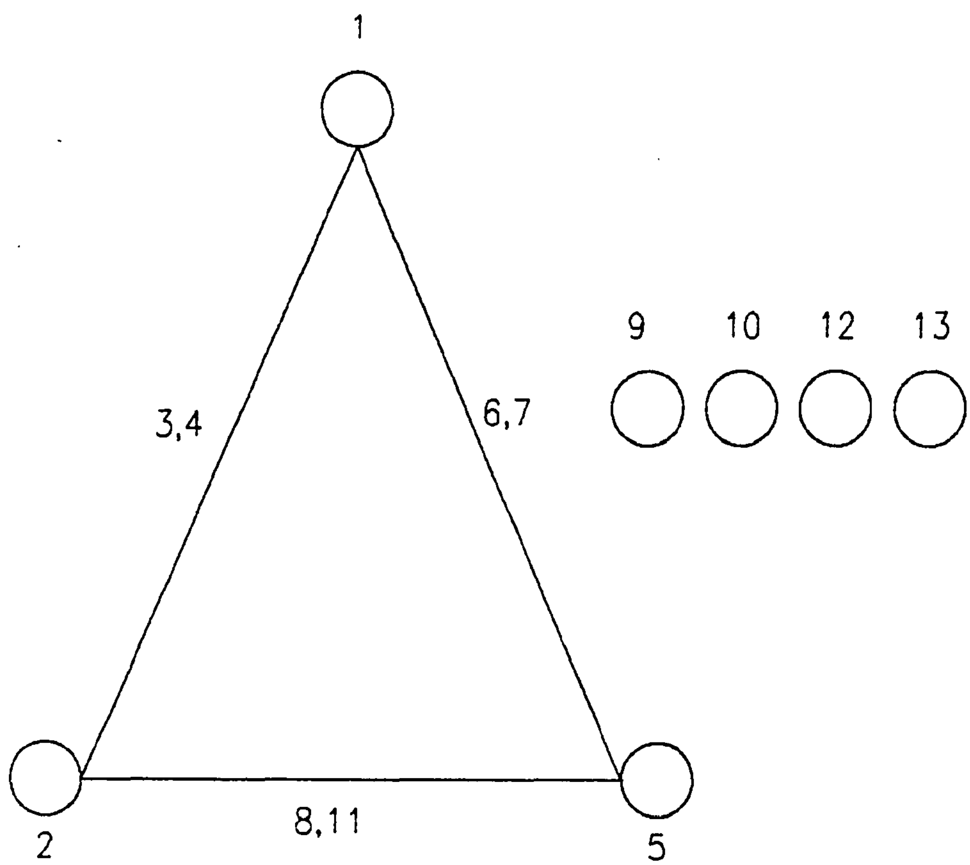
$L_{16}(4 * 2^{7})$ Orthogonal Array



Source: Wu [1976]

Figure 2-4 Linear Graph of

$L_{27}(3^{13})$ Orthogonal Array



Source: Taguchi and Wu [1980]

Figure 2-5 A Summary of Major Contributors

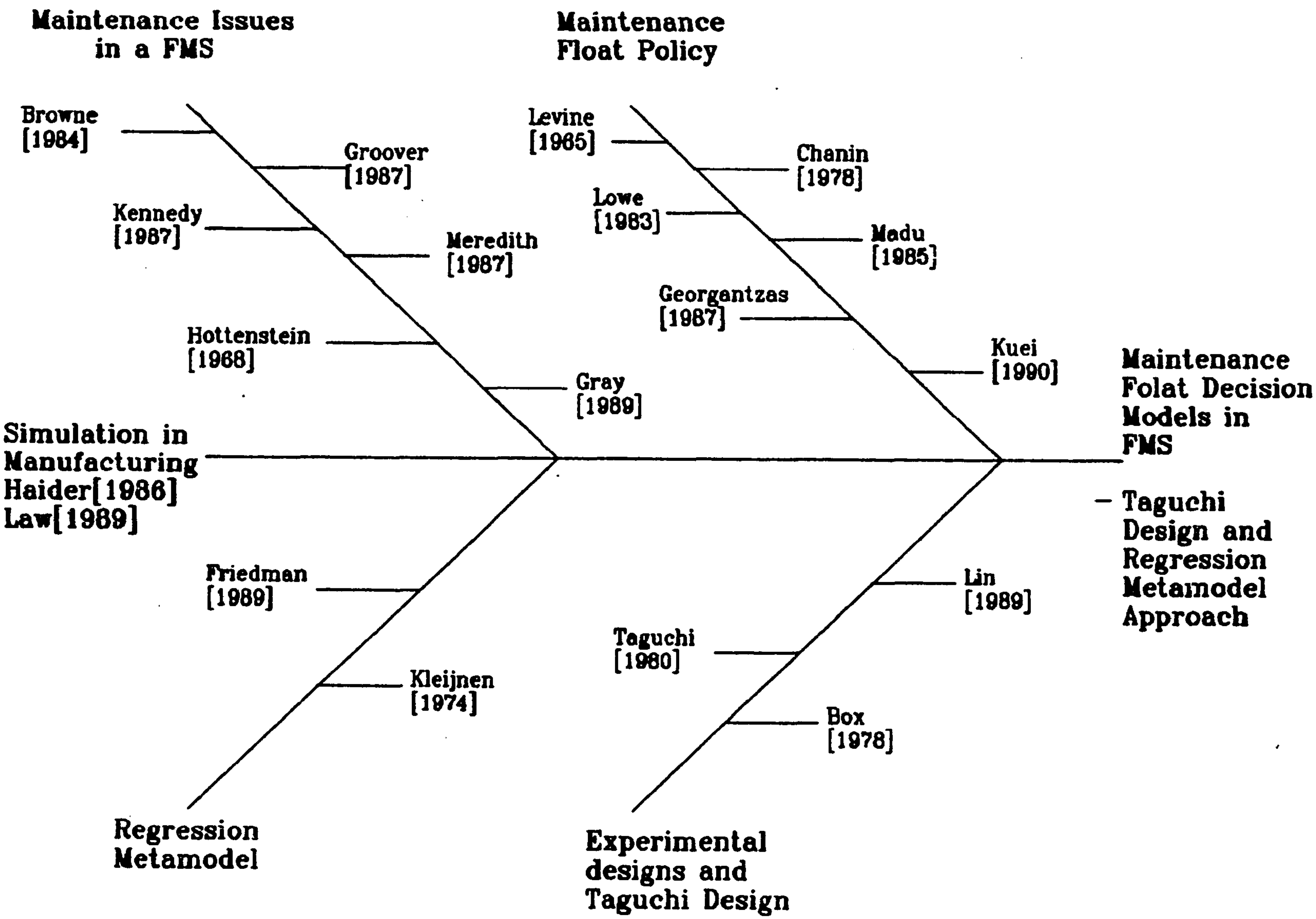
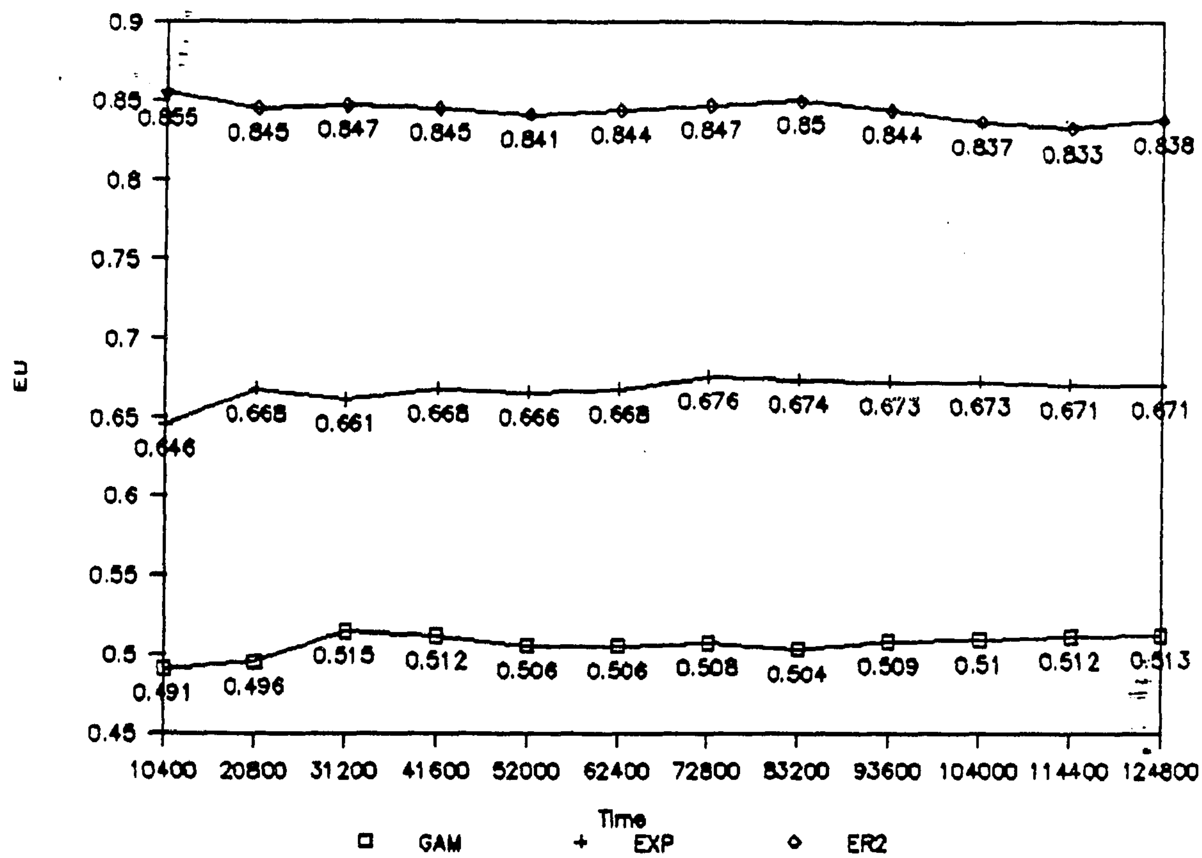


Figure 4—1 EVALUATION OF STEADY STATE



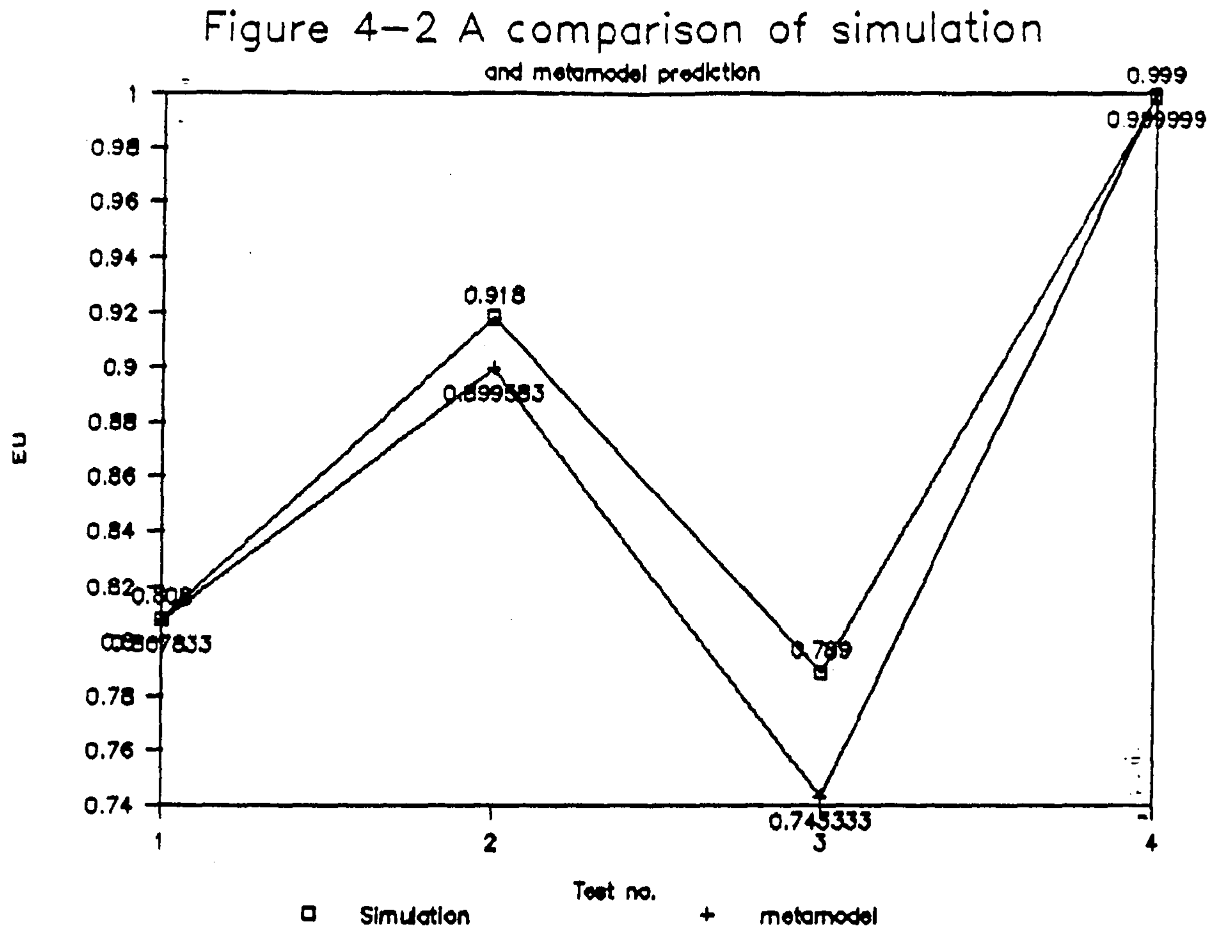


Figure 4-2 A comparison of simulation
and metamodel prediction
EU
Test no.
Simulation
metamodel
0.918
0.899583
0.789
0.743333
0.999
0.999999
1
2
3
4
0.74
0.76
0.78
0.82
0.84
0.86
0.88
0.9
0.92
0.94
0.96
0.98

Figure 4-3 EFFECT OF F

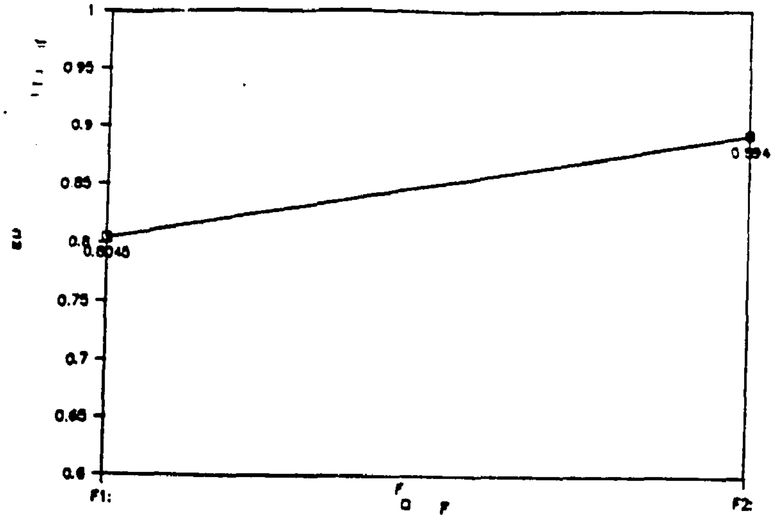


Figure 4-4 EFFECT OF S AND MTBF

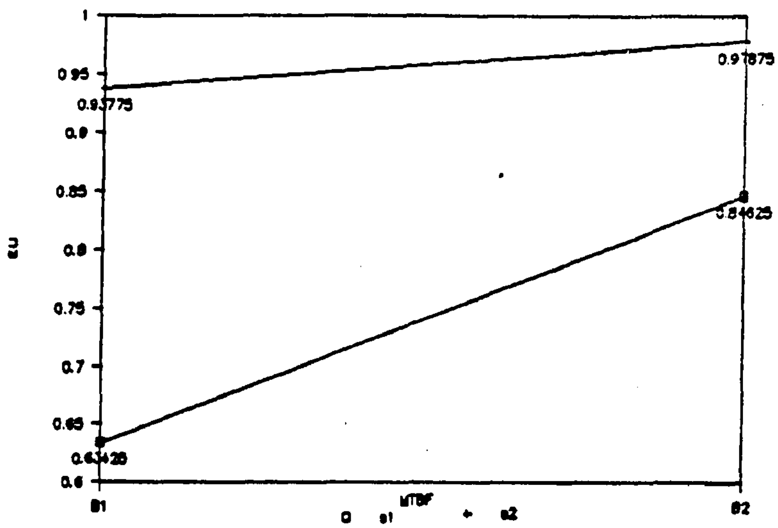


Figure 4-5 EFFECT OF S AND MTTR

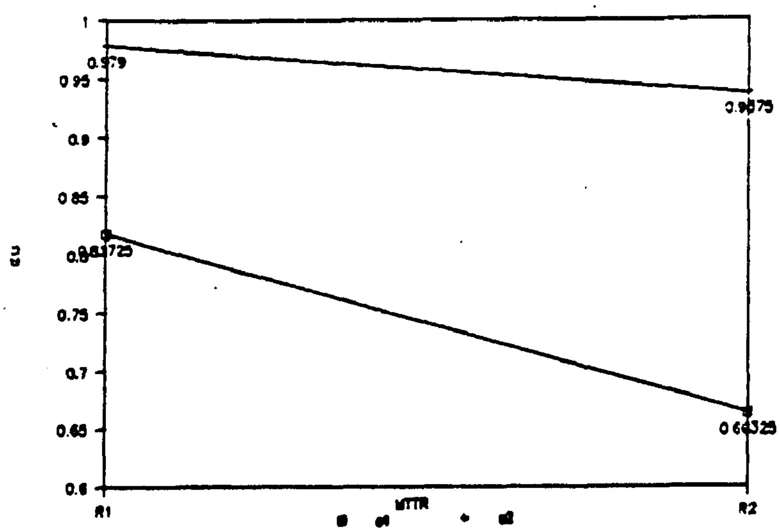


Figure 4-6 Linear graph of L_8 (2^7) orthogonal array (Exponential case)

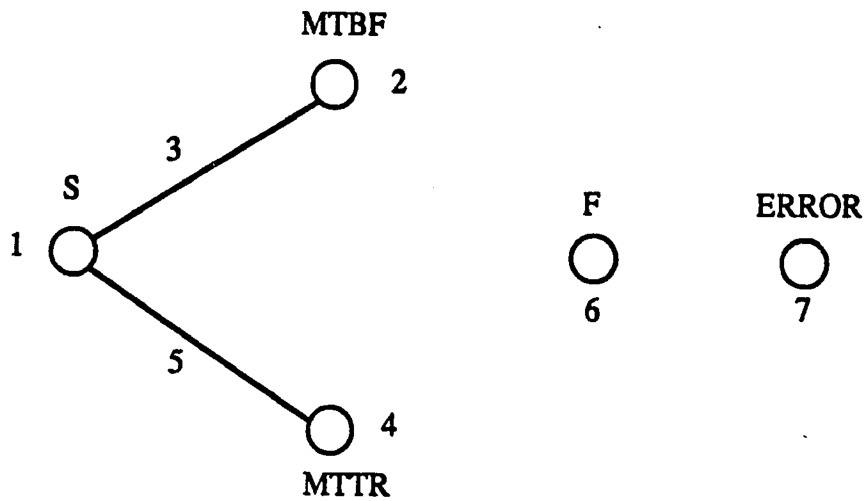


Figure 4-7 Linear graph of L_8 (2^7) orthogonal array (Erlang-2, Gamma cases)

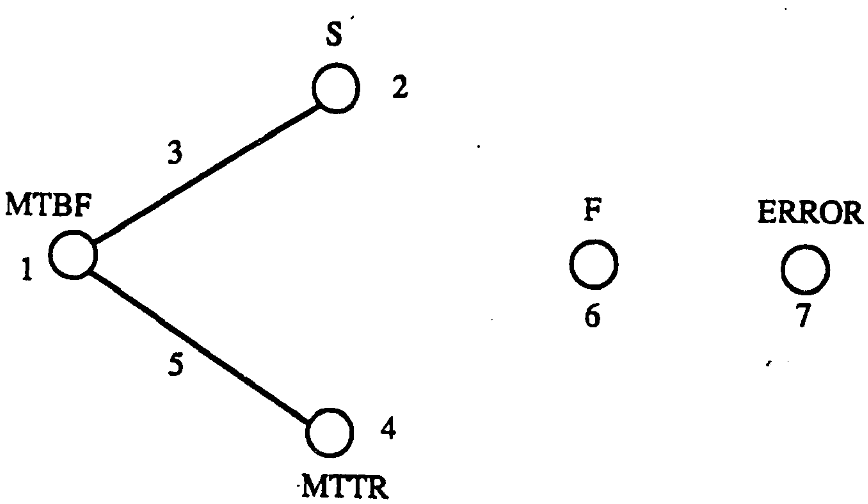


Figure 5-1 Steady state for an FMS

simulation model

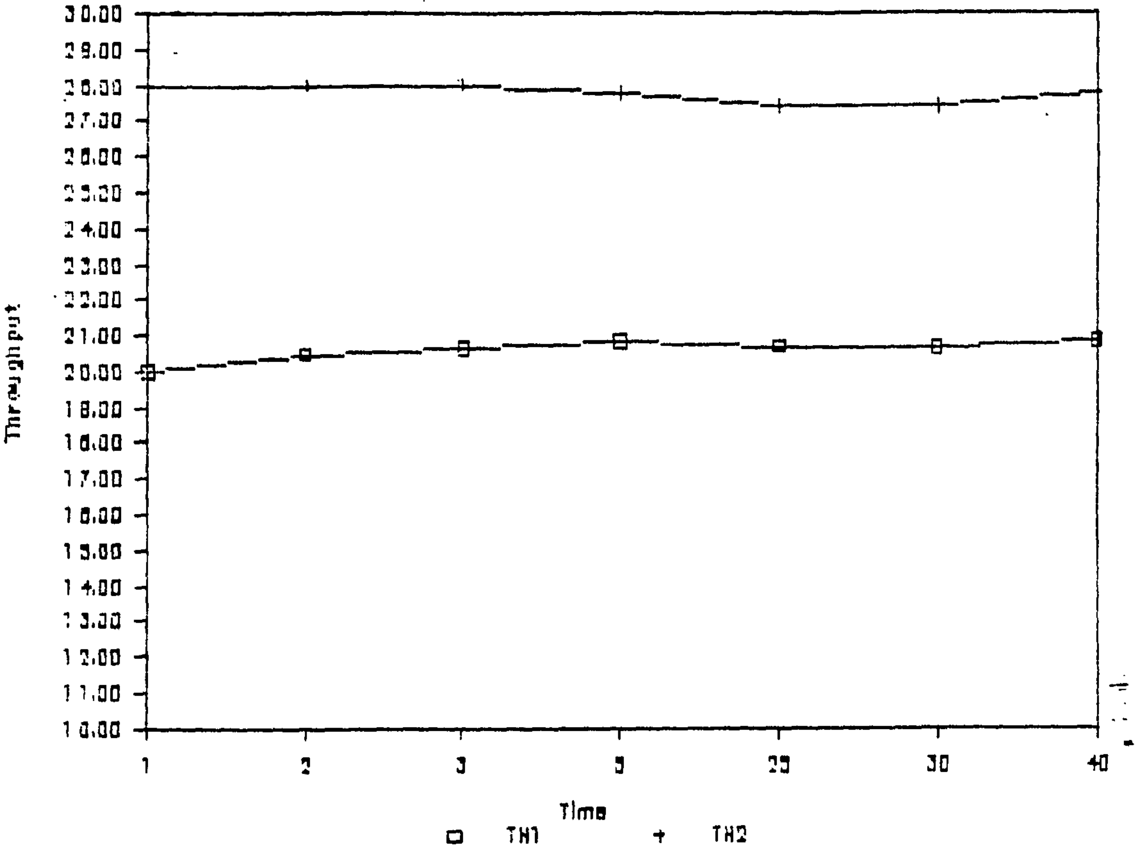


Figure 5-2 EFFECT OF MTTR

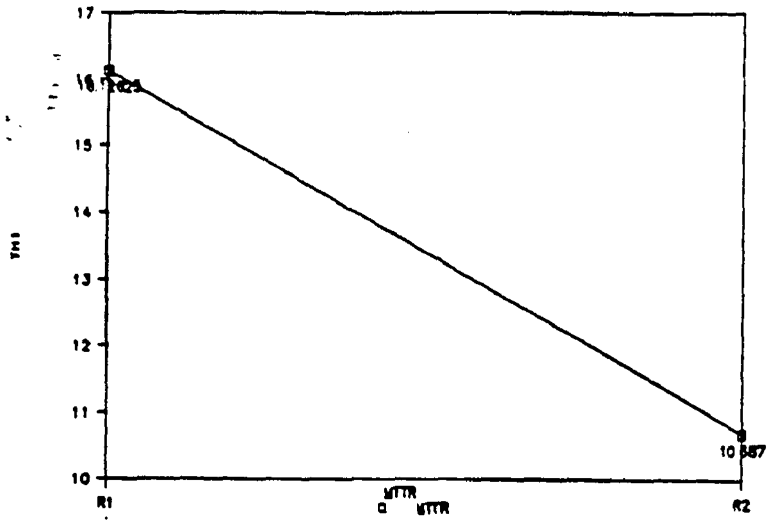


Figure 5-3 EFFECT OF S

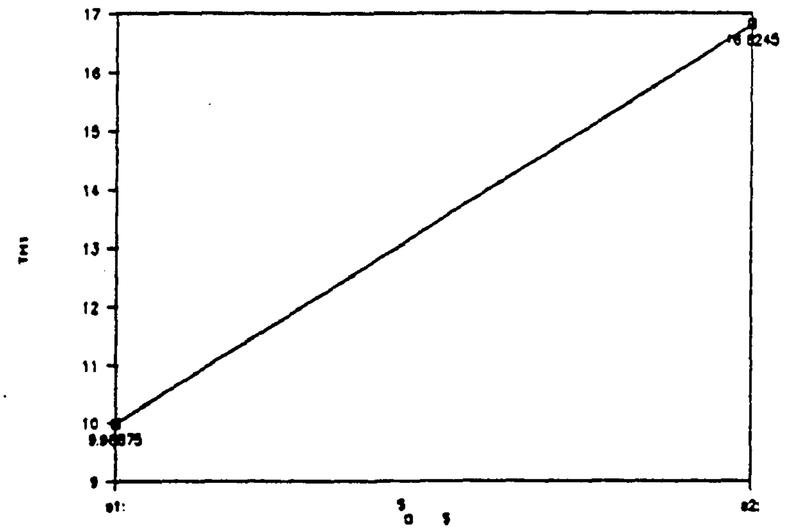


Figure 5-4 EFFECT OF Fb

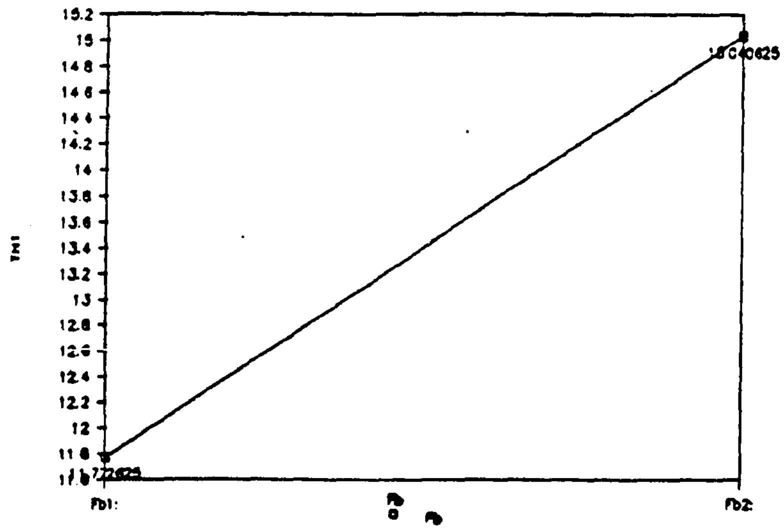


Figure 5–5 EFFECT OF Mb

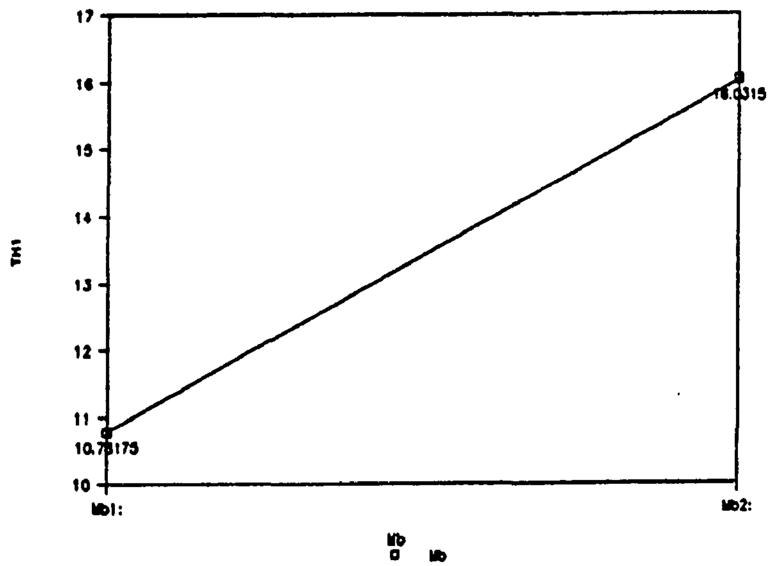


Figure 5–6 EFFECT OF Ma AND Fa

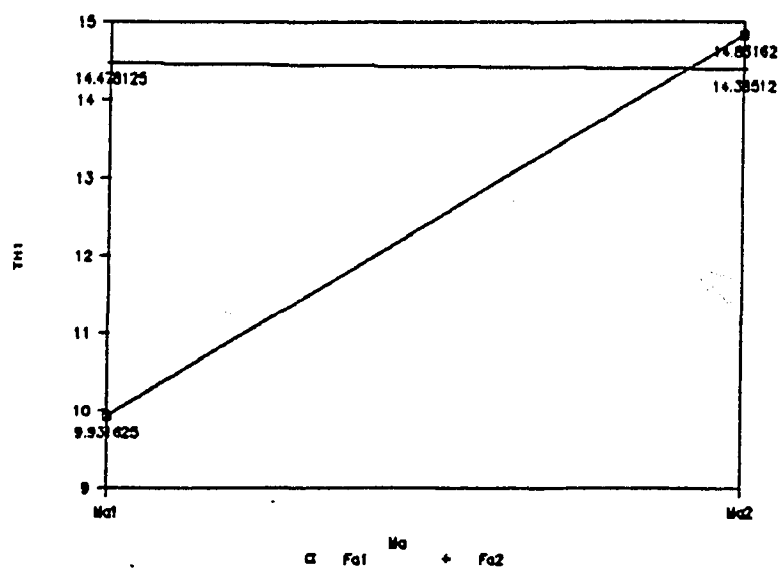


Figure 5-7 A comparison of simulation
and metamodel prediction

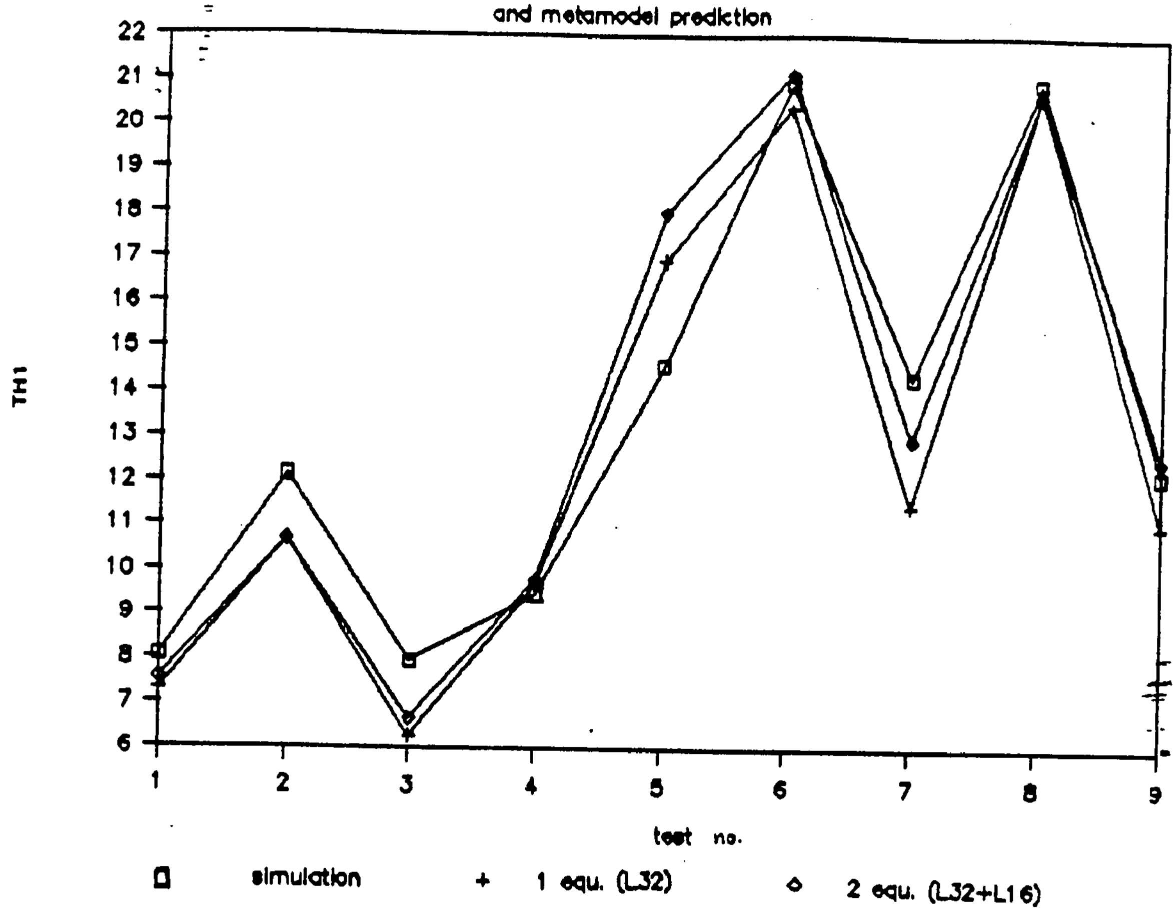


Figure 5-8 Flow Chart for the Search Program

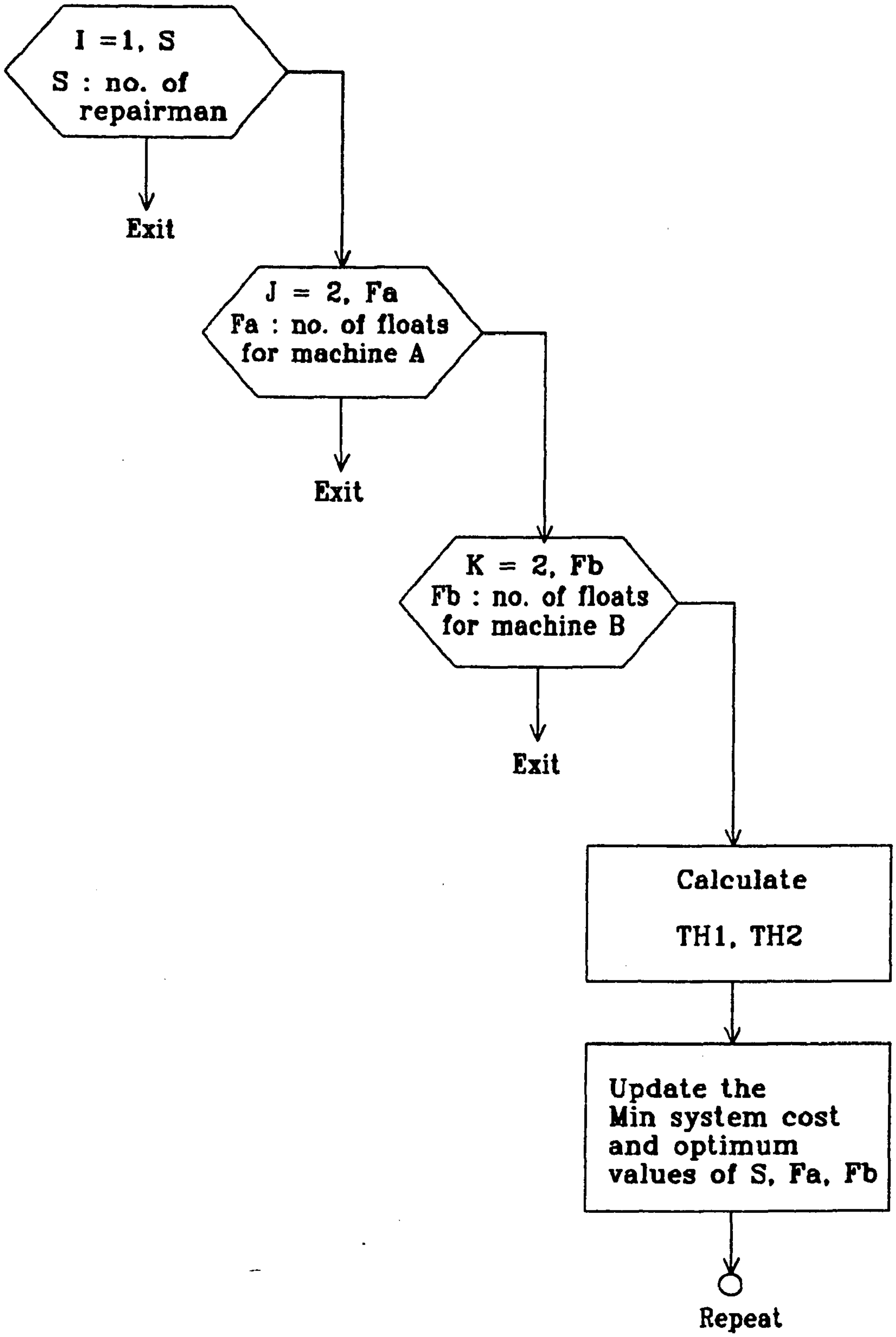


Table 1-1 Definition of Flexibility

1) Machine flexibility: is defined as the ease of change to process a given set of part types.
2) Process flexibility: is defined as the ability to produce a given set of part types.
3) Product flexibility: is defined as the ability to change to process new part types.
4) Routing flexibility: is defined as the ability to process a given set of parts on alternative machines.
5) Volume flexibility: is defined as the ability to operate profitably at varying overall levels.
6) Expansion flexibility: is defined as the ability to easily add capability and capacity.
7) Operation flexibility: is defined as the ability to interchange ordering of operations on a part.
8) Production flexibility: is defined as the universe of part types that can be processed.

Source: Browne [1984]

Table 2-1 Case Studies of Simulation Applications in FMSs

Author(year)	Company	Software	Results
Redmond(1983)	FMC Co.	-	Selection FMS Configuration
Akella et al.	IBM	-	Performance of scheduling policy
Carrie(1986)	Scottish Eng.	MAST	Design/performance predictions
Godziela(1986)	Garrett Turbine	SLAM	Machine & fixture utilization
Mills(1986)	McDonnell Douglas	Manuplan	Reduction in space requirement
Wang (1986)	Intel	PCModel	AGV loading quantity
Bookbinder et al.(1987)	General Motors	SIMAN	The minimum no. of AGVs.
Chisman(1987)	Apple Computer	GPSS	Identify production problem
Gaalman et al. (1987)	DAF	PASCAL	Machine waiting time for a required tool
Knoner(1987)	Siemens	GPSS, FORTRAN	System design and optimization
Higdon(1988)	J. B. Webb Co.	GPSS/H	Design material handling system
Brown(1989)	IBM	SLAM II	Design a factory of future
Tatikonda et al.(1989)	B.O.C. Group	SIMAN	Capacity determina tion.
Fry et al. (1989)	FMC	-	Maximize the Utili. of machine centers.
Chisman(1989)	Apple Computer	GPSS	The performance of the flexible PCB line
Kiran et al. (1989)	General Dynamics	SIMAN	The performance of the final design.

Table 2-2 Summary of major applications of metamodel, experimental design and decision model

Author(Year)	Simulation Model	System performance	Significant Factors	Note
Blanning(1975)	Inventory	Service	Buffer-stock	F.D.
Week et al. (1977)	Job Shop	MJF, MJL, MJE, MJD, LT	LA, DR, DD	F.D.
Kleijnen(1979)	Container	TH	Containers storage	2^{6-2}
Stecke(1982)	MIP	NS	SS, EE, WW	F.D.
Friedman(1984)	M/M/1	L, W, SU	λ, μ	F.D.
Alholou(1986)	Network	PE	NP, MM, PR	F.D.
Wang(1986)	FMS	TH	D, Cart size Configuration	F.D.
Cheng(1987)	MRP	CP	OWC, PDP	F.D.
Diesch(1987)	FMS	S. E.	M/C B.	F.D.
Hira et al. (1987)	Flow Line	EL	N, B, CV	F.D. *
Marks(1987)	Assem.Line	TH	N, P, B, MTTR, MTBF	F.D.
Friedman(1988)	M/M/S	W	λ, μ, S	F.D.
	CPU	T	N terminals, μ Actual P	
	Inventory	TC	D, Review period Target inventory	
Kleijnen(1988)	FMS	TH	Flexible machine one dedicated machine	2^{4-1}
Winters(1988)	FMS	TH	Product mix Assembly time	F.D.
Acacio(1989)	CPU	Delay	NU, RP, μ	3^3
Friedman(1989)	M/M/S	L, W, SU	λ, μ, S	F.D.
	CPU	T, SU, P	N terminals, μ Actual P	
Lin(1989)	Flow Line	TH	N, P, MTTR, MTBF	L_{16} *
Madu et al. (1989)	MFS	EU, W, SU	F, S, CV, N, R MTTR	F.D. *
Shaikh(1989)	Comm-Net	TH, Delay Survi.	LC, PPN, Load, PNL	2^{5-1}
Shang(1989)	Assem.Line	TH	λ, MTBF, MTTR Lot size, Paste-life Line balance	F.D.
Madu et al. (1989)	MFS	EU	F, S, CV, N, R	2^{5-1} * 3^{5-1}
Kuei et al. (1990)	MFS	EU	F, S, N, MTTR	L_{16} *
Madu(1990)	MFS	EU	F, S, R	2^3 *
Sridharan(1990)	MPS	Cost, Sta	LSM, TI, FP, PHM, RP	F.D.

*: decision models are presented
F.D.: factorial design; L_{16}: Taguchi orthogonal array
2^{5-1} etc.: fractional factorial design
Assem.Line: assembly Line; Comm-Net: communication network
Q-N: queuing network system; MFS: maintenance float system

MRP: material requirements planning system
MIP: machine interference problem
FES: flexible electroplating system
TH: throughput; EU: machine utilization
S.E.: system effectivity; M/C B: machine/component breakdowns
Survi.: survivability; EL: efficient of line
T: average total response time; TC: total cost
L: average number of demands in the system
W: average system waiting time per demand
SU: average per server utilization
NS: the no. of machines to assign to the operator
EE: expected operator efficiency loss
SS: service time; WW: patrolling time
λ: average arrival rate; μ: average service rate
D: demand rate; B: capacity of buffer
S: number of servers; N: number of machines
P: process time; F: number of standby units
MTTR: Mean time to repair
MTBF: Mean time between failure
R: MTTR/MTBF; CPU: a time-shared CPU system
CV: the coefficient of variation
LC: link capacity; PPN: ports per node
PNL: percent nodes lost; NU: number of users
RP: routing probability; CP: capacity plan
OWC: operation work contents; PDP: product demand pattern
MJF: mean job flow time; MJL: mean job lateness
MJE: mean job earliness; MJD: mean job due-date
LT: mean labor transfer; LA: the labor assignment
DR: the dispatching rule; DD: the due-date assignment
Cost: lot-size cost; Sta: stability
LSM: lot-sizing method; TI: type of information
FP: freeze proportion; PHM: planning horizon multiplier
RP: replanning periodicity
PE: processing efficiency; NP: the number of processors
MM: the number of memory-modules
PR: the probability of a memory request

Table 2-3 Summary of major applications of Taguchi design

Author(year)	Orthogonal array	Application areas	Experiment forms
Barker(1986)	L_{27}	Butterfly	Physical
Byrne et al. (1987)	L_8, L_9	Elastomeric connector	Physical
Bandurek et al.(1988)	L_{16}	Magnetic card reader	Physical
Dentskevich et al(1988)	L_{16}, L_{18}	Software	Computer Model
Madsen(1988)	L_{27}	Transducer	Physical
Wilson et al. (1988)	L_8	Cart seat cushions	Physical
Schmidt et al. (1989)	L_8	Photoresist	Computer Model
Katz et al. (1989)	L_{18},L_{27},L_{36}	Microchip	Physical & Simulation
Phadke(1989a)	L_{18}, L_{36}	Microchip	Physical & Simulation
Phadke(1989b)	L_{36}	Circuit	Simulation
Lin(1989)	L_{16}	Flow line	Simulation
Kuei et al. (1990)	L_{16}	Production system	Simulation

Table 3-1 Evaluation of three major experimental designs

Criteria	F.D	F.F.D	Taguchi
Small no. of Runs	No	Yes	Yes
Ease of Implementation	Yes	No	Yes
Flexibility of the design	Yes	No	Yes
Desired confounding pattern	-	Yes	Yes
Ease of analysis	Yes	Yes	Yes

F.D.: factorial design
F.F.D: fractional factorial design
Taguchi: Taguchi methods of design
-: not available

Table 3-2 A comparison of number of runs needed between Taguchi orthogonal array and a complete factorial design

Number of factors	Number of levels	Orthogonal array	Number of runs needed for a complete F.D.
3	2	L_4	8
7	2	L_8	128
11	2	L_{12}	2048
15	2	L_{16}	32768
31	2	L_{32}	$2.1474*10^9$
4	3	L_9	81
13	3	L_{27}	1594323

F.D.: factorial design

L_n: the n indicates the number of runs needed for a particular orthogonal array

Table 3-3 A comparison of number of runs needed between Taguchi orthogonal array and a fractional factorial design with different resolutions

Number of factors	Number of levels	Orthogonal array	Number of runs needed for a fractional F.D. III	IV	V
3	2	L_4	4	-	-
7	2	L_8	8	16	-
11	2	L_{12}	16	32	128
4	3	L_9	9	27	-

F.D.: factorial design

L_n: the n indicates the number of runs needed for a particular orthogonal array

III: Resolution III design

IV: Resolution IV design

V: Resolution V design

Table 4-1 $L_{16}(2^{15})$ orthogonal array

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2
3	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2
4	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1
5	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2
6	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1
7	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1
8	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2
9	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
10	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1
11	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1
12	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2
13	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1
14	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2
15	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2
16	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1

Source: Taguchi and Wu (1980)

Table 4-2 Experimental design

Column number	Factor
1	mean time between failure (MTBF)
2	the number of standbys (F)
3	(MTBF)*(F)
4	the number of repairmen (S)
5	(MTBF) * (S)
6	(F) * (S)
7	error message 1
8	mean time to repair (MTTR)
9	(MTBF) * (MTTR)
10	(F) * (MTTR)
11	error message 2
12	(S) * (MTTR)
13	error message 3
14	error message 4
15	error message 5

Table 4-3 The systematic assignment of the levels to the four factors and the simulation results

Run No.	MTBF	F	S	MTTR	EU
1	12	1	1	5	.668
2	12	1	1	10	.495
3	12	1	3	5	.939
4	12	1	3	10	.834
5	12	3	1	5	.798
6	12	3	1	10	.576
7	12	3	3	5	.998
8	12	3	3	10	.980
9	24	1	1	5	.848
10	24	1	1	10	.734
11	24	1	3	5	.980
12	24	1	3	10	.938
13	24	3	1	5	.955
14	24	3	1	10	.848
15	24	3	3	5	.999
16	24	3	3	10	.998

Table 4-4 The ANOVA table for a flexible manufacturing cell

	Factor	Col.1	Col.2	S.S.	D.F	M.S.	F
1	(MTBF)	6.288	7.3	64009	1	64009	52.971***
2	(F)	6.436	7.152	32041	1	32041	26.515***
3	(MTBF)*(F)	6.736	6.852	841	-	-	-
4	(S)	5.922	7.666	190096	1	190096	157.314***
5	(MTBF)*(S)	6.452	7.136	29241	1	29241	24.198***
6	(F) * (S)	6.72	6.868	1369	-	-	-
7	e 1	6.862	6.726	1156	-	-	-
8	(MTTR)	7.185	6.403	38220.25	1	38220.25	31.629***
9	MTBF*MTTR	6.921	6.667	4032.25	-	-	-
10	(F)*(MTTR)	6.837	6.751	462.25	-	-	-
11	e 2	6.789	6.799	6.25	-	-	-
12	(S)*(MTTR)	7.019	6.569	12656.25	1	12656.25	10.474*
13	e 3 .	6.841	6.747	552.25	-	-	-
14	e 4	6.709	6.879	1806.25	-	-	-
15	e 5	6.743	6.845	650.25	-	-	-
	Pooled Error			10875.5	9	1208.388	

*: $F_{1,9,0.95} = 5.12$
**: $F_{1,9,0.99} = 10.56$
***: $F_{1,9,0.999} = 22.86$
S.S. of Error = Σe_i + (MTBF)*(F) + (F)*(S) + (MTBF)*(MTTR) + (F)*(MTTR)
= 10875.5

Table 4-5 Analysis of variance

Source	Mean square	F	Significant level
Regression	0.3662635	50.52	0.0001
error	0.0108755		
R^2= 0.971163			

Estimated parameter	coefficient	t	Significant level
Intercept	0.410875	4.75	0.0864
MTBF	0.024792	7.65	0.0032
F	0.044750	5.15	0.0087
S	0.152875	4.04	0.0378
MTTR	-0.042050	-5.41	0.0078
MTBF*S	-0.007125	-4.92	0.0014
S*MTTR	0.011250	3.24	0.0035

Table 4-6 Computation table of total cost

	S 1	S 2	S 3
F 3	+	1198.58	-
F 2	+	1088.08	969.33
F 1	+	+	* 858.83

+: EU < 0.85
-: infeasible solution
*: minimum cost

Table 4-7 The systematic assignment of the levels to the four factors and the simulation results for Erlang-2 case

Run No.	MTBF	F	S	MTTR	EU
1	24	1	1	5	.701
2	24	1	1	10	.588
3	24	1	3	5	.8672
4	24	1	3	10	.7586
5	24	3	1	5	.7222
6	24	3	1	10	.6126
7	24	3	3	5	.8706
8	24	3	3	10	.782
9	48	1	1	5	.823
10	48	1	1	10	.749
11	48	1	3	5	.9278
12	48	1	3	10	.8636
13	48	3	1	5	.834
14	48	3	1	10	.7688
15	48	3	3	5	.9286
16	48	3	3	10	.8668

Table 4-8 The ANOVA table for a flexible manufacturing cell (Erlang-2 case)

	Factor	Col.1	Col.2	S.S.	D.F	M.S.	F
1	(MTBF)	5.9022	6.7616	46160.52	1	46160.52	922.55***
2	(F)	6.2782	6.3856	720.92	1	720.92	14.41**
3	(MTBF)*(F)	6.313	6.3508	89.30	-	-	-
4	(S)	5.7986	6.8652	71102.22	1	71102.22	1421.03***
5	(MTBF)*(S)	6.2106	6.4532	3678.42	1	3678.42	73.52***
6	(F) * (S)	6.309	6.3548	131.10	-	-	-
7	e 1	6.3358	6.328	3.80	-	-	-
8	(MTTR)	7.6744	5.9894	29326.56	1	29326.56	586.11***
9	MTBF*MTTR	6.4092	6.2546	1493.82	1	1493.82	29.86***
10	(F)*(MTTR)	6.3492	6.3146	74.82	-	-	-
11	e 2	6.338	6.3258	9.30	-	-	-
12	(S)*(MTTR)	6.3512	6.3126	93.12	-	-	-
13	e 3	6.338	6.3258	9.30	-	-	-
14	e 4	6.3268	6.337	6.50	-	-	-
15	e 5	6.3204	6.3434	33.06	-	-	-
	Pooled Error			450.32	9	50.04	-

*: $F_{1,9,0.95} = 5.12$
**: $F_{1,9,0.99} = 10.56$
***: $F_{1,9,0.999} = 22.86$
S.S. of Error = $\Sigma\, e_i$ + (MTBF)*(F) + (F)*(S) + (S)*(MTTR) + (F)*(MTTR) = 450.32

Table 4-9 Analysis of variance for Erlang-2 case

Source	Mean square	F	Significant level
Regression	0.02541375	507.91	0.0001
error	0.00005004		
R^2= 0.997055			

Estimated parameter	coefficient	t	Significant level
Intercept	0.608025	28.65	0.0001
MTBF	0.0045875	8.32	0.0001
F	0.0067125	3.8	0.0042
S	0.112150	20.05	0.0001
MTTR	-0.028720	-12.84	0.0001
MTBF*S	-0.0012635	-8.57	0.0001
MTBF*MTTR	0.0003221	5.46	0.0004

Table 4-10 The systematic assignment of the levels to the four factors and the simulation results for Gamma case

Run No.	MTBF	F	S	MTTR	EU
1	6	1	1	2	.5786
2	6	1	1	5	.4208
3	6	1	3	2	.838
4	6	1	3	5	.6458
5	6	3	1	2	.6022
6	6	3	1	5	.4394
7	6	3	3	2	.8452
8	6	3	3	5	.67
9	12	1	1	2	.7108
10	12	1	1	5	.5892
11	12	1	3	2	.9148
12	12	1	3	5	.7894
13	12	3	1	2	.725
14	12	3	1	5	.6142
15	12	3	3	2	.9174
16	12	3	3	5	.8

Table 4-11 The ANOVA table for a flexible manufacturing cell (Gamma case)

	Factor	Col.1	Col.2	S.S.	D.F	M.S.	F
1	(MTBF)	5.04	6.0608	65127.04	1	65127.04	1089.22***
2	(F)	5.4874	5.6134	992.25	1	992.25	16.59**
3	(MTBF)*(F)	5.5398	5.5618	28.09	-	-	-
4	(S)	4.6802	6.4206	189312.00	1	189312.00	3166.164***
5	(MTBF)*(S)	5.4626	5.6382	1927.21	1	1927.21	32.23***
6	(F) * (S)	5.532	5.5688	84.64	-	-	-
7	e 1	5.558	5.5482	14.44	-	-	-
8	(MTTR)	4.9688	6.132	84564.64	1	84564.64	1414.31***
9	MTBF*MTTR	5.444	5.6568	2830.24	1	2830.24	47.33***
10	(F)*(MTTR)	5.535	5.5658	59.29	-	-	-
11	e 2	5.5538	5.547	2.89	-	-	-
12	(S)*(MTTR)	5.579	5.5218	204.49	-	-	-
13	e 3	5.5686	5.5322	82.81	-	-	-
14	e 4	5.56	5.5408	23.04	-	-	-
15	e 5	5.5628	5.538	38.44	-	-	-
	Pooled Error			538.13	9	59.79	-

*: $F_{1,9,0.95} = 5.12$
**: $F_{1,9,0.99} = 10.56$
***: $F_{1,9,0.999} = 22.86$
S.S. of Error = Σe_i + (MTBF)*(F) + (F)*(S) + (S)*(MTTR) + (F)*(MTTR) = 450.32

Table 4-12 Analysis of variance for Gamma case

Source	Mean square	F	Significant level
Regression	0.05745890	960.98	0.0001
error	0.00005979		
R^2= 0.998442			

Estimated parameter	coefficient	t	Significant level
Intercept	0.4659833	23.15	0.0001
MTBF	0.0182389	8.76	0.0001
F	0.0078750	4.07	0.0028
S	0.1417000	23.18	0.0001
MTTR	-0.0075667	-18.42	0.0001
MTBF*S	-0.0036583	-5.68	0.0003
MTBF*MTTR	0.0029556	6.88	0.0001

Table 4-13 $L_8(2^7)$ orthogonal array

	1	2	3	4	5	6	7
1	1	1	1	1	1	1	1
2	1	1	1	2	2	2	2
3	1	2	2	1	1	2	2
4	1	2	2	2	2	1	1
5	2	1	2	1	2	1	2
6	2	1	2	2	1	2	1
7	2	2	1	1	2	2	1
8	2	2	1	2	1	1	2

Source: Taguchi and Wu [1980]

Table 4-14 Experimental design for exponential case

Column number	Factor
1	S
2	MTBF
3	S*MTBF
4	MTTR
5	S*MTTR
6	F
7	error

Table 4-15 Experimental design for Erlang-2 and Gamma cases

Column number	Factor
1	MTBF
2	S
3	MTBF*S
4	MTTR
5	MTBF*MTTR
6	F
7	error

Table 5-1 $L_{32}(2^{31})$ orthogonal array

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
3	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2
4	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1
5	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2
6	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1	1
7	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1
8	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1	1	1	1	1	1	2	2	2	2
9	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2
10	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1
11	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1
12	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	1	1	2	2	1	1	2	2
13	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1
14	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	2	2	1	1	1	1	2	2
15	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2
16	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	2	2	1	1	1	1	2	2	1	1	2	2	2	2	1	1
17	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
18	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1
19	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1
20	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	1	2	1	2	1	2	1	2
21	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1
22	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1	2
23	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2
24	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1	2	1	2	1	2	2	1	2	1
25	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1
26	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2
27	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2
28	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	1	2	2	1	1	2	2	1
29	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2
30	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	2	1	1	2	1	2	2	1
31	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1
32	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	2	1	1	2	1	2	2	1	1	2	2	1	2	1	1	2

Source: Taguchi and Wu (1980)

Table 5-2 Experimental design

Column number	Factor
1	MTBF for Machine A (Ma)
2	MTBF for Machine B (Mb)
3	(Ma)*(Mb)
4	MTTR
5	(Ma)*(RR)
6	(Mb)*(RR)
7	(S)*(Fa)
8	No. of Repairmen (S)
9	(Ma)*(S)
10	(Mb)*(S)
11	(RR)*(Fa)
12	(RR)*(S)
13	(Mb)*(Fa)
14	(Ma)*(Fa)
15	Float for Machine A (Fa)
16	Float for Machine B (Fb)
17	(Ma)*(Fb)
18	(Mb)*(Fb)
19	error message 1
20	(RR)*(Fb)
21	error message 2
22	error message 3
23	error message 4
24	(S)*(Fb)
25	error message 5
26	Part Sequence (PS)
27	error message 6
28	error message 7
29	error message 8
30	(RR)*(PS)
31	(Fa)*(Fb)

Table 5-3 The systematic assignment of the levels to the seven factors and the simulation results for the FMS

Run No.	Ma	Mb	MTTR	S	Fa	Fb	PS	TH1	TH2
1	120	100	40	1	2	2	1	10.171	13.657
2	120	100	40	1	2	5	2	10.457	13.742
3	120	100	40	4	5	2	2	13.342	17.714
4	120	100	40	4	5	5	1	20.914	27.799
5	120	100	80	1	5	2	1	4.714	6.342
6	120	100	80	1	5	5	2	5.457	7
7	120	100	80	4	2	2	2	3.942	5.142
8	120	100	80	4	2	5	1	6	7.971
9	120	200	40	1	5	2	2	13.371	17.742
10	120	200	40	1	5	5	1	16.599	21.971
11	120	200	40	4	2	2	1	17.342	23.028
12	120	200	40	4	2	5	2	20.571	27.228
13	120	200	80	1	2	2	2	5.542	7.285
14	120	200	80	1	2	5	1	5.428	7.228
15	120	200	80	4	5	2	1	19.457	25.857
16	120	200	80	4	5	5	2	21.971	29.199
17	240	100	40	1	5	2	1	11.428	15.285
18	240	100	40	1	5	5	2	11.685	15.457
19	240	100	40	4	2	2	2	15.457	20.571
20	240	100	40	4	2	5	1	20.914	27.799
21	240	100	80	1	2	2	1	3.514	4.657
22	240	100	80	1	2	5	2	7	9.257
23	240	100	80	4	5	2	2	6.599	8.657
24	240	100	80	4	5	5	1	20.914	27.799
25	240	200	40	1	2	2	2	12.799	16.914
26	240	200	40	1	2	5	1	20.085	26.685
27	240	200	40	4	5	2	1	20.914	27.799
28	240	200	40	4	5	5	2	21.971	29.199
29	240	200	80	1	5	2	2	12.171	16.171
30	240	200	80	1	5	5	1	9.399	12.685
31	240	200	80	4	2	2	1	17.599	23.428
32	240	200	80	4	2	5	2	21.285	28.257

Ma: MTBF of machine a; Mb: MTBF of machine b;
S: the number of repair persons;
Fa: the number of floats for machine a;
Fb: the number of floats for machine b;
PS: part sequence;
TH1: throughput of part 1; TH2: throughput of part 2.

Table 5-4 The ANOVA table for an FMS (Throughput of Type 1)

	Factor	Col.1	Col.2	S.S.	D.F	M.S.	F
1	(Ma)	195.28	231.53	41078.04	1	41078.04	8.41**
2	(Mb)	172.51	231.71	109516.30	1	109516.30	22.43***
3	(Ma)*(Mb)	209.02	217.79	2404.62	-	-	-
4	(RR)	258.02	168.79	248801.10	1	248801.10	50.96***
5	(Ma)*(RR)	219.05	207.76	3979.02	-	-	-
6	(Mb)*(RR)	225.02	201.79	16860.62	1	16860.62	3.45
7	(S)*(Fa)	221.08	205.73	7357.45	-	-	-
8	(S)	157.62	269.19	389009.70	1	389009.70	79.68***
9	(Ma)*(S)	217.39	209.42	1986.02	-	-	-
10	(Mb)*(S)	225.54	201.28	18392.11	1	18392.11	3.77
11	(RR)*(Fa)	226.28	200.53	20711.04	1	20711.04	4.24
12	(RR)*(S)	224.36	202.45	15004.24	1	15004.24	3.07
13	(Mb)*(Fa)	211.11	215.70	660.10	-	-	-
14	(Ma)*(Fa)	192.33	234.48	55503.64	1	55503.64	11.37**
15	(Fa)	169.74	257.08	238383.60	1	238383.60	48.83***
16	(Fb)	186.16	240.65	92779.44	1	92779.44	19.00***
17	(Ma)*(Fb)	221.13	205.68	7465.25	-	-	-
18	(Mb)*(Fb)	206.48	220.34	6003.11	-	-	-
19	e 1	218.53	208.28	3287.05	-	-	-
20	(RR)*(Fb)	212.28	214.53	159.05	-	-	-
21	e 2	205.42	221.39	7972.02	-	-	-
22	e 3	221.56	205.25	8319.12	-	-	-
23	e 4	204.25	222.56	10483.62	-	-	-
24	(S)*(Fb)	226.05	200.76	19983.84	1	19983.84	4.09
25	e 5	211.99	214.82	249.92	-	-	-
26	(PS)	225.39	201.42	17958.02	1	17958.02	3.68
27	e 6	207.39	219.42	4521.02	-	-	-
28	e 7	207.02	219.79	5097.62	-	-	-
29	e 8	223.14	203.68	11834.11	-	-	-
30	(RR)*(PS)	220.13	206.68	5658.25	-	-	-
31	(Fa)*(Fb)	215.28	211.54	437.11	-	-	-
	Pooled Error			87874.48	18	4881.92	

*: $F_{1,18,0.95} = 4.41$
**: $F_{1,18,0.99} = 8.29$
***: $F_{1,18,0.999} = 15.38$

Table 5-5 Analysis of variance for FMS (Throughput of type 1)

Source	Mean square	F	Significant level
Regression	152.216291	18.56	0.0001
error	8.199349		
R^2= 0.844106			

Estimated parameter	coefficient	t	Significant level
Intercept	-10.5987500	-2.20	0.0378
Ma	0.0701000	3.27	0.0032
Mb	0.0511225	5.05	0.0001
MTTR	-0.1394187	-5.51	0.0001
S	2.3244167	6.89	0.0001
Fa	3.2715000	3.07	0.0053
Fb	1.1351667	3.36	0.0026
Ma*Fa	-0.0146333	-2.60	0.0156

Table 5-6 Analysis of variance for FMS (Throughput of type 2)

Source	Mean square	F	Significant level
Regression	268.924448	18.31	0.0001
error	14.684368		
R^2= 0.842301			

Estimated parameter	coefficient	t	Significant level
Intercept	-14.1150208	-2.19	0.0386
Ma	0.0931774	3.25	0.0034
Mb	0.0680881	5.03	0.0001
MTTR	-0.1852203	-5.47	0.0001
S	3.0886458	6.84	0.0001
Fa	4.3370000	3.04	0.0057
Fb	1.4981875	3.32	0.0029
Ma*Fa	-0.0193559	-2.57	0.0167

Table 5-7 A comparison of simulation and metamodel results (TH1)

Ma	Mb	MTTR	S	Fa	Fb	TH1 Simulation	TH1 Metamodel	Error
120	100	40	2	2	2	8.085	7.299	0.097
120	100	40	2	2	5	12.142	10.704	0.118
120	100	80	2	5	2	7.971	6.269	0.214
120	100	80	2	5	5	9.457	9.674	0.023
120	200	40	2	5	2	14.599	16.958	0.162
120	200	40	2	5	5	20.914	20.363	0.026
240	100	40	2	5	2	14.342	11.477	0.200
240	200	40	2	2	5	20.942	20.717	0.010
240	200	80	2	5	2	12.171	11.013	0.095

5-8 A comparison of simulation and metamodel results (TH2)

Ma	Mb	MTTR	S	Fa	Fb	TH2 Simulation	TH2 Metamodel	Error
120	100	40	2	2	2	10.771	9.669	0.102
120	100	40	2	2	5	16.114	14.163	0.121
120	100	80	2	5	2	10.771	8.302	0.229
120	100	80	2	5	5	12.657	12.797	0.011
120	200	40	2	5	2	19.371	22.520	0.163
120	200	40	2	5	5	27.799	27.015	0.028
240	100	40	2	5	2	19.142	15.279	0.202
240	200	40	2	2	5	27.799	27.508	0.010
240	200	80	2	5	2	16.171	14.679	0.092

Table 5-9 Experimental design for additional runs

Column number	Factor
1	Float for Machine A (Fa)
2,4,6	No. of Repairmen (S)
3	(Fa)*(S)
5	(Fa)*(S)
7	(Fa)*(S)
8	MTBF for Machine B (Mb)
9	(Fa)*(Mb)
10	MTBF for Machine A (Ma)
11	(Fa)*(Ma)
12	Float for Machine B (Fb)
13	error message 1
14	error message 2
15	MTTR

Table 5-10 The systematic assignment of the levels to the six factors and the simulation results for addition runs

Run No.	Ma	Mb	MTTR	S	Fa	Fb	TH1	TH2
1	120	100	40	1	2	2	10.171	13.657
2	240	200	80	1	2	5	11.199	14.771
3	120	100	80	2	2	5	4.971	6.742
4	240	200	40	2	2	2	20.914	27.799
5	240	100	80	3	2	2	3.914	5.142
6	120	200	40	3	2	5	16.057	21.314
7	240	100	40	4	2	5	20.914	27.799
8	120	200	80	4	2	2	14.171	18.742
9	120	100	80	1	5	2	4.714	6.342
10	240	200	40	1	5	5	20.914	27.799
11	120	100	40	2	5	5	20.942	27.771
12	240	200	80	2	5	2	18.428	24.542
13	240	100	40	3	5	2	17.942	23.799
14	120	200	80	3	5	5	18.114	24.028
15	240	100	80	4	5	5	20.914	27.799
16	120	200	40	4	5	2	20.857	27.685

Table 5-11 Analysis of variance for FMS with additional runs (Throughput of type 1)

Source	Mean square	F	Significant level
Regression	196.680656	20.96	0.0001
error	9.383169		
R^2= 0.802985			

Estimated parameter	coefficient	t	Significant level
Intercept	-9.10038684	-2.00	0.0533
Ma	0.06075322	3.10	0.0037
Mb	0.05442733	5.87	0.0001
MTTR	-0.14792250	-6.38	0.0001
S	2.21494581	6.52	0.0001
Fa	3.05363939	3.14	0.0034
Fb	1.04025014	3.34	0.0019
Ma*Fa	-0.01151540	-2.24	0.0311

Table 5-12 A comparison of simulation and two metamodels' results (TH1)

Test no.	Simulation	Metamodel (L_{32})	Relative error	Metamodel ($L_{32}+L_{16}$)	Relative error
1	8.085	7.298919	0.09722	7.569807	0.06372
2	12.142	10.704410	0.11839	10.690550	0.11953
3	7.971	6.268668	0.21356	6.668281	0.16343
4	9.457	9.674168	0.02296	9.789031	0.03511
5	14.599	16.957660	0.16156	18.027910	0.23487
6	20.914	20.363160	0.02633	21.148660	0.01122
7	14.342	11.477420	0.19973	12.966320	0.09591
8	20.942	20.716660	0.01076	20.659980	0.01346
9	12.171	11.012920	0.09515	12.492160	0.02638
Average percentage deviation:			0.10507		0.8485

GLOSSARY

CNC machine: computer numerical control machine. This machine consists of three basic components: program of instructions, computer, and processing equipment.

Confounding of effects: the statistic which measures an effect (main effect or higher-order effect) will be identical to the statistic which measures some of the higher-order interaction effects.

Design Generators: higher order interactions (e.g. ABCDE) used to confound with the difference between fractions when generating fractional factorial design.

Design Point: one of the possible combinations of levels of all factors under study.

Design Matrix: a specified set of design points.

Experimental Error: random influences in the execution of the experiment.

Factor: a particular variable which is varied in the experiment.

Interactions: joint action between different factors.

Levels: the different values at which a factor is tested.

L_8: the L stands for Latin Square-like design; 8 is the number of runs. The simplest version of this design is an experiment of seven factors with two levels. This is also known as a saturated design. The most complex version of this design is up to four factors and three pairwise interactions with two levels.

L_{16}: 16 is the number of runs. The simplest version of this design is an experiment of fifteen factors with two levels. The most complex version of this design is up to five factors and ten pairwise interactions with two levels.

L_{32}: 32 is the number of runs. The simplest version of this design is an experiment of thirty one factors with two levels. The most complex version of this design is up to eleven factors and twenty pairwise interactions with two levels.

L_9: 9 is the number of runs. The simplest version of this design is an experiment of four factors with three levels. The most complex version of this design is up to two factors and one pairwise interactions with three levels.

L_{27}: 27 is the number of runs. The simplest version of this design is an experiment of thirteen factors with three levels. The most complex version of this design is up to five factors and four pairwise interactions with three levels.

Main effect: the effect of each of the factors alone.

Mixed factor level designs: such as L_{18}, L_{36} and L_{54}. In these type of designs, the levels of different factors may be varied.

Multiple levels designs: in this type of design, low-level factor design may extend to high-level design.

Orthogonal array: in every pair of columns in the array, all combinations of levels occur equal number of times.

Replication: independent simulation runs with different random number seeds.

Resolution III design: only the main effects can be estimated. Furthermore, the main effects and two-factor interactions are confounded.

Resolution IV design: The main effects can be estimated. In addition, the main effects do not confound with two-factor interactions, however, two-factor interactions are confounded with each other.

Resolution V design: The main effects and two-factor interactions can be estimated. However, they are confounded with higher-order interactions.

Response: is the output of simulation run at a specific design point.

Appendix A-1 Simulation program for a flexible manufacturing cell

```
// JOB TIME=1
// EXEC GPSSV,PARM='C'
//SYSIN DD *
       REALLOCATE XAC,1500,BLO,1500,COM,36400
       SIMULATE
       RMULT      1,5

*
* SINGLE MACHINE LEVEL WITH TOOL FAILURE
* PERFORMANCE MEASURE: MACHINE UTILIZATION
* BY CHU-HUA KUEI 12/6/1989
*
 EXP   FUNCTION   RN2,C24             CV=1
0,0/.1,.105/.2,.223/.3,.357/.4,.511/.5,.693/.6,.916
.7,1.204/.75,1.386/.8,1.609/.84,1.833/.88,2.12/.9,2.303
.92,2.526/.94,2.813/.95,2.996/.96,3.219/.97,3.507/.98,3.912
.99,4.605/.995,5.298/.998,6.215/.999,6.908/.9997,8.112
*
 GAM   FUNCTION   RN1,C24             INVERTED G(L=1,P=2) FUNCTION
0,0/.1,.211/.2,.446/.3,.713/.4,1.022/.5,1.386/.6,1.833/.7,2.408
.75,2.773/.8,3.219/.84,3.665/.88,4.241/.9,4.605/.92,5.051/.94,5.627
.95,5.991/.96,6.438/.97,7.013/.98,7.824/.99,9.21/.995,10.597
.998,11.618/.999,13.816/.9997,16.223
*
* MAJOR DECISION VARIABLES
*
       INITIAL    XB1,1          THE NUMBER OF STANDBY TOOL
       STORAGE    S$REP,1        THE NUMBER OF REPAIRMEN
*
* FAILURE AND REPAIR
*
       GENERATE   ,,,1           CREATE A WORKER
 BACK  SEIZE      TOOL           TURN ON MACHINE TOOL
       ADVANCE    24,FN$GAM      TOOL IS WORKING
```

```
      RELEASE    TOOL             TOOL FAILS
      SPLIT      1,SWITC          SEND IT TO SHOP, GET A STANDBY TOOL
      QUEUE      1                WAIT FOR REPAIR
      ENTER      REP              TAKE OVER REPAIRMEN
      DEPART     1                LEAVE QUEUE
      ADVANCE    5,FN$EXP         REPAIR THE FAILED TOOL
      LEAVE      REP              RELEASE THE REPAIRMEN
      SAVEVALUE  1+,1,XB          INCREASE STANDBY TOOL NO. BY 1
      TERMINATE
*
* STANDBY MODE
*
 SWITC TEST G    XB1,0            CHECK IS THERE ANY STANDBY TOOL
      SAVEVALUE  1-,1,XB          DECREASE STANDBY TOOL NO. BY 1
      TRANSFER    ,BACK           MACHINE IS STILL AVAILABLE
*
* COMPETITION OCCURS
*
      GENERATE   10,FN$EXP,,,1    FAILED TOOL FROM THE REST OF THE SHOP
      QUEUE      1                WAIT FOR REPAIR
      ENTER      REP              TAKE OVER REPAIRMEN
      DEPART     1                LEAVE QUEUE
      ADVANCE    5,FN$EXP         REPAIR THE FAILED TOOL
      LEAVE      REP              RELEASE THE REPAIRMEN
      TERMINATE
*
      GENERATE   ,,124800         TIMER COMES
      TERMINATE  1                SHUT OFF THE RUN
*
      START      1
      RMULT      22,41
      CLEAR
      START      1
      RMULT      97,64
      CLEAR
      START      1
```

```
        RMULT      333,58
        CLEAR
        START      1
        RMULT      9,79
        CLEAR
        START      1
        END
/*
```

A-1 OUTPUT FILE

RELATIVE CLOCK 124800 ABSOLUTE CLOCK 124800

BLOCK COUNTS

BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL
1	0	1	11	0	2093	21	0	12932						
2	0	2094	12	0	2093	22	0	12932						
3	1	2094	13	0	2093	23	0	1						
4	0	2093	14	0	2093	24	0	1						
5	0	4186	15	0	2093									
6	0	2093	16	0	12934									
7	0	2093	17	1	12934									
8	0	2093	18	0	12933									
9	0	2093	19	0	12933									
10	0	2093	20	1	12933									

****

* FACILITIES *

****

FACILITY	NUMBER ENTRIES	AVERAGE TIME/TRAN	-AVERAGE UTILIZATION DURING- TOTAL TIME	AVAIL. TIME	UNAVAIL. TIME	CURRENT STATUS	PERCENT AVAILABILITY	TRANSACTION NUMBER SEIZING	PREEMPTING
TOOL	2094	47.158	.791				100.0	14	

****

* STORAGES *

****

STORAGE	CAPACITY	AVERAGE CONTENTS	ENTRIES	AVERAGE TIME/UNIT	-AVERAGE UTILIZATION DURING- TOTAL TIME	AVAIL. TIME	UNAVAIL. TIME	CURRENT STATUS	PERCENT AVAILABILITY	CURRENT CONTENTS	MAXIMUM CONTENTS
REP	1	.554	15026	4.603	.554				100.0	1	1

QUEUES

QUEUE	MAXIMUM CONTENTS	AVERAGE CONTENTS	TOTAL ENTRIES	ZERO ENTRIES	PERCENT ZEROS	AVERAGE TIME/TRANS	$AVERAGE TIME/TRANS	TABLE NUMBER	CURRENT CONTENTS
1	12	.700	15027	7242	48.1	5.819	11.233		1

$AVERAGE TIME/TRANS = AVERAGE TIME/TRANS EXCLUDING ZERO ENTRIES

Appendix A-2 Simulation program for a flexible manufacturing system

```
// JOB TIME=1
// EXEC GPSSV,PARM='C'
//SYSIN DD *
          REALLOCATE XAC,1500,BLO,1500,COM,36400
          SIMULATE
          RMULT      1,5
*
* FLEXIBLE MANUFACTURING SYSTEM AND MAINTENANCE FLOAT POLICY
* PERFORMANCE MEASURE: THROUGHPUT
* BY CHU-HUA KUEI 1/9/1990
*
* STORAGE CAPACITY DEFINITIONS
*
          STORAGE    S$CARTS,3          NUMBER OF CARTS
          STORAGE    S$MTYPA,2          NUMBER OF TYPE A MACHINES
          STORAGE    S$MTYPB,2          NUMBER OF TYPE B MACHINES
          STORAGE    S$WSPAC,4          NUMBER OF WAIT SPACE
          STORAGE    S$REP,3            NUMBER OF REPAIRMEN
          STORAGE    S$USCA1,2          POOL OF IDLE CARTS AT UNLOAD
          STORAGE    S$USCA2,2          STATION ONE AND TWO
*
          INITIAL    XH1,120            MEAN TIME BETWEEN FAILURE (MACH A)
          INITIAL    XH2,100            MTBF (MACH B)
          INITIAL    XH3,50             MEAN TIME TO REPAIR
          INITIAL    XB1,3              NUMBER OF CARTS
          INITIAL    XB103,2            NUMBER OF FLOAT FOR MACH A
          INITIAL    XB104,4            NUMBER OF FLOAT FOR MACH B
          INITIAL    XB109,4            NUMBER OF FLOAT FOR MACH B
          INITIAL    XB110,2            NUMBER OF FLOAT FOR MACH A
*
          INITIAL    LS$CAL03       IDLE CART AT LOCATION 3 INITIALLY
          INITIAL    LS$CAL04       IDLE CART AT LOCATION 4 INITIALLY
          INITIAL    LS$CAL05       IDLE CART AT LOCATION 5 INITIALLY
*
```

```
 1      VARIABLE   (N$ENTRY-1)@7+1
 2      VARIABLE   100-MH$STIME(PTYP1,STEP1)
 3      VARIABLE   100-MH$STIME(PTYP2,STEP1)
 4      VARIABLE   100-MH$STIME(PTYP2,STEP2)
 5      VARIABLE   (N$GETWS-1)@4+1
*
* VARIABLE FOR LOADING STATION AVAILABILITY
*
 PTLS1 BVARIABLE  FNU$LSPT1
 PTLS2 BVARIABLE  FNU$LSPT2
*
* VARIABLE FOR CART AND MACHINE AVAILABILITY
*
 CANDA BVARIABLE SNF$CARTS*((LR$ATYA1*FNU$MTYA1)+(LR$ATYA2*FNU$MTYA2))
 CANDB BVARIABLE SNF$CARTS*((LR$ATYB1*FNU$MTYB1)+(LR$ATYB2*FNU$MTYB2))
*
* VARIABLES FOR CARTS AND MACHINE OR WAIT SPACE AVAILABILITY
*
 CNAOW BVARIABLE SNF$CARTS*(LR$ATYA1*FNU3+LR$ATYA2*FNU10)+SNF$WSPAC
*
 MACHA BVARIABLE  (LR$ATYA1*FNU$MTYA1)+(LR$ATYA2*FNU$MTYA2)
*
* VARIABLES FOR CARTS AND UNLOADING STATION AVAILABILITY
*
 CNPU1 BVARIABLE  SNF$CARTS*FNU$USPT1
 CNPU2 BVARIABLE  SNF$CARTS*FNU$USPT2
*
 EXP   FUNCTION   RN2,C24            CV=1
0,0/.1,.105/.2,.223/.3,.357/.4,.511/.5,.693/.6,.916
.7,1.204/.75,1.386/.8,1.609/.84,1.833/.88,2.12/.9,2.303
.92,2.526/.94,2.813/.95,2.996/.96,3.219/.97,3.507/.98,3.912
.99,4.605/.995,5.298/.998,6.215/.999,6.908/.9997,8.112
*
* THE AMAP FUNCTION INDICATES WHICH ROW IN THE TYPEALOC
* MATRIX TO SCAN FOR NEAREST TYPE A MACHINE AVAILABILITY
*
```

```
 AMAP  FUNCTION    PF4,D3
1,1/4,2/9,3
*
* THE PART SEQUENCE FUNCTION IS USED TO ADMIT PART TYPES
* INTO THE MODEL IN THE REPEATING CYCLE 1,2,1,2,1,2
*
 PTSEQ FUNCTION    V1,L7
1,TYPE1/2,TYPE2/3,TYPE1/4,TYPE2/5,TYPE1/6,TYPE2/7,TYPE2
*
* MATRIX OF PROCESSING TIME
*
 STIME MATRIX      MH,2,2
       INITIAL     MH1(1,1),15/MH1(1,2),0/MH1(2,1),20/MH1(2,2),10
*
* PREFERRED LOCATIONS OF IDLE CARTS
*
 CLOC  MATRIX      MH,10,10
       INITIAL     MH2(1,1),12/MH2(1,2),12/MH2(1,3),12/MH2(1,4),12
       INITIAL     MH2(1,5),12/MH2(1,6),12/MH2(1,7),12/MH2(1,8),12
       INITIAL     MH2(1,9),4/MH2(1,10),4/MH2(2,1),11/MH2(2,2),11
       INITIAL     MH2(2,3),11/MH2(2,4),11/MH2(2,5),11/MH2(2,6),11
       INITIAL     MH2(2,7),11/MH2(2,8),11/MH2(2,9),3/MH2(2,10),3
       INITIAL     MH2(3,1),10/MH2(3,2),10/MH2(3,3),10/MH2(3,4),10
       INITIAL     MH2(3,5),10/MH2(3,6),10/MH2(3,7),4/MH2(3,8),4
       INITIAL     MH2(3,9),6/MH2(3,10),6/MH2(4,1),9/MH2(4,2),9
       INITIAL     MH2(4,3),9/MH2(4,4),9/MH2(4,5),9/MH2(4,6),9
       INITIAL     MH2(4,7),3/MH2(4,8),3/MH2(4,9),5/MH2(4,10),5
       INITIAL     MH2(5,1),8/MH2(5,2),8/MH2(5,3),8/MH2(5,4),8
       INITIAL     MH2(5,5),8/MH2(5,6),8/MH2(5,7),10/MH2(5,8),10
       INITIAL     MH2(5,9),12/MH2(5,10),12/MH2(6,1),7/MH2(6,2),7
       INITIAL     MH2(6,3),7/MH2(6,4),7/MH2(6,5),7/MH2(6,6),7
       INITIAL     MH2(6,7),9/MH2(6,8),9/MH2(6,9),11/MH2(6,10),11
       INITIAL     MH2(7,1),6/MH2(7,2),6/MH2(7,3),6/MH2(7,4),6
       INITIAL     MH2(7,5),4/MH2(7,6),4/MH2(7,7),6/MH2(7,8),6
       INITIAL     MH2(7,9),8/MH2(7,10),8/MH2(8,1),5/MH2(8,2),5
       INITIAL     MH2(8,3),5/MH2(8,4),5/MH2(8,5),3/MH2(8,6),3
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          INITIAL    MH2(8,7),5/MH2(8,8),5/MH2(8,9),7/MH2(8,10),7
          INITIAL    MH2(9,1),4/MH2(9,2),3/MH2(9,3),4/MH2(9,4),3
          INITIAL    MH2(9,5),6/MH2(9,6),5/MH2(9,7),8/MH2(9,8),7
          INITIAL    MH2(9,9),10/MH2(9,10),9/MH2(10,1),3/MH2(10,2),4
          INITIAL    MH2(10,3),3/MH2(10,4),4/MH2(10,5),5/MH2(10,6),6
          INITIAL    MH2(10,7),7/MH2(10,8),8/MH2(10,9),9/MH2(10,10),10
*
* TRAVEL TIMES BETWEEN ANY TWO LOCATIONS IN THE SYSTEM
*
 TTIME MATRIX        MH,12,12
          INITIAL    MH3(1,1),0/MH3(1,2),1/MH3(1,3),0/MH3(1,4),1
          INITIAL    MH3(1,5),2/MH3(1,6),2/MH3(1,7),3/MH3(1,8),3
          INITIAL    MH3(1,9),4/MH3(1,10),4/MH3(1,11),5/MH3(1,12),5
          INITIAL    MH3(2,1),1/MH3(2,2),0
          INITIAL    MH3(2,3),1/MH3(2,4),0/MH3(2,5),2/MH3(2,6),2
          INITIAL    MH3(2,7),3/MH3(2,8),3/MH3(2,9),4/MH3(2,10),4
          INITIAL    MH3(2,11),5/MH3(2,12),5
          INITIAL    MH3(3,1),0/MH3(3,2),1/MH3(3,3),0/MH3(3,4),1
          INITIAL    MH3(3,5),2/MH3(3,6),2/MH3(3,7),3/MH3(3,8),3
          INITIAL    MH3(3,9),4/MH3(3,10),4/MH3(3,11),5/MH3(3,12),5
          INITIAL    MH3(4,1),1/MH3(4,2),0
          INITIAL    MH3(4,3),1/MH3(4,4),0/MH3(4,5),2/MH3(4,6),2
          INITIAL    MH3(4,7),3/MH3(4,8),3/MH3(4,9),4/MH3(4,10),4
          INITIAL    MH3(4,11),5/MH3(4,12),5
          INITIAL    MH3(5,1),2/MH3(5,2),2/MH3(5,3),2/MH3(5,4),2
          INITIAL    MH3(5,5),0/MH3(5,6),1/MH3(5,7),2 /MH3(5,8),2
          INITIAL    MH3(5,9),3/MH3(5,10),3/MH3(5,11),4/MH3(5,12),4
          INITIAL    MH3(6,1),2/MH3(6,2),2
          INITIAL    MH3(6,3),2/MH3(6,4),2/MH3(6,5),1/MH3(6,6),0
          INITIAL    MH3(6,7),2/MH3(6,8),2/MH3(6,9),3/MH3(6,10),3
          INITIAL    MH3(6,11),4/MH3(6,12),4
          INITIAL    MH3(7,1),3/MH3(7,2),3/MH3(7,3),3/MH3(7,4),3
          INITIAL    MH3(7,5),2/MH3(7,6),2/MH3(7,7),0/MH3(7,8),1
          INITIAL    MH3(7,9),2/MH3(7,10),2/MH3(7,11),3/MH3(7,12),3
          INITIAL    MH3(8,1),3/MH3(8,2),3
          INITIAL    MH3(8,3),3/MH3(8,4),3/MH3(8,5),2/MH3(8,6),2
```

```
        INITIAL    MH3(8,7),1/MH3(8,8),0/MH3(8,9),2/MH3(8,10),2
        INITIAL    MH3(8,11),3/MH3(8,12),3
        INITIAL    MH3(9,1),4/MH3(9,2),4/MH3(9,3),4/MH3(9,4),4
        INITIAL    MH3(9,5),3/MH3(9,6),3/MH3(9,7),2/MH3(9,8),2
        INITIAL    MH3(9,9),0/MH3(9,10),1/MH3(9,11),2/MH3(9,12),2
        INITIAL    MH3(10,1),4/MH3(10,2),4
        INITIAL    MH3(10,3),4/MH3(10,4),4/MH3(10,5),3/MH3(10,6),3
        INITIAL    MH3(10,7),2/MH3(10,8),2/MH3(10,9),1/MH3(10,10),0
        INITIAL    MH3(10,11),2/MH3(10,12),2/MH3(11,1),5/MH3(11,2),5
        INITIAL    MH3(11,3),5/MH3(11,4),5/MH3(11,5),4/MH3(11,6),4
        INITIAL    MH3(11,7),3/MH3(11,8),3/MH3(11,9),2/MH3(11,10),2
        INITIAL    MH3(11,11),0/MH3(11,12),1/MH3(12,1),5/MH3(12,2),5
        INITIAL    MH3(12,3),5/MH3(12,4),5/MH3(12,5),4/MH3(12,6),4
        INITIAL    MH3(12,7),3/MH3(12,8),3/MH3(12,9),2/MH3(12,10),2
        INITIAL    MH3(12,11),1/MH3(12,12),0
*
* PREFERRED LOCATIONS OF TYPE A MACHINES
*
 TYALO MATRIX      MH,3,2
        INITIAL    MH4(1,1),10/MH4(1,2),3/MH4(2,1),10
        INITIAL    MH4(2,2),3/MH4(3,1),3/MH4(3,2),10
*
* PREFERRED LOCATIONS OF TYPE B MACHINES
*
 TYBLO MATRIX      MH,1,2
        INITIAL    MH5(1,1),9/MH5(1,2),4
*
* PREFERRED LOCATIONS OF WAIT SPACE
*
 WSLOC MATRIX      MH,4,4
      ' INITIAL    MH6(1,1),8/MH6(1,2),7/MH6(1,3),6/MH6(1,4),5
        INITIAL    MH6(2,1),5/MH6(2,2),8/MH6(2,3),7/MH6(2,4),6
        INITIAL    MH6(3,1),6/MH6(3,2),5/MH6(3,3),8/MH6(3,4),7
        INITIAL    MH6(4,1),7/MH6(4,2),6/MH6(4,3),5/MH6(4,4),8
*
 LSPT1 EQU         1,F            LOADING STATION, PART TYPE1
```

```
LSPT2 EQU       2,F             LOADING STATION, PART TYPE2
MTYA1 EQU       3,F             MACHINE TYPE A, NO. 1 OF 2
MTYA2 EQU       10,F            MACHINE TYPE A, NO. 2 OF 2
MTYB1 EQU       4,F             MACHINE TYPE B, NO. 1 OF 2
MTYB2 EQU       9,F             MACHINE TYPE B, NO. 2 OF 2
WSPA1 EQU       5,F             WAIT SPACE, NO. 1 OF 4
WSPA2 EQU       6,F             WAIT SPACE, NO. 2 OF 4
WSPA3 EQU       7,F             WAIT SPACE, NO. 3 OF 4
WSPA4 EQU       8,F             WAIT SPACE, NO. 4 OF 4
ULSP1 EQU       11,F            UNLOADING STATION, PART TYPE 1
ULSP2 EQU       12,F            UNLOADING STATION, PART TYPE 2
*
ATYA1 EQU       103,L           "SET" => MACHINE BREAKS DOWN
ATYA2 EQU       110,L
ATYB1 EQU       104,L
ATYB2 EQU       109,L
CALO3 EQU       3,L             "SET" => A CART IS AT LOCATION 3
CALO4 EQU       4,L             "SET" => A CART IS AT LOCATION 4
CALO5 EQU       5,L             "SET" => A CART IS AT LOCATION 5
CALO6 EQU       6,L             "SET" => A CART IS AT LOCATION 6
CALO7 EQU       7,L             "SET" => A CART IS AT LOCATION 7
CALO8 EQU       8,L             "SET" => A CART IS AT LOCATION 8
CALO9 EQU       9,L             "SET" => A CART IS AT LOCATION 9
CAL10 EQU       10,L            "SET" => A CART IS AT LOCATION 10
CAL11 EQU       11,L            "SET" => A CART IS AT LOCATION 11
CAL12 EQU       12,L            "SET" => A CART IS AT LOCATION 12
*
*CLOC  EQU      1,PF            CART LOCATION
*INDEX EQU      2,PF            ROW/COLUMN INDEX FOR MATRICES
*NLOC  EQU      3,PF            NEXT MACHINE'S LOCATION
*MYLOC EQU      4,PF            THIS PART'S LOCATION
*PMLOC EQU      5,PF            PREVIOUS MACHINE'S LOCATION
*RETUR EQU      6,PF            RETURN ADDRESS FROM SUBROUTINE
*ROW   EQU      7,PF            ROW TO SCAN IN MATRICES
*WSLOC EQU      8,PF            WAIT SPACE LOCATION
*
```

```
USCA1 EQU       11,S            POOL OF IDLE CARTS AT UNLOADING
USCA2 EQU       12,S            STATION ONE AND TWO
*
NTYPA SYN       2               NUMBER OF TYPE A MACHINES
NTYPB SYN       2               NUMBER OF TYPE B MACHINES
NUMWS SYN       4               NUMBER OF WAIT SPACES
NCLOC SYN       10              NO. OF FEASIBLE CART LOCATIONS
PTYP1 SYN       1               SYMBOLIC ROW SUBSCRIPT (PART 1)
PTYP2 SYN       2               SYMBOLIC ROW SUBSCRIPT (PART 2)
STEP1 SYN       1               SYMBOLIC COLUMN SUBSCRIPT
STEP2 SYN       2               SYMBOLIC COLUMN SUBSCRIPT
TRUE  SYN       1               SYMBOL FOR "TRUE"
*
PROC1 TABLE     M1,20,10,5      PROCESSING TIME TABLE, PART 1
RAPT1 TABLE     RT,5,5,8,480    PRODUCTION RATE TABLE, PART 1
PROC2 TABLE     M1,20,10,5      PROCESSING TIME TABLE, PART 2
RAPT2 TABLE     RT,5,5,8,480    PRODUCTION RATE TABLE, PART 2
*
* INTRODUCTION OF PARTS INTO THE MODEL
*
      GENERATE  ,,,3,,8PF       PUT 7 PARTS INTO THE MODEL INITIALLY
      TRANSFER  ,TYPE1          TRANSFER TO THE APPROPRIATE SEGMENT
      GENERATE  ,,,4,,8PF
      TRANSFER  ,TYPE2
ENTRY GENERATE  ,,,,,8PF        PROVIDE OTHER PARTS OVER TIME
      GATE LS   NEXTP           PENDING PARTS WAITS UNTIL IT'S NEEDED
      LOGIC R   NEXTP           BLOCK THE NEXT PENDING PART
      TRANSFER  ,FN$PTSEQ       TRANSFER TO THE APPROPRIATE SEGMENT
*
* LOGIC FOR TYPE 1 PART
*
TYPE1 QUEUE     PTLS1           CHECK INTO TYPE 1 LOAD STATION
      TEST E    BV$PTLS1,TRUE   WAIT FOR THE TYPE 1 LOAD STATION
      DEPART    PTLS1           LEAVE QUEUE
      SEIZE     LSPT1           CLAIM THE TYPE 1 LOAD STATION
      ASSIGN    4,LSPT1,PF      ASSIGN THIS PART'S CURRENT LOCATION
```

```
*
* ADJUST PART'S PRIORITY FOR LATER USE OF A STEP 1 MACHINE
*
        PRIORITY   V2
        QUEUE      PTS11            CHECK INTO TYPE 1 QUEUE, STEP1
        TEST E     BV$CANDA,TRUE    WAIT FOR A CART AND A TYPE A MACHINE
        DEPART     PTS11            LEAVE QUEUE
*
* FIND AND CLAIM THE NEAREST IDLE CART AND IDLE TYPE A MACHINE
*
 AAA    TRANSFER   SBR,GETCA,6PF
 BBB    TRANSFER   SBR,GETTA,6PF
*
* THE CART TRAVELS TO THE LOAD STATION
*
        ADVANCE    MH$TTIME(PF1,PF4)
*
        RELEASE    LSPT1            TYPE 1 LOAD STATION IS NOW FREE
*
* THE CART TRAVELS TO THE TYPE A MACHINE
*
        ADVANCE    MH$TTIME(PF4,PF3)
*
        ASSIGN     4,PF3,PF          ASSIGN THE PART'S CURRENT LOCATION
        LEAVE      CARTS            THE CART IS NOW IDLE
        LOGIC S    PF3              SIGNAL THAT THIS CART IS FREE
*
* PROCESSING TIME FOR PART TYPE 1
*
        ADVANCE    MH$STIME(PTYP1,STEP1)
*
        ASSIGN     5,PF3,PF          SAVE THIS STEP 1 MACHINE'S LOCATION
        QUEUE      PTUS1            CHECK INTO UNLOADING STATION QUEUE
        TEST E     BV$CNPU1,TRUE    WAIT FOR THE UNLOADING STATION & CART
        DEPART     PTUS1            LEAVE QUEUE
        SEIZE      ULSP1            CLAIM THE UNLOADING STATION
```

```
CCC    TRANSFER   SBR,GETCA,6PF
       ADVANCE    MH$TTIME(PF1,PF4)
       LEAVE      MTYPA            THE MACHINE A IS NOW FREE
       RELEASE    PF5              FREE THE INDIVIDUAL MACHINE
       ADVANCE    MH$TTIME(PF4,11)
       LEAVE      CARTS            THE CART IS NOW IDLE
       ENTER      USCA1
       LOGIC S    CAL11            SIGNAL THAT AN IDLE CART IS HERE
       LOGIC S    NEXTP            ADMIT ANOTHER PART INTO THE SYSTEM
       RELEASE    ULSP1            LEAVE QUEUE
       TABULATE   PROC1
       TABULATE   RAPT1            UPDATE THE PRODUCTION RATE TABLE
OUTP1  TERMINATE                   FINISHED TYPE 1 PART
*
* LOGIC FOR TYPE 2 PART
*
TYPE2  QUEUE      PTLS2            CHECK INTO TYPE 2 LOAD STATION
       TEST E     BV$PTLS2,TRUE    WAIT FOR THE TYPE 2 LOAD STATION
       DEPART     PTLS2            LEAVE QUEUE
       SEIZE      LSPT2            CLAIM THE TYPE 2 LOAD STATION
       ASSIGN     4,LSPT2,PF       ASSIGN THIS PART'S CURRENT LOCATION
*
* ADJUST PART'S PRIORITY FOR LATER USE OF A STEP 1 MACHINE
*
       PRIORITY   V3
       QUEUE      PTS12            CHECK INTO TYPE 2 QUEUE, STEP1
       TEST E     BV$CANDB,TRUE    WAIT FOR A CART AND A TYPE B MACHINE
       DEPART     PTS12            LEAVE QUEUE
*
* FIND AND CLAIM THE NEAREST IDLE CART AND IDLE TYPE B MACHINE
*
DDD    TRANSFER   SBR,GETCA,6PF
EEE    TRANSFER   SBR,GETTB,6PF
*
* THE CART TRAVELS TO THE LOAD STATION
*
```

```
        ADVANCE    MH$TTIME(PF1,PF4)
*
        RELEASE    LSPT2           TYPE 2 LOAD STATION IS NOW FREE
*
* THE CART TRAVELS TO THE TYPE B MACHINE
*
        ADVANCE    MH$TTIME(PF4,PF3)
*
        ASSIGN     4,PF3,PF         ASSIGN THE PART'S CURRENT LOCATION
        LEAVE      CARTS           THE CART IS NOW IDLE
        LOGIC S    PF3             SIGNAL THAT THIS CART IS FREE
        PRIORITY   V4
*
* PROCESSING TIME FOR PART TYPE 2
*
        ADVANCE    MH$STIME(PTYP2,STEP1)
*
        ASSIGN     5,PF3,PF         SAVE THIS STEP 1 MACHINE'S LOCATION
        QUEUE      PTS22           CHECK INTO THE QUEUE FOR STEP 2
        TEST E     BV$CMAOW,TRUE   WAIR FOR:CART,MACHINE A OR WAIT SPACE
        DEPART     PTS22           LEAVE QUEUE
 FFF    TRANSFER   SBR,GETCA,6PF
*
* IS THE PART MOVING TO A TYPE A MACHINE OR A WAIT SPACE
*
        TEST E     BV$MACHA,TRUE,DOWA2
*
 GGG    TRANSFER   SBR,GETTA,6PF
        ADVANCE    MH$TTIME(PF1,PF4)
        LEAVE      MTYPB           THE PREVIOUS MACHINE IS NOW FREE
        RELEASE    PF5             RELEASE THE INDIVIDUAL MACHINE
        TRANSFER   ,FIN22          GO TO STEP 2
*
 DOWA2  TRANSFER   SBR,GETWS,6PF
        ADVANCE    MH$TTIME(PF1,PF4)
        LEAVE      MTYPB           THE PREVIOUS MACHINE IS NOW FREE
```

```
      RELEASE   PF5              RELEASE THE INDIVIDUAL MACHINE
      ADVANCE   MH$TTIME(PF4,PF8)
      ASSIGN    4,PF8,PF
      LEAVE     CARTS            THIS CART IS NOE IDLE
      LOGIC S   PF8              SIGNAL THE CART IS FREE HERE
      QUEUE     PTS22            CHECK INTO THE QUEUE FOR STEP 2
      TEST E    BV$CANDA,TRUE    WAIT FOR A CART AND A MACHINE A
      DEPART    PTS22            LEAVE QUEUE
HHH   TRANSFER  SBR,GETCA,GPF
III   TRANSFER  SBR,GETTA,GPF
      ADVANCE   MH$TTIME(PF1,PF4)
      LEAVE     WSPAC            THIS WAIT SPACE IS NOW FREE
      RELEASE   PF8              RELEASE THE INDIVIDUAL WAIT SPACE
*
FIN22 ADVANCE   MH$TTIME(PF4,PF3)
      ASSIGN    4,PF3,PF          ASSIGN THIS PART'S CURRENT LOCATION
      LEAVE     CARTS            THIS CART IS NOW IDLE
      LOGIC S   PF3              SIGNAL THAT A CART IS FREE HERE
      ADVANCE   MH$STIME(PTYP2,STEP2)
      ASSIGN    5,PF3,PF          SAVE THIS STEP 2 MACHINE'S LOCATION
      QUEUE     PTUS2            CHECK INTO UNLOADING STATION QUEUE
      TEST E    BV$CNPU2,TRUE    WAIT FOR THE UNLOADING STATION & CART
      DEPART    PTUS2            LEAVE QUEUE
      SEIZE     ULSP2            CLAIM THE UNLOADING STATION
JJJ   TRANSFER  SBR,GETCA,GPF
      ADVANCE   MH$TTIME(PF1,PF4)
      LEAVE     MTYPA            THE MACHINE A IS NOW FREE
      RELEASE   PF5              FREE THE INDIVIDUAL MACHINE
      ADVANCE   MH$TTIME(PF4,12)
      LEAVE     CARTS            THE CART IS NOW IDLE
      ENTER     USCA2
      LOGIC S   CAL12            SIGNAL THAT AN IDLE CART IS HERE
      LOGIC S   NEXTP            ADMIT ANOTHER PART INTO THE SYSTEM
      RELEASE   ULSP2            LEAVE QUEUE
      TABULATE  PROC2
      TABULATE  RAPT2            UPDATE THE PRODUCTION RATE TABLE
```

```
 OUTP2 TERMINATE                         FINISHED TYPE 2 PART
*
* SUBROUTINE TO FIND AND CLAIM NEAREST CART
*
 GETCA ENTER      CARTS             CLAIM CARTS
       ASSIGN     2,NCLOC,PF        INITIALIZE THE SCAN INDEX
*
* IS AN IDLE CART IN THIS LOCATION?
*
 UPCAR GATE LR    MH$CLOC(PF2,PF4),DOWNC
*
       LOOP       2PF,UPCAR         IDLE CART NOT FOUND; SCAN AGAIN
*
* IDLE CART FOUND; ASSIGN THIS CART'S CURRENT LOCATION
*
 DOWNC ASSIGN     1,MH$CLOC(PF2,PF4),PF
*
       LOGIC R    PF1               CLAIM THIS CART
       TEST GE    PF1,ULSP1,EXIT
       LEAVE      PF1
       GATE SNE   PF1,EXIT
       LOGIC S    PF1
 EXIT  TRANSFER   PF,6,1            BACK TO THE MAIN SEGMENT
*
*
* SUBROUTINE TO FIND AND CLAIM NEAREST OR AVAILABLE TYPE A MACHINE
*
*
 GETTA ENTER      MTYPA             CLAIM TYPE A MACHINE
       GATE LR    ATYA1,AOK2        CHECK IF MACHINE IS AVAILABLE
       GATE LR    ATYA2,AOK1        OTHERWISE; GO TO OTHER MACHINE
       ASSIGN     2,NTYPA,PF        INITIALIZE THE SCAN INDEX
       ASSIGN     7,FN$AMAP,PF      DETERMINE THE SCANNING ROW
*
* IS THE NEXT NEAREST TYPE A MACHINE IDLE?
*
```

```
UPTYA GATE U     MH$TYALO(PF7,PF2),DOWTA
*
      LOOP       2PF,UPTYA       NO; CONTINUE TO SCAN
*
* YES; ASSIGN THIS MACHINE'S CURRENT LOCATION
*
DOWTA ASSIGN     3,MH$TYALO(PF7,PF2),PF
      SEIZE      PF3             CLAIM THIS MACHINE
      TRANSFER   PF,6,1          BACK TO THE MAIN SEGMENT
AOK1  SEIZE      MTYA1
      ASSIGN     3,MTYA1,PF
      TRANSFER   PF,6,1
AOK2  SEIZE      MTYA2
      ASSIGN     3,MTYA2,PF
      TRANSFER   PF,6,1
*
*
* SUBROUTINE TO FIND AND CLAIM NEAREST OR AVAILABLE TYPE B MACHINE
*
*
GETTB ENTER      MTYPB           CLAIM TYPE B MACHINE
      GATE LR    ATYB1,BOK2
      GATE LR    ATYB2,BOK1
      ASSIGN     2,MTYPB,PF      INITIALIZE THE SCAN INDEX
      ASSIGN     7,1,PF          DETERMINE THE SCANNING ROW
*
* IS THE NEXT NEAREST TYPE B MACHINE IDLE?
*
UPTYB GATE U     MH$TYBLO(PF7,PF2),DOWTB
*
      LOOP       2PF,UPTYB       NO; CONTINUE TO SCAN
*
* YES; ASSIGN THIS MACHINE'S CURRENT LOCATION
*
DOWTB ASSIGN     3,MH$TYBLO(PF7,PF2),PF
      SEIZE      PF3             CLAIM THIS MACHINE
```

```
*
         GENERATE   480             TIMER COMES EVERY 8 HOURS
         TERMINATE  1               SHUT OFF THE RUN
*
         START      5,NP            TRANSIENT CONDITIONS
         RESET                      REINITIALIZE THE STATISTICAL ACCUM.
         START      35              ANOTHER 200 HOURS (STEAD STATE)
         END
/*
```

A-2 OUTPUT FILE

RELATIVE CLOCK 16800 ABSOLUTE CLOCK 19200
BLOCK COUNTS

BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL
1	0	0	11	0	686	21	0	686	31	0	688	41	0	688
2	0	0	12	0	686	22	0	686	32	0	688	42	0	688
3	0	0	13	0	686	23	0	687	33	0	688	43	0	688
4	0	0	14	0	686	24	0	687	34	0	688	44	0	688
5	1	1598	15	0	686	25	0	687	35	0	688	45	0	913
6	0	1598	16	0	687	26	0	687	36	0	688	46	0	913
7	0	1598	17	0	687	27	0	688	37	0	688	47	0	913
8	0	1598	18	0	687	28	0	688	38	0	688	48	0	913
9	0	685	19	0	687	29	0	688	39	0	688	49	0	913
10	0	686	20	1	687	30	0	688	40	0	688	50	0	913

BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL
51	0	913	61	0	913	71	1	194	81	0	721	91	0	914
52	0	913	62	0	913	72	0	193	82	0	721	92	0	914
53	0	913	63	0	913	73	0	193	83	0	721	93	0	914
54	0	913	64	0	914	74	0	193	84	0	721	94	0	914
55	0	913	65	0	914	75	0	720	85	0	721	95	0	914
56	0	913	66	0	914	76	0	720	86	0	721	96	0	914
57	0	913	67	0	914	77	0	720	87	0	721	97	0	914
58	0	913	68	0	914	78	0	720	88	0	721	98	0	914
59	0	913	69	0	914	79	0	720	89	0	721	99	0	914
60	0	913	70	0	194	80	0	721	90	0	721	100	0	914

BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL
101	0	914	111	0	915	121	0	1602	131	0	848	141	0	913
102	0	914	112	0	915	122	0	1602	132	0	1592	142	0	913
103	0	914	113	0	915	123	0	253	133	0	1592	143	0	911
104	0	914	114	0	4837	124	0	4837	134	0	1592	144	0	911
105	0	914	115	0	4837	125	0	1602	135	0	2	145	0	911
106	0	915	116	0	24650	126	0	1602	136	0	2	146	0	1361

107	0	915	117	0	19813	127	0	1594	137	0	2	147	0	450
108	0	915	118	0	4837	128	0	1592	138	0	8	148	0	911
109	0	915	119	0	4837	129	0	1592	139	0	8	149	0	911
110	0	915	120	0	4837	130	0	2440	140	0	8	150	0	911

BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL
151	0	0	161	0	1	171	0	131	181	0	169	191	0	580
152	0	0	162	0	720	172	0	131	182	0	169	192	2	580
153	0	0	163	0	720	173	0	131	183	0	144	193	0	579
154	0	2	164	0	720	174	0	131	184	0	144	194	0	579
155	0	2	165	0	134	175	0	128	185	0	144	195	0	565
156	0	2	166	0	134	176	0	128	186	0	144	196	0	565
157	0	720	167	0	133	177	0	172	187	0	143	197	0	14
158	0	720	168	0	133	178	0	172	188	0	143	198	0	14
159	0	720	169	0	126	179	0	172	189	0	580	199	0	14
160	0	721	170	0	126	180	0	172	190	0	580	200	0	15

BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL
201	0	35												
202	0	35												


```
****************************************
*                                      *
*              FACILITIES              *
*                                      *
****************************************
```

FACILITY	NUMBER ENTRIES	AVERAGE TIME/TRAN	-AVERAGE UTILIZATION DURING- TOTAL TIME	AVAIL. TIME	UNAVAIL. TIME	CURRENT STATUS	PERCENT AVAILABILITY	TRANSACTION NUMBER SEIZING	PREEMPTING
LSPT1	687	17.198	.703				100.0	15	
LSPT2	913	3.289	.178				100.0		
MTYA1	834	18.629	.924				100.0	15	

MTYB1	461	26.258	.720	100.0	
WSPA1	180	12.233	.131	100.0	
WSPA2	181	11.619	.125	100.0	
WSPA3	180	11.033	.118	100.0	
WSPA4	180	16.311	.174	100.0	
MTYB2	453	28.179	.759	100.0	5
MTYA2	770	19.513	.894	100.0	5
ULSP1	688	5.567	.227	100.0	
ULSP2	915	5.374	.292	100.0	

STORAGES

STORAGE	CAPACITY	AVERAGE CONTENTS	ENTRIES	AVERAGE TIME/UNIT	-AVERAGE UTILIZATION DURING- TOTAL TIME	AVAIL. TIME	UNAVAIL. TIME	CURRENT STATUS	PERCENT AVAILABILITY	CURRENT CONTENTS	MAXIMUM CONTENTS
CARTS	3	1.458	4840	5.061	.486				100.0	2	3
MTYPA	2	1.819	1604	19.054	.909				100.0	2	2
MTYPB	2	1.480	914	27.210	.740				100.0	1	2
WSPAC	4	.549	721	12.798	.137				100.0		2
REP	3	1.622	581	46.910	.540				100.0	2	3
USCA1	2	.225	688	5.494	.112				100.0		2
USCA2	2	.425	915	7.796	.212				100.0	1	2

QUEUES

QUEUE	MAXIMUM CONTENTS	AVERAGE CONTENTS	TOTAL ENTRIES	ZERO ENTRIES	PERCENT ZEROS	AVERAGE TIME/TRANS	$AVERAGE TIME/TRANS	TABLE NUMBER	CURRENT CONTENTS
PTLS1	3	.952	686	201	29.3	23.335	33.006		
PTS11	1	.570	687	186	27.0	13.953	19.133		
PTUS1	1	.000	688	687	99.8	.002	2.000		
PTLS2	1	.000	913	913	100.0	.000	.000		
PTS12	1	.046	913	830	90.9	.858	9.445		
PTS22	2	.241	1635	1026	62.7	2.480	6.660		
PTUS2	1	.000	914	904	98.9	.014	1.299		
REP	6	.250	580	425	73.2	7.262	27.174		

$AVERAGE TIME/TRANS = AVERAGE TIME/TRANS EXCLUDING ZERO ENTRIES

****
*   *
*   TABLES   *
*   *
****

TABLE PROC1

ENTRIES IN TABLE	MEAN ARGUMENT	STANDARD DEVIATION	SUM OF ARGUMENTS	
688	63.357	24.875	43590.000	NON-WEIGHTED

UPPER LIMIT	OBSERVED FREQUENCY	PER CENT OF TOTAL	CUMULATIVE PERCENTAGE	CUMULATIVE REMAINDER	MULTIPLE OF MEAN	DEVIATION FROM MEAN
20	0	.00	.0	100.0	.315	-1.743
30	189	27.47	27.4	72.5	.473	-1.341
40	10	1.45	28.9	71.0	.631	-.938
50	3	.43	29.3	70.6	.789	-.536
OVERFLOW	486	70.63	100.0	.0		

AVERAGE VALUE OF OVERFLOW 78.34

TABLE RAPT1

ENTRIES IN TABLE MEAN ARGUMENT STANDARD DEVIATION SUM OF ARGUMENTS

35	19.657	2.421	688.000	NON-WEIGHTED

UPPER LIMIT	OBSERVED FREQUENCY	PER CENT OF TOTAL	CUMULATIVE PERCENTAGE	CUMULATIVE REMAINDER	MULTIPLE OF MEAN	DEVIATION FROM MEAN
5	0	.00	.0	100.0	.254	-6.051
10	0	.00	.0	100.0	.508	-3.987
15	1	2.85	2.8	97.1	.763	-1.922
20	14	39.99	42.8	57.1	1.017	.141
25	20	57.14	100.0	.0	1.271	2.206

REMAINING FREQUENCIES ARE ALL ZERO

TABLE PROC2

ENTRIES IN TABLE	MEAN ARGUMENT	STANDARD DEVIATION	SUM OF ARGUMENTS	
915	54.048	6.843	49454.000	NON-WEIGHTED

UPPER LIMIT	OBSERVED FREQUENCY	PER CENT OF TOTAL	CUMULATIVE PERCENTAGE	CUMULATIVE REMAINDER	MULTIPLE OF MEAN	DEVIATION FROM MEAN
20	0	.00	.0	100.0	.370	-4.975
30	0	.00	.0	100.0	.555	-3.513
40	1	.10	.1	99.8	.740	-2.052
50	274	29.94	30.0	69.9	.925	-.591
OVERFLOW	640	69.94	100.0	.0		

AVERAGE VALUE OF OVERFLOW 57.71

TABLE RAPT2

ENTRIES IN TABLE	MEAN ARGUMENT	STANDARD DEVIATION	SUM OF ARGUMENTS	
35	26.142	3.078	915.000	NON-WEIGHTED

UPPER LIMIT	OBSERVED FREQUENCY	PER CENT OF TOTAL	CUMULATIVE PERCENTAGE	CUMULATIVE REMAINDER	MULTIPLE OF MEAN	DEVIATION FROM MEAN
5	0	.00	.0	100.0	.191	-6.868
10	0	.00	.0	100.0	.382	-5.244
15	0	.00	.0	100.0	.573	-3.620
20	0	.00	.0	100.0	.765	-1.995
25	11	31.42	31.4	68.5	.956	-.371
30	24	68.57	100.0	.0	1.147	1.253

Appendix A-3 SAS program for regression analysis

```
// JOB
//*MAIN CLASS=SAS
//*SAS PROG FOR MAINTENANCE FLOAT REGRESSION STUDY BY KUEI 2/28/1990
// EXEC SAS,REGION=1000K
//SYSIN DD *
DATA MAIN;
INPUT ID 1-2 MA 4-6 MB 8-10 R 12-13 S 15 FA 17 FB 19 TH1 21-26 TH2 28-33;
CARDS;
01 120 100 40 1 2 2 10.171 13.657
02 120 100 40 1 2 5 10.457 13.742
03 120 100 40 4 5 2 13.342 17.714
04 120 100 40 4 5 5 20.914 27.799
05 120 100 80 1 5 2  4.714  6.342
06 120 100 80 1 5 5  5.457      7
07 120 100 80 4 2 2  3.942  5.142
08 120 100 80 4 2 5      6  7.971
09 120 200 40 1 5 2 13.371 17.742
10 120 200 40 1 5 5 16.599 21.971
11 120 200 40 4 2 2 17.342 23.028
12 120 200 40 4 2 5 20.571 27.228
13 120 200 80 1 2 2  5.542  7.285
14 120 200 80 1 2 5  5.428  7.228
15 120 200 80 4 5 2 19.457 25.857
16 120 200 80 4 5 5 21.971 29.199
17 240 100 40 1 5 2 11.428 15.285
18 240 100 40 1 5 5 11.685 15.457
19 240 100 40 4 2 2 15.457 20.571
20 240 100 40 4 2 5 20.914 27.799
21 240 100 80 1 2 2  3.514  4.657
22 240 100 80 1 2 5      7  9.257
23 240 100 80 4 5 2  6.599  8.657
24 240 100 80 4 5 5 20.914 27.799
25 240 200 40 1 2 2 12.799 16.914
26 240 200 40 1 2 5 20.085 26.685
```

```
27 240 200 40 4 5 2 20.914 27.799
28 240 200 40 4 5 5 21.971 29.199
29 240 200 80 1 5 2  9.971 13.285
30 240 200 80 1 5 5  9.399 12.685
31 240 200 80 4 2 2 17.599 23.428
32 240 200 80 4 2 5 21.285 28.257
34 240 200 80 1 2 5 11.199 14.771
35 120 100 80 2 2 5  4.971  6.742
36 240 200 40 2 2 2 20.914 27.799
37 240 100 80 3 2 2  3.914  5.142
38 120 200 40 3 2 5 16.057 21.314
40 120 200 80 4 2 2 14.171 18.742
42 240 200 40 1 5 5 20.914 27.799
43 120 100 40 2 5 5 20.942 27.771
44 240 200 80 2 5 2 18.428 24.542
45 240 100 40 3 5 2 17.942 23.799
46 120 200 80 3 5 5 18.114 24.028
48 120 200 40 4 5 2 20.857 27.685
DATA TEST1; SET MAIN;
PROC PRINT DATA=TEST1;
PROC GLM;
  MODEL  TH1=MA MB R S FA FB FA*MA;
OUTPUT OUT = NEWRES PREDICTED = YHAT RESIDUAL = RESID;
PROC PLOT DATA = NEWRES;
  PLOT RESID * YHAT;
//
```

GENERAL LINEAR MODELS PROCEDURE

DEPENDENT VARIABLE: TH1

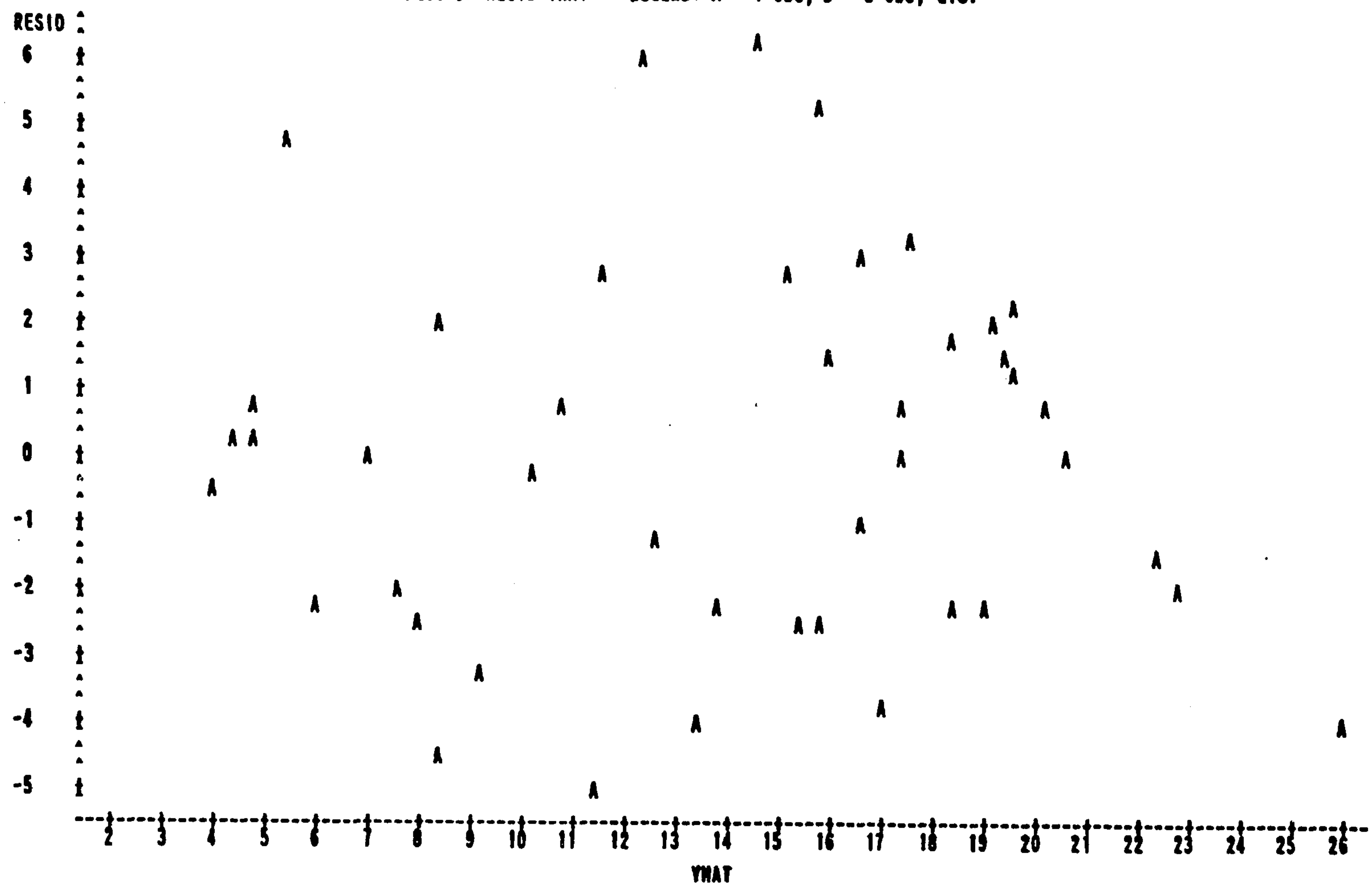
SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PR > F	R-SQUARE	C.V.
MODEL	7	1376.76459542	196.68065649	20.96	0.0001	0.802985	21.9072
ERROR	36	337.79410301	9.38316953		ROOT MSE		TH1 MEAN
CORRECTED TOTAL	43	1714.55869843			3.06319597		13.98261364

SOURCE	DF	TYPE I SS	F VALUE	PR > F	DF	TYPE III SS	F VALUE	PR > F
MA	1	26.98061420	2.88	0.0986	1	90.43307887	9.64	0.0037
MB	1	323.16377605	34.44	0.0001	1	323.16377605	34.44	0.0001
R	1	420.71607384	44.84	0.0001	1	381.92406120	40.70	0.0001
S	1	359.20795669	38.28	0.0001	1	398.36597824	42.46	0.0001
FA	1	94.46067011	10.07	0.0031	1	92.23779929	9.83	0.0034
FB	1	104.97524996	11.19	0.0019	1	104.97524996	11.19	0.0019
MA*FA	1	47.26025457	5.04	0.0311	1	47.26025457	5.04	0.0311

PARAMETER	ESTIMATE	T FOR H0: PARAMETER=0	PR > ^T^	STD ERROR OF ESTIMATE
INTERCEPT	-9.10038684	-2.00	0.0533	4.55354842
MA	0.06075322	3.10	0.0037	0.01956953
MB	0.05442733	5.87	0.0001	0.00927429
R	-0.14792250	-6.38	0.0001	0.02318572
S	2.21494581	6.52	0.0001	0.33993569
FA	3.05363939	3.14	0.0034	0.97395315

FB	1.04025014	3.34	0.0019	0.31100624
MA*FA	-0.01151540	-2.24	0.0311	0.00513105

PLOT OF RESID*YHAT LEGEND: A = 1 OBS, B = 2 OBS, ETC.



Appendix A-4 FORTRAN program for searching optimum maintenance float policy on an unreliable FMS

```
// JOB
// EXEC WATFIV
//SYSIN DD *
$JOB
C
C A SEARCH PROGRAM FOR OPTIMUM MAINTENANCE FLOAT POLICY
C ON AN UNRELIABLE FMS
C
C DECLARATION
      REAL TH1,TH2,CS,CFA,CFB,DTH1,DTH2,TOT,STOT,TH11,TH12
      REAL TH21,TH22,TH23,OTH1,OTH2
      INTEGER S,FA,FB,MA,MB,MTTR
      INTEGER OS,OFA,OFB,OOS,OOFA,OOFB
C
10    READ, S,FA,FB,MA,MB,MTTR,CS,CFA,CFB,DTH1,DTH2
      IF (S .EQ. -1) GO TO 999
      TOT=0.0
C
      DO 300 I=1,S
          OS=I
          DO 200 J=2,FA
              OFA=J
              DO 100 K=2,FB
                  OFB=K

TH11=-10.59875+0.0701*MA+0.0511225*MB-0.13941875*MTTR

TH12=2.32441667*I+3.2715*J+1.13516667*K-0.01463*J*MA
                  TH1=TH11+TH12
                  TH21=-14.11502083+0.09317743*MA+0.06808813*MB
                  TH22=-0.18522031*MTTR+3.08864583*I+4.337*J
                  TH23=1.4981875*K-0.0193559*J*MA
                  TH2=TH21+TH22+TH23
```

```
                IF ((TH1 .LE. OTH1) .OR. (TH2 .LE. OTH2)) GO TO
100
                STOT=CS*I+CFA*J+CFB*K
                IF (TOT .EQ. 0.0) THEN
                    TOT=STOT
                    OOS=OS
                    OOFA=OFA
                    OOFB=OFB
                    OTH1=TH1
                    OTH2=TH2
                ELSE
                IF (STOT .LE. TOT) THEN
                    TOT=STOT
                    OOS=OS
                    OOFA=OFA
                    OOFB=OFB
                    OTH1=TH1
                    OTH2=TH2
                ENDIF
                ENDIF
100   CONTINUE
200   CONTINUE
300   CONTINUE
C
      PRINT,'TOTAL COST= ',TOT
      PRINT,'OPTIMUM NUMBER OF REPAIR PERSONS= ',OOS
      PRINT,'OPTIMUM NUMBER OF FLOAT FOR MACHINE A= ',OOFA
      PRINT,'OPTIMUM NUMBER OF FLOAT FOR MACHINE B= ',OOFB
      PRINT,'THROUGHPUT OF PART TYPE 1= ',OTH1
      PRINT,'THROUGHPUT OF PART TYPE 2= ',OTH2
      GO TO 10
C
999   PRINT,'END OF RUN'
      STOP
      END
$ENTRY
```

```
3,5,5,100,100,40,200,50,60,15,17
-1,0,0,0,0,0,0,0,0,0
$STOP
/*
//
```

A-4 OUTPUT FILE

```
     $ENTRY
TOTAL COST=          950.0000000
OPTIMUM NUMBER OF REPAIR PERSONS=           2
OPTIMUM NUMBER OF FLOAT FOR MACHINE A=            5
OPTIMUM NUMBER OF FLOAT FOR MACHINE B=            5
THROUGHPUT OF PART TYPE 1=          15.3139000
THROUGHPUT OF PART TYPE 2=          20.2779800
END OF RUN
```

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