BUFFER OPTIMIZATION AND ROBUST DESIGN STUDIES IN ASYNCHRONOUS ASSEMBLY SYSTEMS USING DESIGN OF EXPERIMENTS APPROACH

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ABSTRACT

BUFFER OPTIMIZATION AND ROBUST DESIGN STUDIES IN ASYNCHRONOUS ASSEMBLY SYSTEMS USING DESIGN OF EXPERIMENTS APPROACH

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This research concentrates on the buffer specification problem of the design of asynchronous assembly systems (AAS). The objectives of the research are to determine an optimal area of buffers and to design AAS that are robust to noise factors. In order to determine an optimal area of buffers in which the throughput yields to maximum, the design of experiments (DoE) approach and discrete-event simulation are used, and appropriate buffer levels are identified accordingly. Studies indicated that determining an optimal area provided the design engineer the much needed flexibility to choose the buffer sizes within a range. The DoE approach also offered substantial information on the AAS that can serve the design engineer as an invaluable guideline and enable one to design the AAS with a better understanding. Furthermore, the use of DoE approach as an optimization tool is proposed, principally in cases where little known on the AAS that will be designed. Case studies using the DoE approach as a heuristic optimization method are presented. Additionally, in an attempt to study its effect, in some studies, the number of pallets has been considered as a decision variable. Studies conducted throughout this research indicated that the DoE approach to be an effective methodology.

Robust design study is essential to design AAS that are insensitive to uncontrollable factors. Several systems have been investigated and analyses revealed the necessity of robust design study in AAS. Future research areas are suggested.

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NOMENCLATURE

AAS	:	Asynchronous Assembly Systems
DoE	:	Design of Experiments
FAS	:	Flexible Assembly Systems
FMS	:	Flexible Manufacturing Systems
GA	:	Genetic Algorithms
SQG	:	Stochastic Quasigradient Methods
TP	:	Throughput
jr	:	jam rate(s)
jct	:	jam clear time(s)
$\mathbf{b_i}$	:	buffer between station i and $i+1$
$\mathit{variance}_{wrtnf}$	:	variance with respect to noise factors

APPENDICES:

l_i	:	the effect of buffer i
m	:	mean
v	:	variance
r	:	replications of each run
$\mathbf{z_r}$	:	number of units produced for particular buffer at given replication r
α	:	level of significance
df	:	degree of freedom
CI	:	confidence interval

CHAPTER 1

INTRODUCTION

1.1. ASSEMBLY

1.1.1. THE HISTORY OF ASSEMBLY

The history of assembly is almost as long as the history of crafts. Thousand years ago, people started assembling parts in order to make a serviceable item. Yet, the modern assembly differs from the ancient assembly mainly by its goal. The modern assembly process aims to produce products that are high in quality and low in cost.

Throughout its history, the assembly process was modernized mainly by two ideas. The first one was the principle of interchangeability. The principle of interchangeability, which was developed in the 1800s, introduced the idea that the parts that are used to make a finished product must be interchangeable between product units[4]. Standardization of parts, in other words, interchangeability, simplified the assembly process by bringing the same specifications for assembly parts.

Division of labor was the second major idea for modern assembly systems [22]. Work simplification, standardization, and specialization are the philosophies behind the idea of division of labor. Briefly, complex or long assembly tasks can be divided into a number of smaller tasks. Each task builds a part of the assembly and performs independently. Since each task is given to different operator, operators can quickly develop their skills for these repetitive operations.

Combining these two ideas, the assembly process improved its facility, speed and quality. Mass production became easier and replacement parts could be used for more durable products. Using these improvements, Henry Ford and other innovators developed assembly lines in the 1900s. Although assembly lines did not change the total processing time, they drastically reduced the cost of production and increased the production volume. As a result of these developments, high-priced objects became affordable to most. This obvious advantage made assembly lines embraced and in the first half of the century, most of the efforts were on increasing the applications on assembly lines.

It is almost in the second half of this century that the idea of replacing operators by machines appealed designers. Initially, machines are used for basic and too repetitive tasks. Technological improvements and recently the rapid progression of computers made possible to produce more complex machines and robots.

1.1.2. ASSEMBLY TYPES

Today, there are two types of assembly; manual and automatic. Manual assembly is the traditional assembly where human operators work. Manual assembly may be preferred in the case of low production volume and complex operation.

On the other hand, automatic assembly is necessary for high production volume. Automatic assembly is composed of workstations that automatically perform the easy or otherwise uneconomical tasks, and a transfer system which moves the assemblies from one workstation to another. Automatic assembly is also divided into two; hard and flexible automation.

In hard automation, the line is designed for a single product. Even minor changes in product design can cause the line to be outmoded. Recent advances in automation and the development of low-cost controllers have resulted in programmable workstations and flexible flow lines. In a flexible assembly system a workstation can perform alternative tasks. Flexibility is becoming more important as rapid technological innovation and intense competition shorten product life cycles [4].

Another classification of the assembly systems is:

1. Synchronous Assembly Systems
2. Asynchronous Assembly Systems

In synchronous assembly systems, each workstation has exactly the same amount of time to operate on each unit of product. At the end of this cycle time C, the transfer system automatically moves each unit to the next station. Although synchronous lines can exactly balance production, unless slack time is built into each station, the randomness of performance occasionally will cause some items not to be completed. Extra time must be allowed in the fixed cycle time to cushion against task time variability.

On the contrary, asynchronous assembly systems allow some measure of autonomy from workstation to workstation [55]. In asynchronous lines, the station removes a new unit from the handling systems as soon as it has completed the previous unit, performs the required tasks, and then forwards the unit on to the next station. Parts need not be passed on incomplete. Likewise, when two adjacent workers finish early, the second worker can begin the next part early and increase the chance of finishing on time[4]. Obviously, asynchronous assembly systems have advantage over synchronous assembly systems. When a stoppage occurs at individual stations in an asynchronous system, the rest of the system continues to operate, while in a synchronous system would stop entirely [55] .

1.1.3. ASSEMBLY LINES

An assembly line is a set of sequential workstations, typically connected by a continuous material handling system. The line is designed to assemble component parts and perform any related operations necessary to produce a finished product. The product is passed down the line, visiting each station in sequence. Upon exiting the final station, the product is complete. The line is operated such that the stations are simultaneously busy. Upon completion of its assigned tasks on an item, the station passes the item to the next station, obtains a new item from its predecessor station, and repeats its tasks [4] .

An assembly line may consist of one or more components. The total assembly time equals to the sum of the separate operation process times. The number of operations and operation contents are basically determined by the structure of the assembly and the complexity of the assembly work. An assembly is usually composed of a number of components or subassemblies. If the total assembly work is too complex, engineers tend to break the entire assembly work into a number of operations, making each operation responsible for one or more subassemblies. Depending on its complexity, a subassembly may further be broken into components, and then operations may be defined for one or more components. The question is how to determine the level of complexity at each operation [22].

1.2. DEVELOPMENT OF ASSEMBLY SYSTEMS

Engineers and scientists have engaged in multidisciplinary analyses, learning that proper work conditions (i.e., job content, tooling and fixtures, workstations, etc.) provide operators with safer and more productive jobs. Time and motion study, analysis of human performance and ergonomics have been introduced to industry. At this stage, assembly job design begins to integrate human behavior into workstation design. Consequently, efficiency at the workstation level is greatly improved [22].

As more and more components are included, line efficiency eventually becomes a problem. Efficiency improvement at the component level does not guarantee overall performance efficiency. Line-integration concept therefore are introduced. The line designer must take a system view and a structural approach. First, a cost objective must be defined based on both market analysis and manufacturing conditions. Then the product cost structure must be understood. Usually, this is defined by the product characteristics and the manufacturing environment. By comparing the cost objective and the cost structure, the line designer may conduct a study for production feasibility and affordability. At this stage, questions such as resource availability, production capacity, the speed of the scale-up, and engineering skills must be answered. Derived from this study is a line design concept that involves a number of interrelated subjects (i.e., tooling strategy, material handling system, line size, line configuration, flexibility needed for future engineering changes or line-capacity adjustment, and space strategy.) The mission of line design is then to convert the design concept into a physical line [22] .

1.3. DESIGN PROBLEMS OF FLEXIBLE MANUFACTURING / ASSEMBLY SYSTEMS (FMS/FAS)

FMS/ FAS design problems are very important regarding the complexity of these problems. However, the major FMS / FAS research has been oriented towards operation problems of these systems [49]. FMS design problems are difficult to model, because the number of trade-offs that have to be incorporated into the models is very large.

In FMS design problems, another important issue is the dynamic structure of the system. We can use some analytical tools to determine a parameter of the system, but input to these tools is quite dynamic and an optimal solution for the current part mix may become a suboptimal one for the next part mix. Therefore, in analytical solutions, we can see that the decomposition technique is applied (i.e., type of product mix is assumed constant at any given time).

Stecke [79] presents a through discussion of FMS design problems. She partitions design problems into initial specification and subsequent implementation decisions. The initial specification decisions are given as follows.

- Specification of the part types to be produced in the system,
- Determination of the process plans for parts and specification of the numbers and types of machines,
- Specification of the flexibilities that are required,
- Determination of the type of FMS,

- Specification of the material handling system and its capacity,
- Specification of the sizes of buffers
- Specification of the computer hierarchy,
- Determination of the vendors.

The subsequent implementation decisions are given as follows.

- Specification of the FMS layout,
- Determination of the number of the pallets,
- Specifications of the fixtures' design and their numbers,
- Determination of the general planning and control objectives,
- Development of the necessary software.

Stecke presents these problems in a sequential manner. Although some of these problems can be addressed simultaneously, the whole design problem cannot be solved in one step. Therefore, a sequential and iterative solution method has to be developed.

1.4. OBJECTIVES AND CONTRIBUTIONS OF THIS RESEARCH

In this research, we will concentrate on the specification of the buffer sizes in the asynchronous assembly systems. We have two objectives:

1. determining an optimal area in AAS where the throughput is maximum or near maximum,
2. studying the *robustness* and finding the robust designs in AAS.

The first objective addresses a weakness of optimization studies. Previous studies in optimization of buffer sizes found an optimal solution and terminated the optimization at that point [55,54,79,27,77]. However, our consultations with the design engineers indicated that in many cases, these optimal solutions may not be implemented as proposed, due to restrictions that may occur, such as cost, space, etc. Thus, many applications in the industry need the flexibility to choose the buffer sizes within the range that leads to the maximum or near maximum throughput. For this purpose, we use the DoE approach to determine the buffer ranges that give the maximum or near maximum throughput, hence determine an optimal area in AAS.

Robust design study in AAS is essential to eliminate the undesired effects of the uncontrollable factors on the throughput. Previous studies entirely ignored these effects [55,54,79,27,77]. So far, the uncontrollable factors such as jam rates and jam clear times are assumed to be constant factors (i.e., unchanging) and optimization was conducted accordingly. However, our experiences and consultations also indicated that such factors may affect the throughput considerably. Consequently, the optimal solution(s) proposed may not give the anticipated efficiency or improvement. Thus, a study on the effects of the uncontrollable factors is the key to have robust AAS designs.

In addition, we propose the use of DoE approach as the practical optimization tool especially when little information on the system is available. We also study the optimization problem where number of pallets is not fixed and also considered as a decision variable in an attempt to study its effect on the throughput.

Concisely, the main contributions of this research are as follows.

- determines an optimal area where almost all solutions are optimum or near optimum; hence gives the design engineer the flexibility of choosing buffer specifications within the proposed buffer ranges,
- design the system that is robust to uncontrollable factors by determining the buffer ranges that give insensitive throughput against uncontrollable changes in the noise (uncontrollable) factors.

Furthermore, this research

- extends the applications of the design of experiments (DoE) approach to the design phase of the AAS,
- suggests that the DoE approach may be used as a practical optimization tool and provides case studies where the DoE approach is used for the optimization,
- studies the effects of the number of pallets in the system.

1.5. ORGANIZATION OF THE FOLLOWING CHAPTERS

Chapter 2 lists the previous studies in the assembly systems and transfer lines as well as the studies using the design of experiments approach with a concentration on the robust design studies.

Chapter 3 explains the DoE approach, robust design, and the techniques used in this research, in addition to detailed reasons of why it is the DoE approach that satisfies our objectives.

Chapter 4 first defines the problem studied (i.e., determining an optimal area in AAS), then discusses the systems and the conclusions of the analyses. Mainly, the systems and the optimal solutions that are proposed in previous studies[55] are considered and the buffer ranges that define an optimal area are determined. The studies where the DoE is used as a proposed practical optimization tool are also presented.

Chapter 5 also defines the problem investigated in this chapter (i.e., robust design of AAS) and presents the systems and the conclusions of the analyses of the studies conducted.

Chapter 6 reviews the studies conducted in this research and suggests what can be done in further study.

CHAPTER 2

LITERATURE REVIEW

In this chapter, we review the literature in two main groups, namely (1) studies in assembly systems or assembly-like systems, and (2) studies using the design of experiments (DoE) approach and robust design studies. The first two sections address to the first group where assembly systems or assembly-like systems are studied, and the next two sections review the second group where DoE is used and/or robust systems are designed.

There are numerous studies in the area of assembly systems. In this chapter, we will present the studies involving modeling, design, and analysis of assembly systems, with a concentration on buffer allocations and studies using similar modeling ideas. First, we will review the studies in transfer lines (2.1.). Then, we will review the studies in assembly systems (2.2.).

The DoE approach exists since early 1920s. Consequently, there are several applications of the DoE approach in literature. In the section 2.3., we will review studies using the DoE approach in manufacturing systems as well as studies concentrated on improving the DoE techniques and extending its applications.

The robust design is a special application of the DoE approach which gained popularity in the last two decades. Consequently, there is limited literature available on robust design. In section 2.4. we will review the robust design studies in several industries.

2.1. TRANSFER LINES

Conway et. al. [24] examine serial production systems. Several scenarios are investigated. Simulation is used except for a few simple cases that could be solved analytically. Cases where workstations do not fail and cases with unreliable workstations are considered. Altiok and Stidham [2] consider allocation of buffer capacity to systems with more general service time distributions. Altiok and Perros [3] consider splitting and merging into parallel stations as units pass down the line. Masso and Smith [57] determine the minimal total buffer capacity required for a three-stage line to reach its maximum level of system performance. Their technique allocates the given quantity of total buffer capacity among the individual buffer storage areas. Okamura and Yamashina [64] study the allocation of buffer stock in two-stage automatic transfer lines for balanced and unbalanced cases. Hollier and Satir [40] maintain the balance of a series production system with different numbers of parallel machines at each stage by controlling inter-stage stocks. Ho et. al. [38,39] use perturbation analysis and gradient method to study the effect of cycle times and buffer sizes on the throughput of open transfer lines. Okamura and Yamashina [65] analyze buffer storage for multistage transfer line systems.

2.2. MODELING, DESIGN, AND ANALYSIS OF ASSEMBLY SYSTEMS

The literature of design problems in assembly systems is very broad. Since this research deals with the buffer allocation part of the design problems of assembly systems, we have concentrated on the studies in buffer allocation. In addition, we have reviewed the assembly systems studies that use similar modeling and/or analysis ideas to that of this research as well as studies using simulation. Section 2.2.1. reviews studies dealing with the buffer allocation problem. Section 2.2.2. covers studies using simulation. Section 2.2.3. covers other studies in assembly systems or assembly-like systems.

2.2.1. BUFFER ALLOCATION

The buffer optimization study using the Stochastic Quasigradient methods (SQG) approach [55] has special importance in this research, since we have investigated the systems and the optimal solutions determined in this paper. Liu and Sanders study a variety of assembly systems that are subject to blocking and starvation effects. They use a hybrid algorithm which applies a queuing network model to set the number of pallets in the system and then an SQG algorithm to set the buffer spacings to obtain optimal systems throughput. They remark that the combined Queuing Network-SQG method appears to perform well in obtaining a near optimal solution in this discrete optimization example, even though the SQG method was primarily designed for application to differentiable performance functionals. They finally conclude that while a number of both theoretical and practical problems remain to be resolved, a heuristic version of the SQG method appears to be a reasonable technique for analyzing optimization problems for certain complex manufacturing systems.

Simon and Hopp [76] study the availability of inventory in an assembly-like flow system. The system is balanced and assembly machine is fed from two storage buffers of two input machine that are subject to random failures. They compute the system's average throughput and average inventories and formulate the sum of inventory costs as well as shortage cost. They then optimize the buffer sizes accordingly.

Diwan [27] applies the Genetic Algorithms (GA) approach for buffer optimization in AAS. The systems are subject to starvation and blocking and several systems with one single loop, with inspections stations and repair loops are studied. In addition, the cost modeling methodology for such systems with repair loops is developed in order to simultaneously optimize system parameters, cost functions, and quality control issues.

So [77] determines buffer capacities for general flexible manufacturing systems with multiple products. He uses an approximation scheme to determine buffer capacities and simulation experiments to study the validity of the approximation scheme under various situations.

2.2.2. SIMULATION

Doydum and Perreira [28] present a Monte Carlo modeling, simulation, and inferencing method to take the methodology applicable to the designs of assemblies with irregular and complex cross sections. Ketcham and Watt [47] review a parametric simulation system called SIMBED. SIMBED has been developed to represent the characteristics of flexible manufacturing systems with multiple products and flexible parts routings. Buzacott and Hanifin [18] develop a simulation model for transfer lines and review early results with the results of their simulation models. Bullinger and Sauer

[17] use a simulation model for planning progress of a system designed for the assembly of fork lifts in assembly modules and automated guided vehicles. The application of this simulation model allows them to evaluate different solutions and layouts.

2.2.3. OTHER STUDIES

Dallery and Gershwin [25] review the flow line systems. They classify the models as asynchronous, synchronous, and continuous; the major features as blocking, processing times, failures, and repairs; and the major properties as conservation of flow, flow rate-idle time, reversibility. The relationships among different models are also included in the review of models. Exact and approximate methods for obtaining quantitative measures of performance are surveyed. The exact methods are used for small systems. The approximate methods that are used for large systems are generally based on decomposition and apply the exact methods for small systems.

Di Mascolo et. al. [26] study the assembly lines with fixed and same cycle times at all machines, random breakdowns, and buffers with finite capacity. They approximate the behavior of such systems by a continuous flow model, then analyze the behavior using a decomposition technique. They also develop an algorithm to calculate the production rate and average buffer sizes. Gershwin [31] develops an efficient approximate decomposition method for the evaluation of performance measures for the Assembly / Disassembly Networks (i.e., networks of queues in which assembly or disassembly takes place). This decomposition approach is based on system characteristics such as unreliable machines, finite buffers, blocking and starvation exist.

Johri [43] studies the engineering a printed circuit board assembly line of AT&T with unreliable machines for a desired capacity and flow time. For this purpose, the number of machines needed, buffer sizes, the input lot sizes, and loading sequence are determined. This study shows that proper lot sizing and sequencing can increase the capacity of the line by more than 10%.

Kamath and Sanders [46] develop an analytical approximation method that can be used to determine the steady-state performance of automatic assembly systems for a given assignment of operators. The analytical method involves the simultaneous solution of two coupled queuing models; one of the models calculates the waiting time for an operator resource, while the other computes the waiting time for a workstation resource. Blumenfeld [12] develops an analytical model for comparing the throughputs of assembly systems with fixed cycle times and flexible cycle times that vary from job to job. Results indicate that an assembly system with variable cycle times can operate at a significantly higher throughput than one with fixed cycle times, provided there is sufficient buffer storage space between workstations to accommodate queuing.

Bulgak and Sanders [16] present the implementation of hybrid procedures involving the use of analytical performance evaluation techniques, discrete event simulation, and Monte Carlo optimization methods for the stochastic design optimization of asynchronous flexible assembly systems (AFAS) with statistical process control (SPC) and repair loops. They develop an approach simultaneously analyzing the interactions between product quality and optimal/near optimal system design.

Graves and Redfield [33] discuss an optimization procedure to assign tasks to workstations and select assembly equipment for each workstation for a multiproduct assembly system. Venkateshwar and Sanders [85] develop an approximation algorithm for closed asynchronous automatic assembly systems with multiple products. They discuss the pallet optimization, buffer allocation, and pallet allocation. Winters and Burstein [91] discuss a tool for estimation of the impact of various product and process options on the maximal level of system output. The study is conducted with an actual flexible assembly system (FAS) using the discrete-event simulation.

Yano [92] develops an algorithm to find optimal planned lead-times for two-level assembly systems. Planned lead-times are determined with the objective of minimizing the sum of inventory holding costs and tardiness costs. Yoosufani et. al. [93] study the effect of symmetry of parts of the time taken to handle parts during manual assembly, which can be used by design engineers when considering design for ease of assembly. Toczylowski and Hindi [84] discuss the formulation and solution of an aggregate multistage capacitated scheduling problem. They consider production systems whose set of end products has a flat component structure and group these end products into families of items having similar component structures, similar productivity factors and inventory costs, and sharing common major setups. Ghosh and Gagnon [32] study extensively the assembly line balancing. Quantitative developments and qualitative issues are addressed at both the strategic and tactical levels. They also assess our progress in assembly system design and operation. Chan et. al. [21] develop a reconfigurable fixturing system for robotic assembly. Such fixtures can reduce the lead times and manufacturing costs in small batch production, which is common in today's flexible automation. Carter [20] describes the robot assembly task time that is derived from laboratory tests and industrial experience. He further explains the use of data sheet for estimating part assembly times at a two-arm robotic assembly station.

McCormick et. al. [59] study the transient behavior (the correlation between certain operation finish times) in a flexible assembly line with multiple products. They consider an assembly line with m stations and finite-capacity buffers and calculate how long it takes such a system to reach steady state for a given cyclic schedule. Saboo and Wilhelm [74] develop a model to estimate the transient performance of assembly networks. In another study, Wilhelm et. al. [89] introduce an approach for capacity planning and material flow management in small-lot assembly lines. Wilhelm and Wang [90] study component accumulation (kitting) for more effective material flow management. Mathematical models are presented to describe kit earliness, kit tardiness, and in-process time for component inventory and a sensitivity analysis is also used.

McGinnis et. al. [60] discuss the main problems for printed circuit card assembly process and review the models and solution methods. Srinisvan and Sanii [78] study the process planning for electronic assembly with Artificial Intelligence (AI) approach. Lacksonen and Joshi [51] develop an algorithm based on graph theory to minimize the number of printed circuit board components that must be inserted manually. The algorithm, which handles the parts that can be gripped in two possible directions, aims to improve process planning. Ahmadi et. al. [1] study concurrency through experimental analysis of the system's functional operations. They analyze an extremely complex workcell with a high degree of concurrency. Khwaja and Radhakrishnan [48] develop a design for odd-form components whose handling poses significant constraints on the flexibility of the systems.

2.3. DESIGN OF EXPERIMENTS (DoE) APPROACH AND ITS APPLICATIONS

Section 2.3.1. presents the recent papers on the use of DoE approach as well as some texts that provide substantial information on DoE. Section 2.3.2. discusses applications of DoE approach in industry.

2.3.1. RECENT STUDIES ON THE USE OF DoE APPROACH

The DoE approach is a powerful method in designing for value (i.e., cost and quality.) Consequently, there are many studies and texts written covering several areas. Texts on the DoE are excellent handbooks for the experimenter [56,62,61,14,37,71].

Recent studies on the DoE approach concentrate on explaining the DoE as well as expanding its applications. The work by Coleman and Montgomery [23] discusses the DoE approach in general and give valuable information. In his recent article in Quality Process, Gunter [35] discusses the DoE at a basic level and compares it to the traditional experimental approach, which can be called "one-factor-at-a-time" approach. Blake et. al. [11] discuss the key issues of the 1990s that have to be considered when applying the DoE approach in quality improvement.

In the area of developing new strategies and designs for the DoE approach, Vining and Schaub [86] propose a methodology for estimation of both mean and variance functions. They pursue two distinct approaches: a one-step approach which, in absence of any information about the process variance, initially assumes that the process variance is constant over the region of the interest; and a one-step, semi-Bayesian approach which attempts to develop an appropriate experimental plan in light of prior information about the nature of the variance function. Then they compare these two approaches in a simulation study to illuminate their relative advantages and disadvantages. Nguyen [63] discusses the construction of near-orthogonal arrays for the situations where orthogonal array design cannot be applied.

2.3.2. APPLICATIONS OF THE DoE APPROACH

The DoE approach exists since 1920s. It was originally developed for agricultural studies and its applications were extended eventually. In this section, we mention some studies in manufacturing systems using DoE approach.

One of the early applications on the assembly systems or assembly-like systems is developed by Law [52]. He uses a 2^3 full factorial design to study the effects of the system configuration, relative stage position, and buffer capacity allocation in automatic transfer lines. He conducts the experiments using a discrete-time computer model simulation. In this study, he states that second and third-order interactions can be important.

Hubele et. al. [41] apply the DoE approach to the task of characterizing the inspection capability of the machine vision component of an automated laser hole-drilling and inspection system for gas turbine engine manufacturing. The machine is designed with a closed loop algorithm. The authors state that "this study provided a better understanding of the system's capabilities and the user's design requirements, which has yielded system improvements."

Leung and Sanders [54] use a factorial experimental design based on the discrete event simulation results to discuss the effects of different design factors on the performance of automatic assembly systems with tunnel-gated stations. These design factors are the jam probability of the stations, the repair time of the stations, the balance of the line, the buffer size between adjacent stations, and the position of the tunnel-gated station in the combined buffer.

Jim Quinlan et. al. [72] use a modified DoE approach to identify the factors with important effects on the shrinkage of the speedometer casing. Using an orthogonal array, they determine that eight factors as important and design the casing accordingly.

One of the recent studies using DoE approach is conducted by Schaub and Montgomery [75]. They apply the DoE approach to the stereolithography (SL) of turbine engine airfoils. The process of rapid prototyping is a valuable asset to the aerospace industry in that model engine parts may be produced in a solid form within a week of developing the design. This replaces the older technique of producing a casting mold and making a traditional model, which can take up to six months. Schaub and Montgomery study the variables that will allow holding tighter tolerances. They state that the use of statistically designed experiments resulted in increased process knowledge not only for the particular test situation, but also indirectly for the overall operation of the SL process.

2.4. ROBUST DESIGN AND ITS APPLICATIONS

Robust design is introduced and made popular by Taguchi. Therefore, the first applications and still most of the applications are from Japan, although in the last two decades it gained popularity in the North America and Europe. Consequently, we have covered some studies on Taguchi's contributions to robust design, as well as the recent studies on the robust design. Section 2.4.1. presents the studies on the use of robust design and Taguchi's contributions. Section 2.4.2. discusses the application of robust design in industry.

2.4.1. RECENT STUDIES ON THE USE OF ROBUST DESIGN AND TAGUCHI'S CONTRIBUTIONS

Belegundu and Zhang [7] discuss the robustness of the designing mechanical systems or components under uncertainty is considered. The basic idea is to ensure quality control at the design stage by minimizing sensitivity of the response to uncertain variables by proper selection of design variables. Parkinson et. al. [68] describe a general approach for robust optimal design. The method allows a designer to explicitly consider and control, as an integrated part of the optimization process, the effects of variability in design variables and parameters on a design. Kusiak and Feng [50] discuss the robust design at the tolerance design phase of the design of a product or a process.

Using a parametric approach reduces simulation development time for evaluating system interactions in a FMS or FAS environment. Benjamin et. al. [10] develop an approach to design robust systems using discrete-event simulation. Mayer and Benjamin [58] study robustness in manufacturing systems using simulation. Wild [88] proposes a strategy for the use of design of experiments and simulation for robust design studies.

Literature on the Taguchi's contribution is divided into two, as the supporters and the critics. While supporters like Byrne et. al. [19] suggest that the techniques developed by Taguchi should be applied as they are, the critics, among whom Box is the most referred, argue that some of the techniques introduced by Taguchi are inefficient, if not misleading. Box et. al. [14] reviewed the Taguchi's contributions extensively. A brief article by Hendrix [36] is a recent example on the critique of the techniques introduced by Taguchi. Itano [42] deals with and uses only a small part of the Taguchi's contribution. He states that in applying Taguchi methodology the sensible user must only pick and use those elements which are relevant to the problem in hand. Contrary to what the literature seems to be saying there is no virtue in striving to include an Orthogonal Array or to look for different types of noise every time unless there is a good reason to do so. There are texts written on the Taguchi's contributions and robust design and they provide substantial information [6,30,69,70,73,80,81,83].

2.4.2. APPLICATIONS OF ROBUST DESIGN IN INDUSTRY

Among the leading pioneers of robust design in the USA is the AT&T Bell Laboratories [8]. Many papers of AT&T co-authored by Kacker (from National Bureau of Standards) and engineers from the AT&T Bell Laboratories.

The study by Kacker and Shoemaker [45] is important in this research, since we follow a sequence that is similar to that is described in this paper. Kacker and Shoemaker apply the robust design principles to improve the process of multiplexers where the major problem is the variability in the index of refraction in manufacture and in the field, which is caused largely by changes in relative humidity. Since the control of humidity is difficult and expensive, the experiment is designed to make the filter-making process to be less sensitive to humidity changes by reducing the variance.

Another paper by Kacker and et. al. [44] describes one of the earlier experiments at AT&T to optimize the process of forming contact windows in 3.5 μm complementary metal-oxide semiconductor (CMOS) circuits. As a large scale integrated circuit chip has many thousand such windows, it is vitally important to produce windows with target dimensions. The application of the robust design shows the variance of the window size being reduced four-fold with a substantial reduction in the process time. From ITT Cannon, White [87] uses a modified sequential approach to reduce the variance in gold plating thickness on pin contacts by over 60%. Bandurek, Disney, and Bendell [5] applied the robust design approach to the placement of surface mounted components on a printed circuit board. The robust design techniques are slightly modified in order to identify the critical noise factors which it may be possible to control at some other date. Steve Orr et. al. [66] apply robust design approach to better understand and design a new product. For an investment of $1,140 they claim a calculated saving by the plating source of $300,000 per annum and an improvement in yield from 0% to 86.7%.

CHAPTER 3

METHODOLOGY:

DESIGN OF EXPERIMENTS (DoE) AND ROBUST DESIGN

3.1. INTRODUCTION

In the last decades, several optimization methods such as Stochastic Quasigradient methods (SQG) have been used to solve design problems in flexible assembly systems. However, these methods have important weaknesses that are discussed below.

- They aim to find *the* optimal solution, not to search an optimal *area*. In other words, they do not provide the flexibility of choosing the buffers within a range which in fact is essential in many cases in practice.
- They completely ignore the changes in uncontrollable factors in the system, thus their possible effect on the throughput. Consequently, the solution(s) they propose may not give the expected efficiency and improvement.

In view of this, we propose the use of design of experiments (DoE) approach to overcome such shortcomings of these optimization methods. The DoE approach is chosen for the following reasons:

- Because it allows us to study the factors in different levels, the effects of the factors and their interactions as a total, and most importantly to identify the important effects, the DoE approach suits best for determining the buffer ranges that determine an optimal area where throughput is maximum or near maximum.

- The robust design enables the system response (throughput) to be robust (i.e., stable, unchanging) to uncontrollable factors. Clearly, robust design is the unique method to determine the ranges of buffers in which the throughput is unchanging even though the uncontrollable factors change in a small range. The DoE approach and the statistical techniques that are discussed in next sections constitute the core of the robust design.

The following sections (3.2. and 3.3.) discuss the DoE approach and the techniques we will use in this research. The sections 3.4. and 3.5. review the robust design and its techniques. Although the robust design is a specific case of the applications of the DoE approach, we considered that it is more applicable to present it in a different section. The section 3.5 summarizes the methodology and techniques we will use in this research.

3.2. DoE APPROACH

The DoE approach covers many important topics. In the following sections, however, we will mention the definitions and the arguments that are used throughout this research. First, we will describe the approach generally, then discuss the strategies for the designing phase and the comprehensive steps of the DoE approach.

3.2.1. INTRODUCTION

The design of experiments (DoE) approach enables one to study the factors and their interactions and to recognize how they affect the response. In other words, the DoE approach is basically a set of experiments in which purposeful changes are made to the input variables of a process or system so that one may observe and identify the reasons for changes in the output of the response [62]. Consequently, the DoE approach provides substantial information on the system in addition to suggesting the solutions to the problem.

In the DoE approach, the factors have two or more levels. In this research, we will define two levels (i.e., low and high levels) for each factor and choose the appropriate design among the strategies discussed in the following section, accordingly.

3.2.2. THE STRATEGIES FOR CHOOSING THE EXPERIMENTAL DESIGN

There are three main design strategies for the DoE approach: ***full factorial designs***, ***fractional factorial designs***, and ***orthogonal arrays***. The ***full factorial design*** (see **Figure 3.1.**) enables the experimenter to study all the factors and their interactions. When the interaction effects are considered as potentially important and if it is economically or timely feasible, the full factorial design is recommended. The nomenclature definition of the full factorial design is a^b where

a : number of levels of each factor (which is 2, in all cases of this research)

b : number of factors

An example of the full factorial designs, a 2^4 design, is illustrated in **Figure 3.1.** The design of sixteen experimental runs provides information on the four main factors and all of their interactions.

On the contrary, the ***fractional factorial design*** (see **Figure 3.2.**) offers more economical and less time-consuming designs where the experimenter can study most of the factors and their interactions. However, the trade-off is that we lose some of the information on the effects of the main factors and/or their interactions, due to *confounding*.

In order to reduce the number of the experimental runs required, some of the interactions and/or main factors are assigned to the same column, i.e. *confounded*. In other words, the confounded factors' and/or interactions' effects are not distinguishable from one another. However, there are several types of design resolutions available that confound the main effects with interactions of different number of factors (see Appendix 1, section 1.1.)

The nomenclature definition of the fractional factorial design is a_d^{b-c} where

a : number of levels of each factor (which is 2, in all cases of this research)

b : number of factors

c : the fraction level; i.e., the a^c experiments will not be conducted, comparing to the full factorial design of a^b

d : the resolution level (see Appendix 1, section 1.1.)

The 2_{IV}^{8-4} design is disclosed in **Figure 3.2.** as an example of the fractional factorial designs with IV resolution. In this design, eight factors can be examined as well as their interactions of three and less factors in sixteen runs, instead of 256-run full factorial alternative.

The third design strategy is using the ***orthogonal arrays*** (see **Figure 3.3.**). They are, in fact, fractional factorial designs based on using symmetrical subsets of all the combinations of factor levels in the corresponding full factorials. Although they were discovered considerably earlier, it is only in the last two decades that they became popular and associated with Taguchi methodology. Taguchi, a renown Japanese expert on quality, modified the orthogonal arrays in such a way that they now are easy to use and provide an important practical alternative for the experimenters who want to study many factors in a very small number of experimental runs. Orthogonal arrays emphasize the investigation of the main factors with a small design, while ignoring most of the interactions [9].

The nomenclature definition of orthogonal arrays is $L_a\ (b^c)$ where

a : number of experimental runs

b : number of levels of each factor (which is 2, in all cases of this research)

c : number of columns in the array

Arrays can have factors with many levels, although two and three level factors are most commonly encountered. An $L_{16}\ (2^{15})$ array, as illustrated in **Figure 3.3.**, for example, can handle up to fifteen factors at two levels each, under sixteen experimental conditions.

L_{12}, L_{18}, L_{36} and L_{54} arrays are among a group of specifically designed arrays that enable the designer to focus on the main effects. Such an approach helps to increase the efficiency and reproducibility of small scale experimentation. Among them, the L_{18} is the most widely used array for DoE applications of AT&T Bell Laboratories, Xerox Corporation, ITT, and other corporations [82].

3.2.3. THE COMPREHENSIVE STEPS OF THE DoE APPROACH

We follow the basic DoE steps as suggested by Montgomery [62]:

1. Recognition and statement of the problem.
2. Choice of factors (decision variables) and levels. (the levels are chosen as two for all factors)
3. Selection of the response variable. (our response variable is the throughput)
4. Choice of the experimental design. (the design alternatives are discussed in the section 3.2.2. ; in addition, the replications for all cases are determined as ten for each experimental run)
5. Performing the experiment. (discrete-event simulation is used)
6. Data analysis. (discussed in the next section)
7. Conclusions and recommendations. (follow-up runs and confirmation testing should also be performed to validate the conclusions from the experiment)

The objective of the DoE approach is to improve the system by selecting the appropriate levels of the factors. If, for example, the system can be improved by the increase in the system response , then the conclusion phase will propose choosing the high levels for the factors that have important positive effects and the low levels for the factors that have important negative effects. In other words, in the DoE approach, the important effects are determined and then the appropriate levels of these factors that have important effects are suggested. Finding which factors have important effects is the analysis phase which is discussed in the following section.

3.3. DATA ANALYSIS PHASE OF THE DoE APPROACH AND THE STATISTICAL TECHNIQUES USED FOR DATA ANALYSIS

Data analysis step combines several techniques such as F-test, t-test, normal probability plotting, and residual analysis to analyze the results (throughputs) obtained from the experimental runs of the DoE using discrete-event simulation. The analyses are used to identify the important effects on the response and to verify that results and conclusions are objective rather than judgmental in nature. If the experiment has been designed correctly and if it has been performed according to the design, then the statistical techniques required are not elaborate [62].

Briefly, the steps of the analysis phase of the DoE approach and techniques used can be outlined as follows.

- apply the F-test and t-test to the results of the experimental runs to verify the experimenting and the results obtained (see Appendix 1, section 1.2.2.),
- calculate the effects of the decision variables (see Appendix 1, 1.2.3.),
- plot the effects on the normal probability paper by applying the normal probability data plotting techniques (see Appendix 1, 1.2.4.),
- determine the important effects and make conclusions accordingly,
- calculate the residuals and plot the residuals (residual analysis) to verify the conclusions made above,

- make final conclusions accordingly.

The complete steps of the analysis phase of the design of experiments (DoE) approach are demonstrated in a flow-chart in **Figure 3.4.** The statistical techniques used in this phase are explained in the Appendix 1, section 1.2.

3.4. ROBUST DESIGN

Robust design is an important application of the DoE approach that aims to reduce the variability of the system against uncontrollable factors. Although it basically uses the DoE approach and techniques, robust design has a special design, called "the inner-array outer design", and a different objective. Therefore, we present the robust design in a different section from the DoE approach. In the following sections, the robust design and basic definitions such as control factors and noise (uncontrollable) factors, the inner-array outer array design, and the steps of the robust design are briefly discussed.

3.4.1. INTRODUCTION AND BASIC DEFINITIONS (NOISE FACTORS, CONTROL FACTORS, AND $variance_{wrtnf}$)

Robust design is the ability to design a product or process to be resistant to various environmental factors that change uncontrollably [73]. In other words, robustness of a product or a process is considered as its ability to perform as expected, even when faced with forces or conditions that tend to degrade its performance [29].

Robust design is used to improve the performance without controlling or eliminating causes of variation. It is the phase where certain parameters of a product or process are set to make the performance less sensitive to causes of variation [73].

Factors can be grouped in two main groups, as *control factors* and *noise factors. Control factors* are those factors that can be controlled in the design of a product, the design of a process, or during a process. In this research, the control factors are the buffer sizes in the AAS. On the contrary, *noise factors (uncontrollable factors)* are the factors that cannot be controlled or are preferred not to be controlled for cost reasons. Noise factors may be controlled temporarily, but on a continuous basis they are either too expensive or impossible to control [73]. In this research, jam rates (the probability of the jam occurrences at a workstation) and jam clear times (the time required to clear the jam from a workstation) are considered as noise factors.

Robust design aims to lower the effect of noise, in other words to reduce variance. In order to separate this type of variance, we will use the term *variance with respect to noise factors* ($variance_{wrtnf}$) henceforth. The $variance_{wrtnf}$ is the variance of the system response (throughput) considering the change in control factors [45]. It measures the variability of the throughput with the same configuration of buffers while the noise factors change. In this research, the $variance_{wrtnf}$ is used to define the variance of the throughput (TP) while the buffers configuration is kept fixed and noise factors change.

Robust design is used to reduce the effect of noise (reduce $variance_{wrtnf}$) by choosing the proper level for control factors. In robust design, the major emphasis is placed on true control factors and very little emphasis on true noise factors. Primarily, noise factors are used in experiments to expose the robust levels of control factors [73].

3.4.2. THE INNER-OUTER ARRAY DESIGN

The main design strategy for robust design is called as "the inner-outer array design" (see **Figure 3.5.**). This design strategy separates the control factors from the noise factors by using inner and outer arrays, respectively. The noise factors are assigned to the outer array to find some level of a control factor that does not result in much variation in the TPs (i.e., $variance_{wrtnf}$) in spite of the noise factors definitely being present.

The secondary part of the design strategy is to find the most suitable design for both control factors and noise factors among the strategies discussed in section 3.2.2., namely full factorial design, fractional factorial design, and orthogonal array. The choice must be made accordingly.

Figure 3.5. demonstrates an example of the inner-outer array design for seven control factors and three noise factors, with the L_8 (2^7) and L_4 (2^3) orthogonal arrays, respectively.

3.4.3. THE COMPREHENSIVE STEPS OF THE ROBUST DESIGN

The steps to follow for robust design are fundamentally similar to those of the DoE. Yet, because the objectives of the DoE and robust design are different, there are important distinctions in some steps. The DoE aims to increase the throughput. On the contrary, robust design targets the reduction of the $variance_{wrtnf}$. As a result, considerable differences occur in the choice of factors, choice of experimental design, and analysis phases between the DoE and robust design.

In this research, we follow the basic robust design steps as Ross suggests [73]:

I. The planning phase:

1. State the problem(s) and the objective(s) of the experiment.
2. Select the response variable(s).
3. Select the factors that may influence the selected response variables.
4. Identify control and noise factors.
5. Select levels for the factors.
6. Select the appropriate design (full, fractional, or orthogonal array) for control factors.
7. Assign control factors (and interactions) to the columns of the selected design which occupies the inner array
8. Select the appropriate design (full, fractional, or orthogonal array) for noise factors.
9. Assign noise factors to columns of the selected design that occupies the outer array.

II. The conducting phase:

10. Conduct tests described by experiment runs in selected designs (i.e., according to the specific configurations that are described).

III. The analysis phase:

11. Analyze and interpret results of the experimental design (aim to reduce the $variance_{wrtnf}$).

12. Conduct confirmation experiment.

The analysis phase is discussed in detail in the following section.

3.5. THE ANALYSIS PHASE OF ROBUST DESIGN AND THE STATISTICAL TECHNIQUES USED FOR DATA ANALYSIS

Although robust design is a special application of DoE approach, the objectives of the DoE approach and robust design are very different. While the DoE approach aims to increase the throughput by choosing the factors with important effects at their high levels (low level, if the effect is negative), the robust design concentrates on reducing the variability of the throughput by choosing the factors with important effects at their low levels (high level, if the effect is negative).

Consequently, there are some fundamental differences in use of the techniques. In robust design, the normal probability technique has a different results column; $variance_{wrtnf}$. This column is composed by the variances of TP with respect to the noise factors corresponding to each buffer configuration (i.e., the row of the inner-array design.) The calculation of the $variance_{wrtnf}$ is discussed in Appendix 1, section 1.3.1.

The steps of the analysis phase of the robust design can be outlined as follows.

- apply the F-test and t-test to the results of the experimental runs (throughputs) to verify the experimenting and the results obtained,

- calculate the $variance_{wrtnf}$ for each row of the inner array as described by Kacker [45],
- calculate the effects of the $variance_{wrtnf}$ and plot the effects on the normal probability paper by applying the normal probability data plotting techniques,
- determine the important effects and make conclusions accordingly,
- calculate the residuals and plot the residuals (residual analysis) to verify the conclusions made above,
- make final conclusions accordingly.

Complete steps of the analysis phase of the robust design are demonstrated in a flow-chart in **Figure 3.6.** The statistical techniques used in this phase are explained in the Appendix 1, section 1.3.

3.6. THE SUMMARY OF OUR METHODOLOGY

We use the design of experiments (DoE) approach to overcome the shortcomings of the commonly used optimization methods, such as Stochastic Quasigradient methods (SQG).

We have two objectives in this research for which the DoE approach is the most suitable methodology:

- determining an optimal area by identifying the appropriate buffer ranges that give maximum or near maximum throughput,
- robust design of the AAS against noise factors.

The DoE approach allows one to study the effects of the factors and the interactions, and the importance of these effects on the system response. Although the robust design is a special application of the DoE approach, the goal of the robust design differs. The DoE approach aims to improve the system by increasing the system response (throughput). Conversely, robust design aims to improve the system by reducing the variance of the throughput with respect to noise factors (i.e., uncontrollable factors). Apart from this important difference in their objectives, other steps and techniques used in the DoE approach and robust design are similar, as discussed in previous sections.

In the following chapters, the objectives of this research and studies conducted for these purposes are discussed. Chapter 4 covers the first objective, that is the determining an optimal area of buffer sizes that give maximum or near maximum throughput. For this purpose, we will determine the appropriate levels of the buffer sizes. Chapter 5 discusses the robust design studies. In this chapter, we will include the noise factors, which are the jam rates and jam clear times, into the systems. Our objective is to determine the appropriate levels of control factors (i.e., the buffer sizes) that reduce the variance of the throughput with respect to noise factors ($variance_{wrtnf}$). Finally, Chapter 6 reviews the research as a total and make suggestions for further study.

Figure 3.1. 2^4 full factorial design

exp.	factors (main factors and interactions)													
#	1	2	3	4	12	13	14	23	24	34	123	124	134	234	1234
1	-	-	-	-	+	+	+	+	+	+	-	-	-	-	+
2	+	-	-	-	-	-	-	+	+	+	+	+	+	-	-
3	-	+	-	-	-	+	+	-	-	+	+	+	-	+	-
4	+	+	-	-	+	-	-	-	-	+	-	-	+	+	+
5	-	-	+	-	+	-	+	-	+	-	+	-	+	+	-
6	+	-	+	-	-	+	-	-	+	-	-	+	-	+	+
7	-	+	+	-	-	-	+	+	-	-	-	+	+	-	+
8	+	+	+	-	+	+	-	+	-	-	+	-	-	-	-
9	-	-	-	+	+	+	-	+	-	-	-	+	+	+	-
10	+	-	-	+	-	-	+	+	-	-	+	-	-	+	+
11	-	+	-	+	-	+	-	-	+	-	+	-	+	-	+
12	+	+	-	+	+	-	+	-	+	-	-	+	-	-	-
13	-	-	+	+	+	-	-	-	-	+	+	+	-	-	+
14	+	-	+	+	-	+	+	-	-	+	-	-	+	-	-
15	-	+	+	+	-	-	-	+	+	+	-	-	-	+	-
16	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+

- : low level of the factor, + : high level of the factor

Figure 3.2. 2_{IV}^{8-4} fractional factorial design (resolution IV)

5=234, 6=134, 7=123, 8=124

exp	factors:														
run	1	2	3	4	5	6	7	8							
#	interactions:				234	134	123	124	12	13	14	23	24	34	1234
1	-	-	-	-	-	-	-	-	+	+	+	+	+	+	+
2	+	-	-	-	-	+	+	+	-	-	-	+	+	+	-
3	-	+	-	-	+	-	+	+	-	+	+	-	-	+	-
4	+	+	-	-	+	+	-	-	+	-	-	-	-	+	+
5	-	-	+	-	+	+	+	-	+	-	+	-	+	-	-
6	+	-	+	-	+	-	-	+	-	+	-	-	+	-	+
7	-	+	+	-	-	+	-	+	-	-	+	+	-	-	+
8	+	+	+	-	-	-	+	-	+	+	-	+	-	-	-
9	-	-	-	+	+	+	-	+	+	+	-	+	-	-	-
10	+	-	-	+	+	-	+	-	-	-	+	+	-	-	+
11	-	+	-	+	-	+	+	-	-	+	-	-	+	-	+
12	+	+	-	+	-	-	-	+	+	-	+	-	+	-	-
13	-	-	+	+	-	-	+	+	+	-	-	-	-	+	+
14	+	-	+	+	-	+	-	-	-	+	+	-	-	+	-
15	-	+	+	+	+	-	-	-	-	-	-	+	+	+	-
16	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+

- : low level of the factor, + : high level of the factor

Fig. 3.3. $L_{16}(2^{15})$ Orthogonal Array Design

exp	factors														
run	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
#	a	b	ab	c	ac	bc	ab	d	ad	bd	ab	cd	ac	bc	abc d
1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	+	+	+	+	+	+	+	+
3	-	-	-	+	+	+	+	-	-	-	-	+	+	+	+
4	-	-	-	+	+	+	+	+	+	+	+	-	-	-	-
5	-	+	+	-	-	+	+	-	-	+	+	-	-	+	+
6	-	+	+	-	-	+	+	+	+	-	-	+	+	-	-
7	-	+	+	+	+	-	-	-	-	+	+	+	+	-	-
8	-	+	+	+	+	-	-	+	+	-	-	-	-	+	+
9	+	-	+	-	+	-	+	-	+	-	+	-	+	-	+
10	+	-	+	-	+	-	+	+	-	+	-	+	-	+	-
11	+	-	+	+	-	+	-	-	+	-	+	+	-	+	-
12	+	-	+	+	-	+	-	+	-	+	-	-	+	-	+
13	+	+	-	-	+	+	-	-	+	+	-	-	+	+	-
14	+	+	-	-	+	+	-	+	-	-	+	+	-	-	+
15	+	+	-	+	-	-	+	-	+	+	-	+	-	-	+
16	+	+	-	+	-	-	+	+	-	-	+	-	+	+	-

- : low level of the factor, + : high level of the factor

Figure 3.4. The complete steps of the analysis phase of the DoE approach

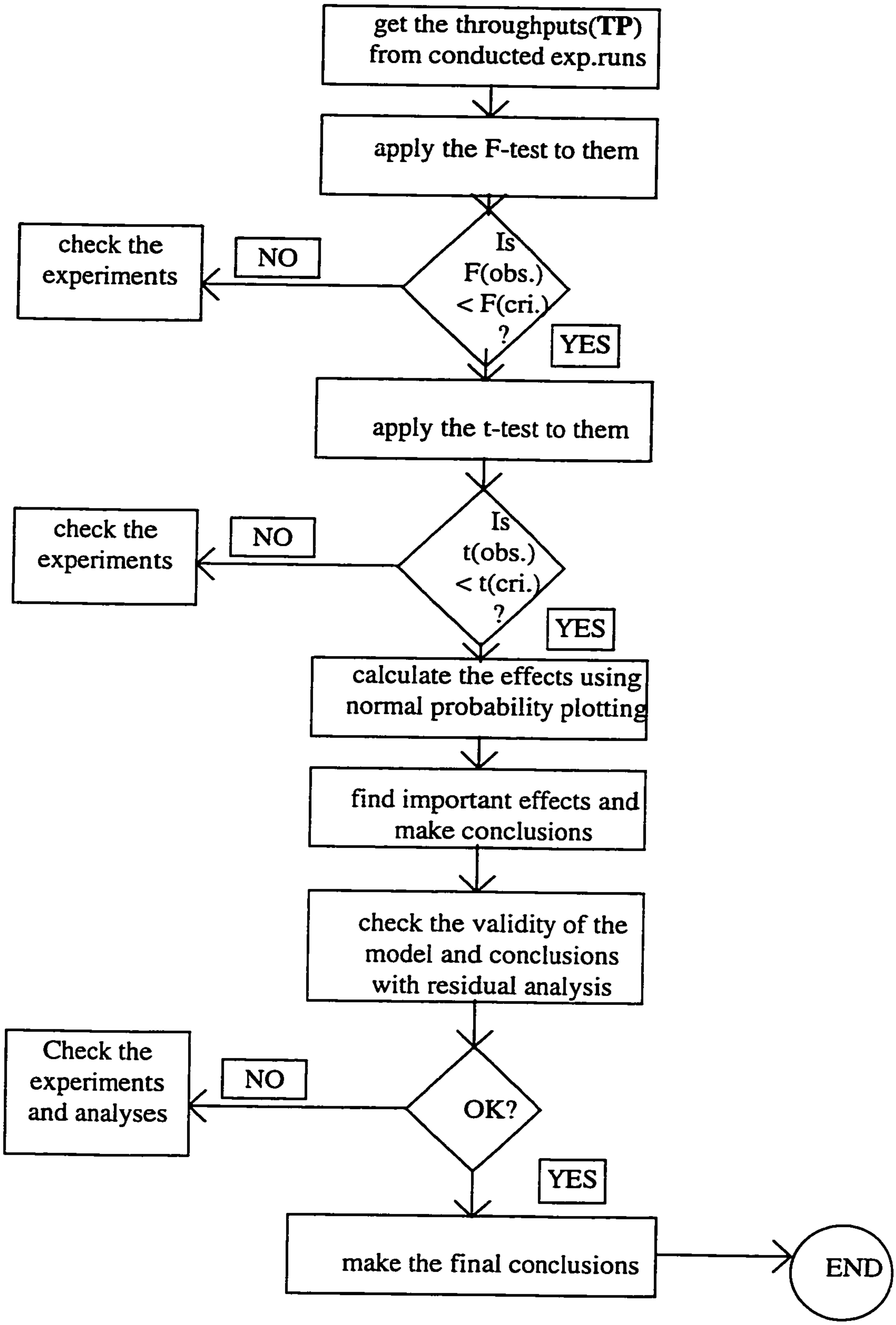


Fig. 3.5. Robust design for 7 control factors and 3 noise factors with L_8 (2^7) and L_4 (2^3) orthogonal arrays (L_8 * L_4 = 32 runs)

nomenclature: TP_{ij} : The system response (Throughput) with *i*th order of control factors configuration and *j*th order of noise factors configuration.

- : low level of the factor, + : high level of the factor

Noise Factors

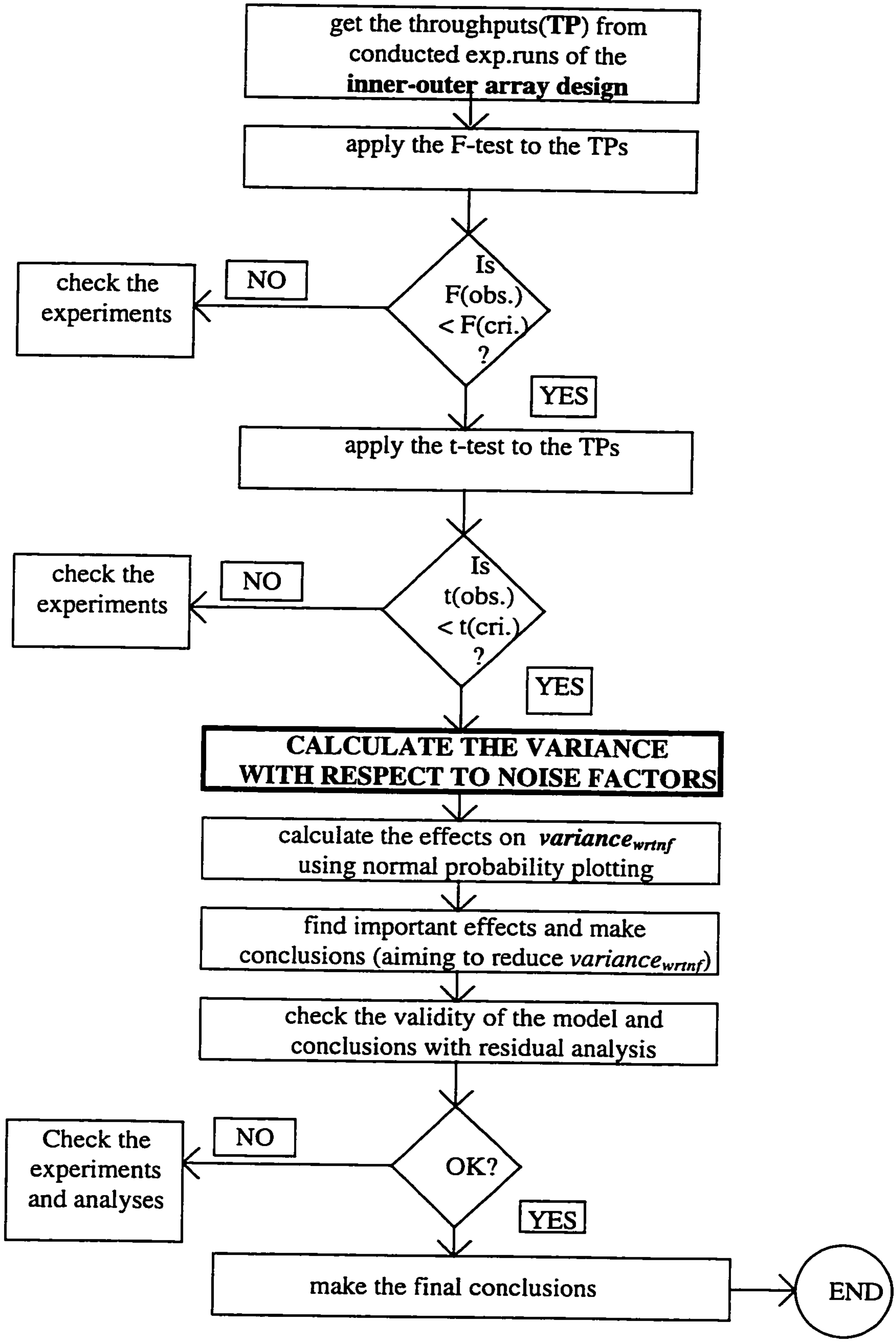
1	2	3	4	run	
-	-	+	+	*1*	*fac*
-	+	-	+	*2*	*tor*
-	+	+	-	*3*	*s*

Control Factors

factors

run	*1*	*2*	*3*	*4*	*5*	*6*	*7*				
1	-	-	-	-	-	-	-	TP_{11}	TP_{12}	TP_{13}	TP_{14}
2	-	-	-	+	+	+	+	TP_{21}	TP_{22}	TP_{23}	TP_{24}
3	-	+	+	-	-	+	+	TP_{31}	TP_{32}	TP_{33}	TP_{34}
4	-	+	+	+	+	-	-	TP_{41}	TP_{42}	TP_{43}	TP_{44}
5	+	-	+	-	+	-	+	TP_{51}	TP_{52}	TP_{53}	TP_{54}
6	+	-	+	+	-	+	-	TP_{61}	TP_{62}	TP_{63}	TP_{64}
7	+	+	-	-	+	+	-	TP_{71}	TP_{72}	TP_{73}	TP_{74}
8	+	+	-	+	-	-	+	TP_{81}	TP_{82}	TP_{83}	TP_{84}

Figure 3.6. The complete steps of the analysis phase of the robust design



CHAPTER 4

DETERMINING AN OPTIMAL AREA IN ASYNCHRONOUS ASSEMBLY SYSTEMS USING DESIGN OF EXPERIMENTS (DoE)

The design optimization of the asynchronous assembly systems is a complete task, thus needs many assumptions to simplify the problem that results in a problem-solving-approach focused only in one area. Consequently, the studies conducted have so far used the stochastic optimization algorithms and terminated their studies at a particular optimal solution. In this research, we have enlarged the optimal area by determining an optimal area of control factors. In addition, by conducting these studies, we can also provide the design engineer the information on the effects of the decision variables, the design engineer can have a guideline and design the system more consciously.

For this purpose, we use the DoE approach and propose the optimal/near optimal buffer ranges that give the maximum or near maximum throughput (TP). In other words, we determine an optimal area of buffers by identifying the optimal ranges. The DoE approach provides the information needed by both determining the decision variables that affect the throughput most and optimizing the process (i.e., determining an area in which the important factors give best possible response [62]). Therefore, by using the DoE approach, we study the effects of decision variables (i.e., buffer sizes) and identify the ranges of buffers that give the maximum/near maximum systems response (i.e., throughput), thus determine an optimal area.

In addition to determining an optimal area, we propose that the Doe approach can also be used as a heuristic optimization tool (see section 4.4.2.). Because of its special design and substantial information it provides on both the variables and the system, DoE approach can be used to determine an optimal/near optimal area for the buffer sizes.

In this chapter, we are also interested in the effect of the number of pallets in the system. In an attempt to study its effect on the throughput, we have studied the cases where the number of pallets is also considered as a decision variable (see section 4.4.1.).

The following section, 4.1., reviews the asynchronous assembly systems (AAS). Section 4.2. defines the objective studied in this chapter as well as the system parameters. Section 4.3. discusses the methodology we will use to determine an optimal area.

Section 4.4. presents the studies conducted. Several types of AAS are studied. Section 4.4.1. discusses the studies in systems previously optimized using the Stochastic Quasigradient Methods (SQG). Section 4.4.2. presents the studies where the DoE approach is used as the optimization method. Finally, the conclusion of the studies conducted and our objective are discussed in section 4.5.

4.1. ASYNCHRONOUS ASSEMBLY SYSTEMS

Assembly systems can be classified as synchronous and asynchronous assembly systems. In synchronous assembly systems all stations have identical cycle time (i.e., operation time of each product unit.) When one unit of cycle time passes, the product is automatically moved to next station. On the contrary, in asynchronous assembly systems (AAS) workstation can work more independently. The removal of the product unit from the workstation may occur after the workstation completes its operation. Clearly, the asynchronous systems ate more beneficial, because when a stoppage occurs at a workstation, the rest of the system can continue to operate, whereas in a synchronous system the entire assembly process also immediately stops [55].

There are two common configurations for AAS: In one configuration, there is the single station where alternative tasks are performed by either a human operator or robot, and transporters carry both parts and assemblies to and from one single fixed location. The other configuration is the assembly line, where a number of assembly stations are arranged in a series configuration joined by a transport system. Since the assembly is usually carried on a fixtured pallet on the transporter and the pallets must be returned from the final assembly station to the first one to receive a new assembly base, the actual configuration of the system is most often an oval rather than a line, which is called a closed-loop assembly system [36] (see Figure 4.1.) The closed-loop asynchronous assembly configuration ranges in size from two or three stations in flexible robotic assembly systems up to well over one hundred stations in certain high speed (usually hard automated) assembly machines [55].

Automated assembly systems are capital intensive and must be kept running to be justifiable. Breakdowns of single workstation or the entire system are particularly important issues in design of such systems. As the number of workstation in the system increases, the probability of all stations being operational decreases. Buffers, though expensive to install and maintain, provide a means for insulating workstations from failures elsewhere in the system, thus improving station utilizations [4].

A station may not be operational for the following reasons [4]:

1. Station failure (jam)
2. Total system failure
3. Station blocked
4. Station starved

Station failures, i.e. jams, are caused by events such as a fractured tool, quality out-of-control signal, missing/defective part program, or jammed mechanism. Although the failed station must stop producing, other stations may continue provided that they are fed product and have space for sending completed product. A total system failure occurs if all stations are not operational, in the events such as a power outage or an error in the central system controller. When the preceding buffer is empty or the following buffer is full, the station is not operational either. In the former condition, the workstation is *starved*; in the latter it is *blocked.*

In this research we are particularly interested in the blocking and starvation effects, because they are dependent on the buffer sizes and the number of pallets in the system. Station i is blocked if on completion of a cycle it is unable to pass the part to the station $i+1$. The inability to pass the part may be due to a failure of a downstream station with the intermediate buffer between these stations currently being full. If station $i+1$ is down, and its input buffer is full, then station i must remain idle while it waits for downstream space for the just completed part. On the other hand, station i is starved, if an upstream failure has halted the flow of parts into station i. In other words, even if operational, a starved station will become idle.

In brief, material handling systems (i.e., pallets) and buffers have a great importance on the system and the throughput, due to above mentioned effects and jams. Buffers allow workstations to start production cycles independently and the number of pallets affects the number of completed tasks to be carried forward. Consequently, the design optimization of buffer sizes and the number of pallets have an important part among the engineering design optimization problems in asynchronous assembly systems.

4.2. DEFINITION OF THE OBJECTIVE AND SYSTEM PARAMETERS

The objective of this chapter is to determine an optimal area for the buffer sizes in asynchronous assembly systems. For this purpose, we will determine the appropriate ranges for decision variables (i.e., buffer sizes) that give maximum system response (i.e., throughput: TP). In other words, our objective is *to find the appropriate levels for buffers where the TP will be maximum.* In order to determine the appropriate levels, thus ranges, we first study the effects of the buffers on the TP and choose the levels of the buffers with important effects accordingly, then define the ranges (both levels) for other buffers.

In addition to this objective, we attempt to study the effects of the number of pallets in the AAS as well as proposing the use the DoE approach as a heuristic optimization tool. In order to study how the number of pallets affects the throughput, we add it as a decision variable in the systems discussed in section 4.4.1. (see Design 2) Section 4.4.2. presents the cases where the DoE approach is used as the heuristic optimization method.

System parameters:

The systems we investigate are closed-loop asynchronous assembly systems as described in section 4.1. and in Figure 4.1. In such systems, a set of assembly stations are arranged in tandem according to the order of assembly operations performed.

Consequently, the major parameters that will be considered throughout this research as follows.

1. cycle time for each station; deterministic and 5 time units,
2. unit transport time for the pallets; deterministic and 1 time unit per buffer unit,
3. jam rate (i.e., the probability of the jam occurrence at each station; see below),
4. jam clear time (i.e., the time needed to make the station operational again; see below),
5. mix of assembly types; constant at any given time,
6. buffer sizes between each pair of workstations (see below),
7. number of pallets in the system; kept fixed in most studies (see below).

The probability of jam occurrences is expressed in percentile and kept fixed; jam rates are determined in each study. Jam clear times are expressed with geometric distributions with a mean of which is also determined in each study. It is assumed that jam rates and jam clear times are independent.

The distance between two adjacent stations (connected by a transfer chain or conveyor) and the pallet dimensions determine the number of pallets that can be accommodated between these adjacent stations. The maximum amounts for these Work-In-Process (WIP) inventories between each pair of stations in the system constitute the buffer sizes [27].

Selecting an appropriate buffer sizes for the transport systems of automated manufacturing systems is a complex task that must account for random fluctuations in production rates by the individual stations as well as for transport delays that are a part of material handling system [27]. If buffer sizes are too large, then transport delays are excessive and more in-process inventories must be input into the system to accommodate the large buffer sizes. If the buffer sizes are too small, then small processing delays will cause buffer to fill, and upstream workstations will be blocked from releasing complete work piece. With a fixed number of pallets in the system, there is always an optimal buffer configuration capable of reducing blocking and starvation effects considerably to yield a maximum possible production rate [27,6]. Therefore, in most studies, we will keep the number of pallets fixed, with the exception of some studies presented in section 4.4.1. where we have studied the effects of the number of pallets in the system.

4.3. METHODOLOGY

In this chapter, we have followed a standard sequence of the DoE approach as described in section 3.2.3. the methodology can be summarized as follows.

The objective described in the previous section can be generally addressed as follows. In the given AAS parameters, find the optimal buffer levels of the AAS to yield a maximum or near maximum achievable production rate (i.e., throughput: TP). Accordingly, the decision variables are the buffer sizes between the pair workstations and the objective is to find the appropriate buffer levels that maximize the TP.

In order to accomplish this objective, the DoE approach is used. The low and high levels of buffer sizes are chosen based on the optimal solutions previously determined using SQG optimization methods [55] (see Table 2.1. in appendix 2). Then, the appropriate experimental design is selected among the strategies described in section 3.2.2. (see the *Design 1* in the table, page 55). In these designs, the buffer levels are varied systematically for each run. Experiments are conducted using the modified version of the discrete-event simulation program written by Diwan [27] and following the buffer configurations for each run defined in the selected design. Expected mean value and the variance of the TP for each run (10 replications conducted for each run) are obtained from the simulation runs. Then, the effect of each buffer space is calculated using the methodology described in Appendix 1, section 1.2.3. Then, by applying the normal probability paper technique, the effects of buffers are plotted to graph and the large effects (i.e., the ones that are distinguishable) are identified. To verify these conclusions, residual analysis is applied for diagnostic checks and final conclusion is made as follows. The buffers with large positive effects are chosen fixed at their high levels and buffers with large negative effects are chosen fixed at their low levels. Other buffers (i.e., the ones with no large effect on the TP) can be chosen within a range. Therefore, by keeping the ones with large effects fixed, we provide the flexibility to choose other buffers within a range. Consequently, we provide the design engineer as many alternatives as possible for buffer size selections. In order to verify these final conclusions, confirmatory experiments are conducted.

In addition, in an attempt to study the effects of number of pallets, we add it as a decision variable and select a design accordingly (see *Design 2* in the table, page 55; in section 4.4.) Then we follow the sequence described above.

DoE as the optimization method:

The initial levels of buffer sizes are chosen with two different approach. In the first study, the initial levels are chosen considering the previous studies and engineering knowledge (see Appendix 2, section 2.2.1.). In the second study, the initial values are chosen without taking any previous knowledge into consideration (see Appendix 2, section 2.2.1.)

In order to perceive that we are in the optimal area, we simultaneously check the effects of the buffers and the variance range of the TP in that particular set of experiments. We stop when the effects of buffers are small (or indistinguishable) as well as the variances of the any pairs of the TPs in that particular set of experiments (i.e., $variance_{anytwoTP}$) are small enough. The variances of the TPs (i.e., $variance_{anytwoTP}$) are calculated for each combination of the TPs. The $variance_{anytwoTP}$ is calculated as follows.

$$mean_{anytwoTP(ij)} = (TP_i + TP_j)/2$$

$$variance_{anytwoTP(ij)} = [\, 2*(TP_i^{\,2} + TP_j^{\,2}) - mean^2_{anytwoTP(ij)}] \,/\, 2$$

where TP_i and TP_j are the throughputs obtained from the experimental runs i and j, respectively.

In brief, the methodology for the buffer sizes optimization using the DoE approach can be outlined as follows.

- choose the initial levels for the buffer sizes
- select the appropriate design (see section 3.2.2. and the table in section 4.4.)
- conduct the set of the experiment using discrete-event simulation
- analyze the data using normal probability plotting, identify the important effects and choose the levels accordingly
- apply the residual analysis to verify the conclusion
- make the final conclusion accordingly (determine the buffer levels)
- then, conduct the next set of experiment, analyze the data, and choose the appropriate levels of buffers accordingly.
- continue experimenting until the effects are indistinguishable and $variance_{anytwoTP}$ is small enough.

4.4. IMPLEMENTATION

We have first investigated several systems that were previously studied by using Stochastic Quasigradient Methods (SQG) as the optimization methods and determined the optimal area for buffer sizes using the DoE approach. In addition, we have studied the effects of the number of pallets in such systems. Finally, we have applied the DoE approach as the optimization tool to AAS. Following sections present the conclusions of these studies. The following table 4.1. lists all Tables and Figures used in these studies.

Table 4.1. Tables and Figures used in the following studies:

Section	4.4.1.				4.4.2.		
system	**Type 1**	**Type 2**	**Type 3**	**Type 4**	**systems**	**Type 5**	**Type 6**
Tables & Figures:					**Design optimization:**		
designs for buffers (Design 1)	2_{IV}^{10-5}	2_{IV}^{10-5}	2_{IV}^{10-5}	2_{IV}^{10-5}	**designs for Type 5&6**	2^5	L_{16} (2^{15})
designs for buffers and pallets (Design 2)	2_{III}^{11-6}	2_{III}^{11-6}	2_{III}^{11-6}	2_{III}^{11-6}	**initial ranges of buffers**	Table 4.5.1.	Table 4.6.1.
initial ranges for Design 1&2	Table 4.1.1.	Table 4.2.1.	Table 4.3.1.	Table. 4.4.1.	***optimal buffer ranges***	*Table 4.5.2.*	*Table 4.6.2.*
buffer ranges that define the optimal area (for Design1)	*Table 4.1.2.*	*Table. 4.2.2.*	*Table. 4.3.2.*	*Table. 4.4.2.*	**graphs of the analyses of last step**	Figure 4.5.1. & 4.5.2.	Figure 4.6.1. & 4.6.2.
graphical results of the analyses of Design 1	Figure 4.1.1. & 4.1.2.	Figure 4.2.1. & 4.2.2.	Figure 4.3.1. & 4.3.2.	Figure 4.4.1. & 4.4.2.	**explana tions of steps**	App., section 2.2.1.	App., section 2.2.2.
graphical results of the analyses of Design 2	App., Figure 2.1.1. & 2.1.2.	App., Figure 2.2.1. & 2.2.2.	App., Figure 2.3.1. & 2.3.2.	App., Figure 2.4.1. & 2.4.2.	**graphs of the analyses of the steps**	App., Figure 2.5.1.1. to 2.5.3.2.	App., Figure 2.6.1.1. to 2.6.5.2.
results of exp. runs of Design 1	App., Table 2.1.1.	App., Table 2.2.1.	App., Table 2.3.1.	App., Table 2.4.1.	**results of exp. runs of steps**	App., Table 2.5.1.1. to 2.5.4.1.	App., Table 2.6.1.1. to 2.6.6.1.
results of exp. runs of Design 2	App., Table 2.1.2.	App., Table 2.2.2.	App., Table 2.3.2.	App., Table 2.4.2.	**conclu-sions of steps**	App., Table 2.5.1.2. to 2.5.3.2.	App., Table 2.6.1.2. to 2.6.5.2.

App. : Appendix

4.4.1. DETERMINING THE OPTIMAL AREA FOR THE SYSTEMS PREVIOUSLY STUDIED WITH THE SQG AS THE OPTIMIZATION METHOD

In this research, we have extended the SQG optimization study by determining the optimal area for buffer sizes. Liu and Sanders applied the Stochastic Quasigradient methods (SQG) to optimize the buffer allocations in the asynchronous flexible assembly systems [55]. This research proposes the use of the DoE approach to overcome the shortcoming of the SQG study (i.e., not being able to provide an optimal range for the decision variables) which is necessary in most cases in practice. For this purpose, we have determined the appropriate levels of buffers using the DoE approach.

Secondly, we studied the effect of the number of pallets in AAS by adding it as a decision variable (Design 2 studies). Studies with four systems indicated a significant effect of the number of pallets in AAS. In all cases it affected the TP significantly, thus we were not able to find an optimal buffer configuration. The results and conclusion of these studies are presented in Appendix 2, section 2.1.

Following discusses the conclusions of optimal area studies (Design 1 studies) for each type of system, then makes final conclusions.

Type 1 Systems (Uniform Stations That Are Subject To Jam):

In their study, Liu and Sanders stated that if all stations in an AAS have the same performance characteristics, the buffer sizes can be expected to be the same [55]. In our study, we have observed that the buffers may have different sizes, even though all stations are uniform. In other words, some buffers needed large space while some could be chosen within a range. Thus, by conducting this study, we could provide a flexibility for buffer size selections. The proposed optimal buffer size ranges for the engineering design phase of the buffer sizes for Type 1 systems and results of the confirmatory experiments are disclosed in Table 4.1.2.

Type 2 Systems (Stations 2, 3, and 7 Subject To Jam; With Same Jam Rate):

We have found that the buffer between two non-zero-jam-rate stations (b_2) needs the most buffer size, a conclusion which supports the one by Liu and Sanders (i.e., we should allocate more buffer units to the buffer between stations 2 and 3; b_2; [55]). In addition, we have discovered that all other buffers between the non-zero-jam-rate stations also affect the TP. Our conclusions of the optimal buffer sizes in such systems and results of the confirmatory experiments are listed in Table 4.2.2.

Type 3 (Stations 2 4, and 6 Subject To Jam; With Same Jam Rates):

Analyses showed that the buffers adjacent to any non-zero-jam-rate stations needed the most space, with one exception; b_1. Although it is between a jam free station and a non-zero-jam-rate station and has relatively small buffer size, b_1 needed a small space; a conclusion that contradicts to the statement by Liu and Sanders (i.e., we should allocate more buffer units between any stations with high jam rates; [55]). The next two buffers needed large space, as expected. There is another interesting result we have gathered in this study: All buffers have somewhat considerable effect on the TP, although the three mentioned above are the most important ones. Thus, it is advisable to choose as many among the b_6, b_7, b_8, b_9, and b_{10} as possible at low levels and for the b_4

and b_5 at high levels. Our conclusions for the optimal buffer sizes in Type 3 systems and the confirmatory experiments are listed in Table 4.3.2.

Type 4 Systems (All Stations Are Subject To Jam)

This study supported the conclusion by Liu and Sanders stating that the best buffer allocation pattern is to have larger buffer sizes before and after high-jam-rate stations in order to decouple the interaction effects. These interaction effects at a station can be from both high-jam-rate stations or low-jam-rate stations. The largest two effects, namely b_1 and b_2 , represent the buffers between the stations with low-level and high-level jam rate and have relatively broad size, yet still need the largest size possible. The third effect, b_{10} (also needs large space), and the effect, b_4 (needs small space), are between two low-level-jam-rate stations. Following this conclusion, we have suggested the optimal buffer ranges listed in Table 4.4.2. and confirmatory experiments corroborated with our conclusion, as seen in the same table.

Conclusion:

We have reached important conclusions in this study. We have shown the statements made by Liu and Sanders studying the same systems do not necessarily reflect the real character of the systems (see section 4.4.1., Type 1 and Type 3 systems). In other words, previous studies in literature not necessarily provided enough information to make general conclusions. However, by using the DoE approach, we have collected substantial information on the systems and the effects of the buffers, which offers design engineer a considerable amount of flexibility and a better understanding in design. Furthermore, we have studied the effect of the number of pallets in the systems.

In brief, using the DoE approach, we were able to study these systems in such detail, thus gather information that would help one design such systems more in control.

4.4.2. DETERMINING THE OPTIMAL AREA FOR THE SYSTEMS STUDIED WITH THE DoE APPROACH AS THE OPTIMIZATION METHOD

The following presents the conclusions of the studies using the DoE approach to optimize the buffer sizes. Two types of systems are studied; Type 5 with all stations subject to jam and Type 6 with some stations subject to jam. The jam clear time is same for all stations in both systems and modeled by a geometric distribution with a mean of 20 time units. We have chosen the mean as four times longer than the cycle time based on the consultations with design engineers. It is widely accepted to choose the number of pallets 3-4 per station. Hence, based on the literature such as [27], we have chosen 4 pallets per station. The detailed information on how the experiments are conducted is presented in Appendix 2, section 2.2.

Type 5 (all stations are subject to jam):

The Type 5 systems have stations with different jam rates, as demonstrated in Table 4.5.1. The total number of pallets is 20 for such systems with five stations.

The initial buffer ranges are selected considering the results found in section 4.4.1. and engineering knowledge. Hence, we were able to reach the optimal buffer ranges in the 4^{th} step, as listed in Table 4.5.2.

Type 6 (some stations are subject to jam):

The Type 6 systems have some stations that are subject to jam with different jam rates (see Table 4.6.1.). There are fifteen station in the system and the number of the pallet is chosen as 20 pallets.

The initial buffer ranges are selected without considering the engineering knowledge or conclusions of previous research, thus, it took six steps to reach the optimal area (see Table 4.6.2.) However, considering the randomness of the initially selected levels, the DoE approach again indicated to be effective optimization tool.

Conclusion:

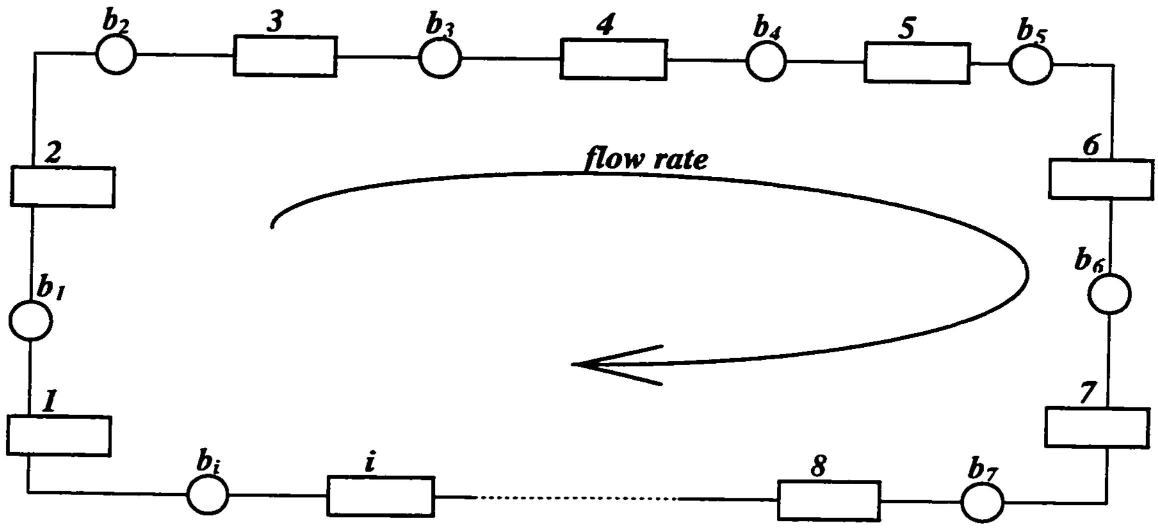
DoE is a powerful tool to predict the optimal results by studying the effects of the decision variables [75]. Thus, based on the previous studies of optimization of a process or a product, such as [75,72] and our studies discussed in this chapter, we propose the DoE approach as the practical optimization tool for the optimization of buffer sizes in assembly systems. Because the DoE approach gives extensive information on the system as well as the parameters, using the DoE approach for optimization will provide broad interior information on the system to be designed. Thus, the optimization results obtained through the DoE approach will serve the designer as not only the optimal results but also the invaluable guidelines about the system. Therefore, it is our advice to use the DoE approach in practice, especially when the system to be designed is not well-known.

4.5. CONCLUSION

In this chapter, we have studied several systems to determine the optimal buffer ranges. In the first part, we have used the optimal results previously obtained by SQG methods and determined the optimal buffer ranges, hence defined the optimal area. For this purpose, we have worked with four different systems. In the second part, we have used the DoE approach as the optimization tool and determined the optimal buffer ranges for two different types of systems.

The first part of the study showed that by using the DoE approach one can gather the information that it is not possible by using other optimization methods, such as SQG methods. The DoE approach not only presents the data on how the decision variables affect the system response, but also provides invaluable information on the system. Consequently, using the DoE approach, one can design the systems with a better understanding as well as having flexibility to choose the buffers within the ranges determined by the DoE approach. Thus, it is our advice to use the DoE approach to determine the optimal area that is needed in most cases in practice.

The second part of the study showed that the DoE approach is a powerful tool for optimization as well. Using the DoE approach as the practical optimization tool for the optimization of buffer sizes furnishes comprehensive internal information on the system. Consequently, the optimal buffer ranges determined by the DoE approach assist as the invaluable guidelines about the system. Therefore, we recommend the use of the DoE approach in practice, especially when the system to be designed is not well-known.



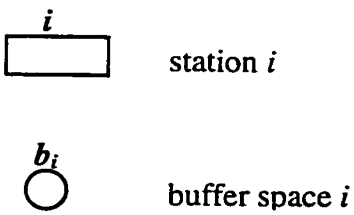


Figure 4.1. Closed-loop Asynchronous Assembly Systems

Table 4.1.1. The initial ranges for Design 1 and Design 2 of Type 1 systems

The initial ranges of buffers (for Design 1 and Design 2)

buffers	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}
-	2	2	2	2	2	2	2	2	2	2
+	3	3	3	3	3	3	3	3	3	3

for Design 1:

number of pallets: 20 pallets

The ranges of pallets (for Design 2)

number of pallets in the system	
-	20
+	21

for Design 1 and Design 2:

jam clear time: geometric distribution with a mean of 18 time units

the neutral levels of jam rates:

station	1	2	3	4	5	6	7	8	9	10
jam rate	1	1	1	1	1	1	1	1	1	1

Table 4.1.2. The optimal buffer ranges for Type 1 systems and confirmatory experiments

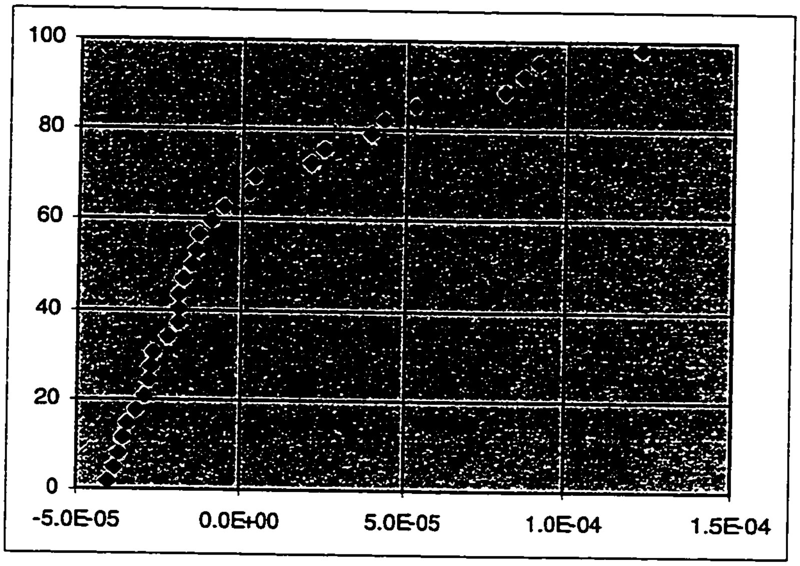
The conclusion of buffer configurations for optimal area:

buffers	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}
-	2	2	2	3	3	2	2	3	3	2
+	3	3	3	3	3	3	3	3	3	3

confirmatory experiments:

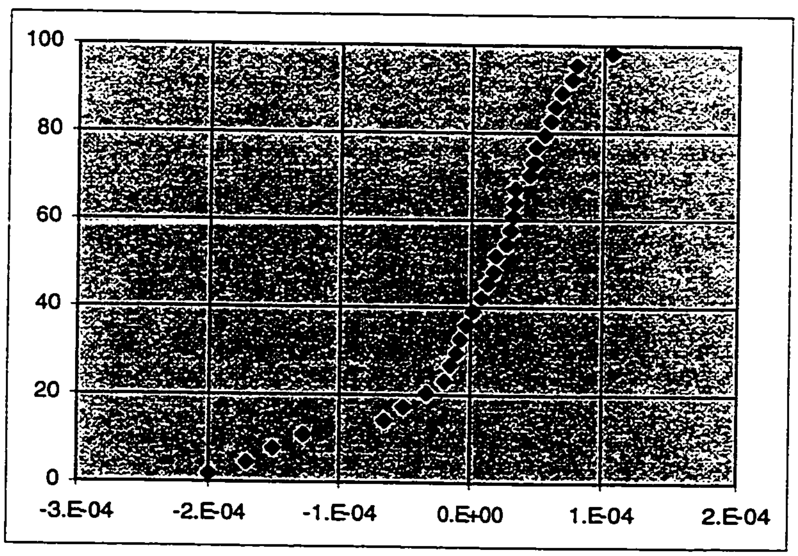
buffer configurations	TP	variance (10^{-10})
2,3,2,3,3,3,3,3,3,2	.143300	125881
2,3,2,3,3,2,2,3,3,2	.143302	125625
3,2,2,3,3,2,3,3,3,2	.143307	124216

Figure 4.1.1. The effects of buffers of Type 1 systems



$l_4=1.23*10^{-4}$, $l_9=0.91*10^{-4}$, $l_5=0.87*10^{-4}$, $l_8=0.81*10^{-4}$

Figure 4.1.2. The residuals of buffers of Type 1 systems



$^{*}\, p_k = 100 * [(k-0.5)/k]$

Table 4.2.1. The initial ranges for Design 1 and Design 2 of Type 2 systems

The initial ranges of buffers (for Design 1 and Design 2)

buffers	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}
-	5	16	5	4	4	4	5	4	4	4
+	6	17	6	5	5	5	6	5	5	5

for Design 1:

number of pallets: 40 pallets

The ranges of pallets (for Design 2)

number of pallets in the system	
-	40
+	45

for Design 1 and Design 2:

jam clear time: geometric distribution with a mean of 36 time units

the neutral levels of jam rates:

station	1	2	3	4	5	6	7	8	9	10
jam rate	0	3	3	0	0	0	3	0	0	0

Table 4.2.2. The optimal buffer ranges for Type 2 systems and confirmatory experiments

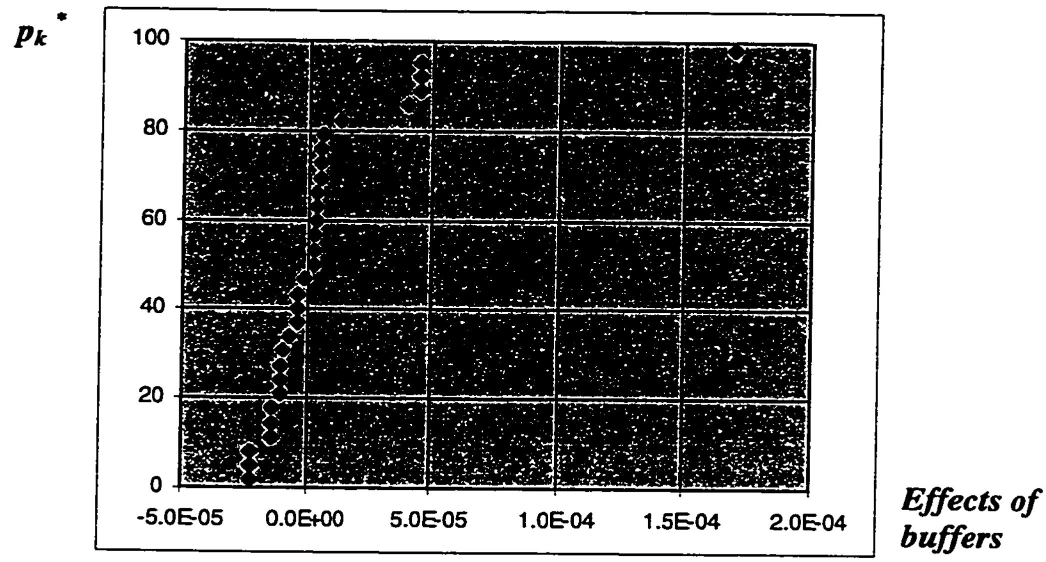
The conclusion of buffer configurations for optimal area:

buffers	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}
-	5	17	6	5	5	5	5	4	4	4
+	6	17	6	5	5	5	6	5	5	5

confirmatory experiments:

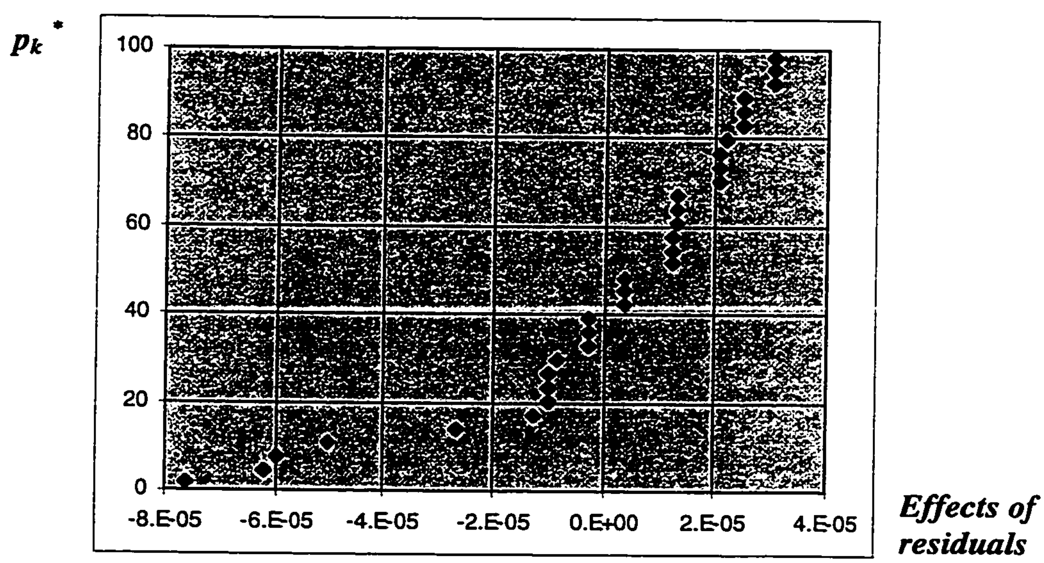
buffer configurations	TP	variance (10^{-10})
5,17,6,5,5,5,6,4,4,4	.130044	195269
5,17,6,5,5,5,5,4,5,5	.130054	195253
5,17,6,5,5,5,5,5,5,5	.130054	195253
6,17,6,5,5,5,5,4,4,4	.130040	197196

Figure 4.2.1. The effects of buffers of Type 2 systems



$l_2=1.69*10^{-4}$, $l_3=l_4=l_5=0.45*10^{-4}$, $l_6=0.39*10^{-4}$

Figure 4.2.2. The residuals of buffers of Type 2 systems



$^{*}\, p_k = 100 * [(k\text{-}0.5)/k]$

Table 4.3.1. The initial ranges for Design 1 and Design 2 of Type 3 systems

The initial ranges of buffers (for Design 1 and Design 2)

buffers	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}
-	4	9	10	11	11	4	4	4	4	4
+	5	10	11	12	12	5	5	5	5	5

for Design 1:

number of pallets: 40 pallets

The ranges of pallets (for Design 2)

number of pallets in the system	
-	40
+	45

for Design 1 and Design 2:

jam clear time: geometric distribution with a mean of 36 time units

the neutral levels of jam rates:

station	1	2	3	4	5	6	7	8	9	10
jam rate	0	3	0	3	0	3	0	0	0	0

Table 4.3.2. The optimal buffer ranges for Type 3 systems and confirmatory experiments

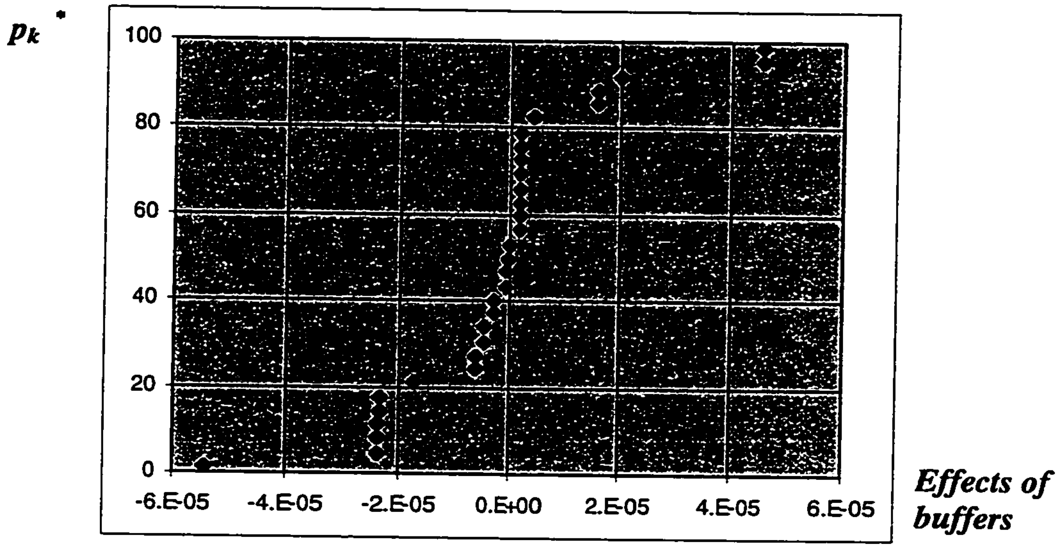
The conclusion of buffer configurations for optimal area:

buffers	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}
-	4	10	11	11	11	4	4	4	4	4
+	4	10	11	12	12	5	5	5	5	5

confirmatory experiments:

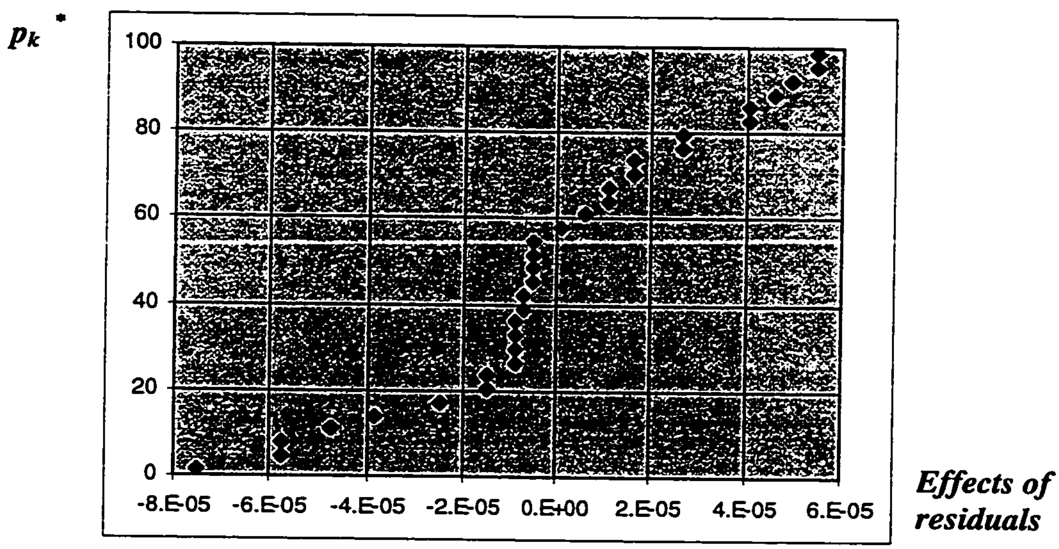
buffer configurations	TP	variance (10^{-10})
4,10,11,11,11,4,4,4,4,4	.129004	459765
4,10,11,11,12,4,4,5,4,4	.129019	447259
4,10,11,12,12,5,5,4,4,4	.128995	444505
4,10,11,12,12,4,4,4,4,4	.129028	445386

Figure 4.3.1. The effects of buffers of Type 3 systems



l_1=-5.43*10^{-5}, l_2=l_3=4.57*10^{-5}

Figure 4.3.2. The residuals of buffers of Type 3 systems



* p_k = 100 * [(k-0.5)/k]

Table 4.4.1. The initial ranges for Design 1 and Design 2 of Type 4 systems

The initial ranges of buffers (for Design 1 and Design 2)

buffers	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}
-	11	14	5	6	6	11	11	5	7	3
+	12	15	6	7	7	12	12	6	8	4

for Design 1:

number of pallets: 50 pallets

The ranges of pallets (for Design 2)

number of pallets in the system	
-	50
+	60

for Design 1 and Design 2:

jam clear time: geometric distribution with a mean of 18 time units

the neutral levels of jam rates:

station	1	2	3	4	5	6	7	8	9	10
jam rate	0.5	3	0.5	0.5	0.5	0.5	3	0.5	0.5	0.5

Table 4.4.2. The optimal buffer ranges for Type 4 systems and confirmatory experiments

The conclusion of buffer configurations for optimal area:

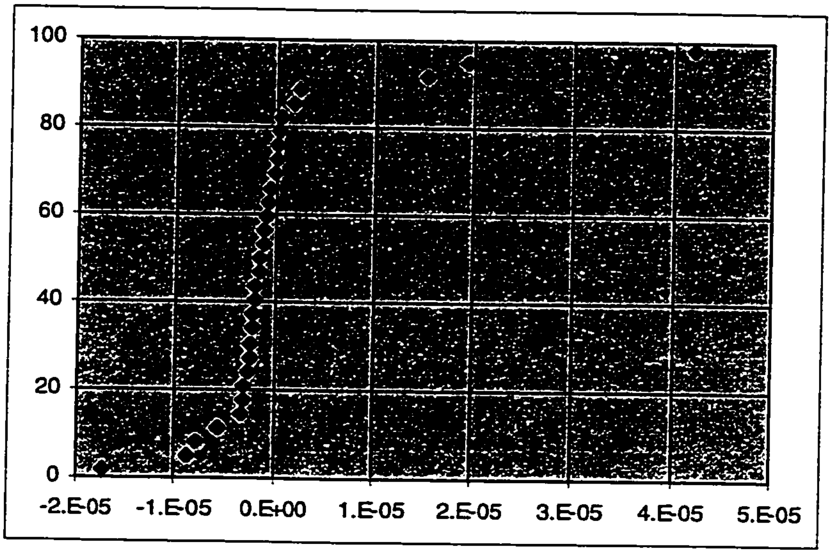
buffers	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}
-	**12**	**15**	**5**	**6**	**6**	**11**	**11**	**5**	**7**	**4**
+	**12**	**15**	**6**	**6**	**7**	**12**	**12**	**6**	**8**	**4**

confirmatory experiments:

buffer configurations	**TP**	**variance (10^{-10})**
12,15,5,6,7,11,12,5,7,4	.150656	119326
12,15,6,6,6,12,11,6,8,4	.150653	120718
12,15,5,6,7,11,11,5,8,4	.150658	119135
12,15,5,6,6,12,12,5,7,4	.150665	120366

Figure 4.4.1. The effects of buffers of Type 4 systems

p_k *

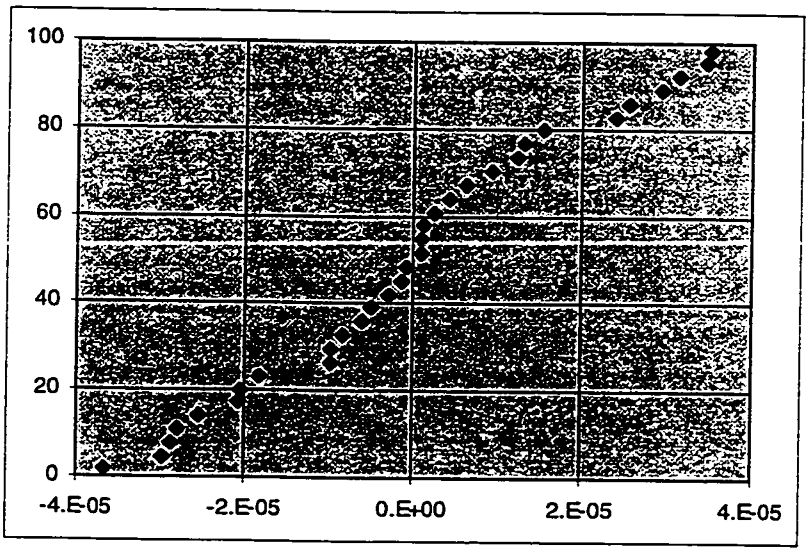


Effects of buffers

l_1=4.19*10^{-5}, l_2=1.93*10^{-5}, l_4=-1.73*10^{-5}, l_{10}=1.52*10^{-5}

Figure 4.4.2. The residuals of buffers of Type 4 systems

p_k *



Effects of residuals

* $p_k = 100 * [(k-0.5)/k]$

Table 4.5.1. The initial buffer ranges for Type 5 systems for the optimization with DoE

buffers	b_1	b_2	b_3	b_4	b_5
-	2	5	4	8	4
+	3	7	5	11	5

jam clear time: geometric distribution with a mean of 20 time units, number of pallets:20

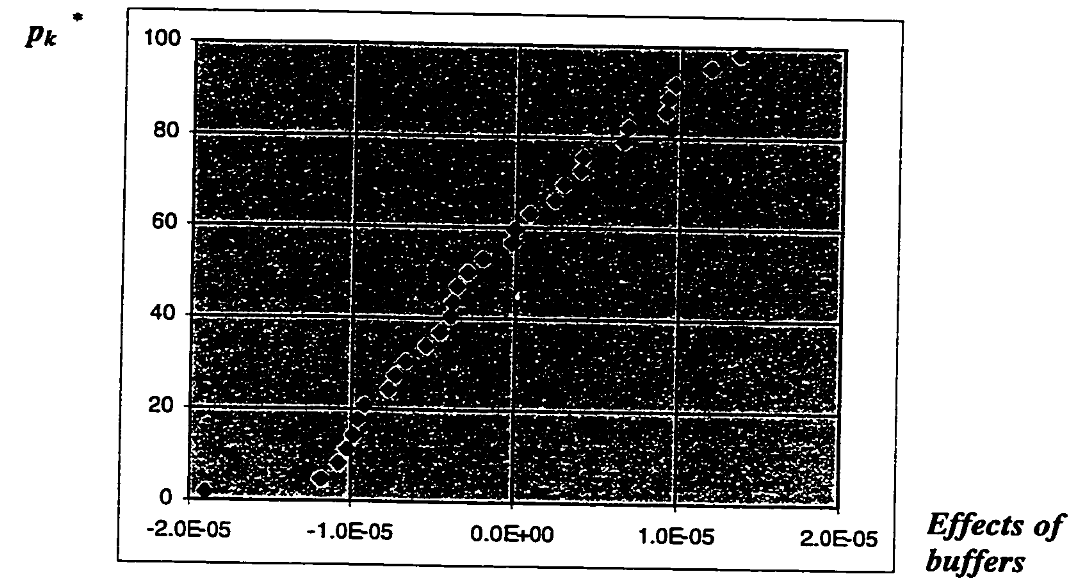
jam rates:

station	1	2	3	4	5
jam rates	0.5	3	0.5	5	0.5

Table 4.5.2. The optimal buffer ranges for Type 5 systems for the optimization with DoE (conclusion of 4th step)

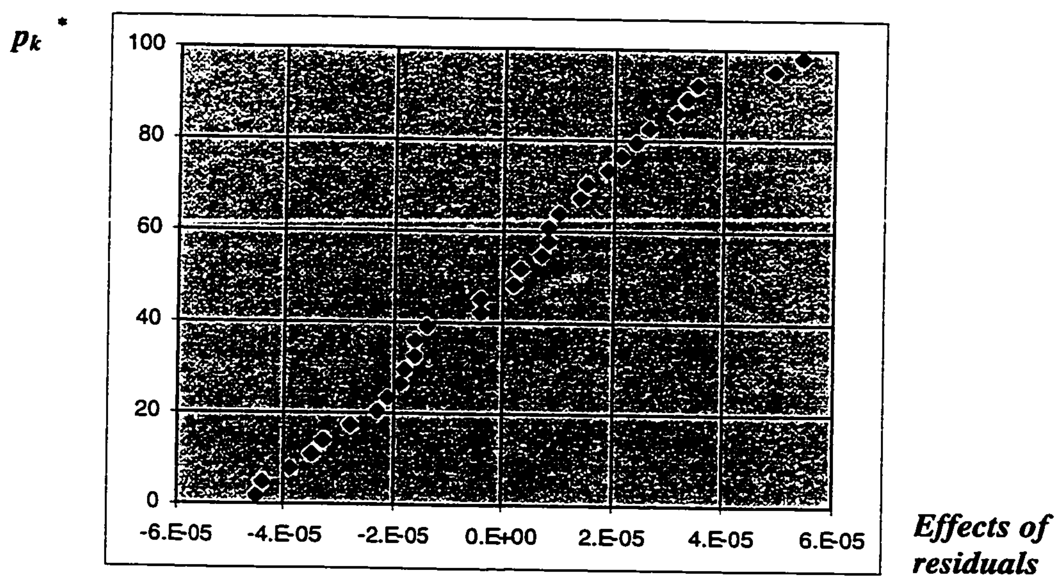
buffers	b_1	b_2	b_3	b_4	b_5
-	**3**	**6**	**8**	**9**	**3**
+	**4**	**7**	**9**	**10**	**4**

Figure 4.5.1. The effects of buffers of Type 5 systems (conclusion; 4th step)



$l_2 = -1.9*10^{-5}$

Figure 4.5.2. The residuals of buffers of Type 5 systems (conclusion; 4th step)



* $p_k = 100 * [(k-0.5)/k]$

Table 4.6.1. The initial values of buffer ranges for Type 6 systems for the optimization with DoE

buffers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
-	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
+	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6

jam clear time: geometric distribution with a mean of 20 time units, number of pallets:60

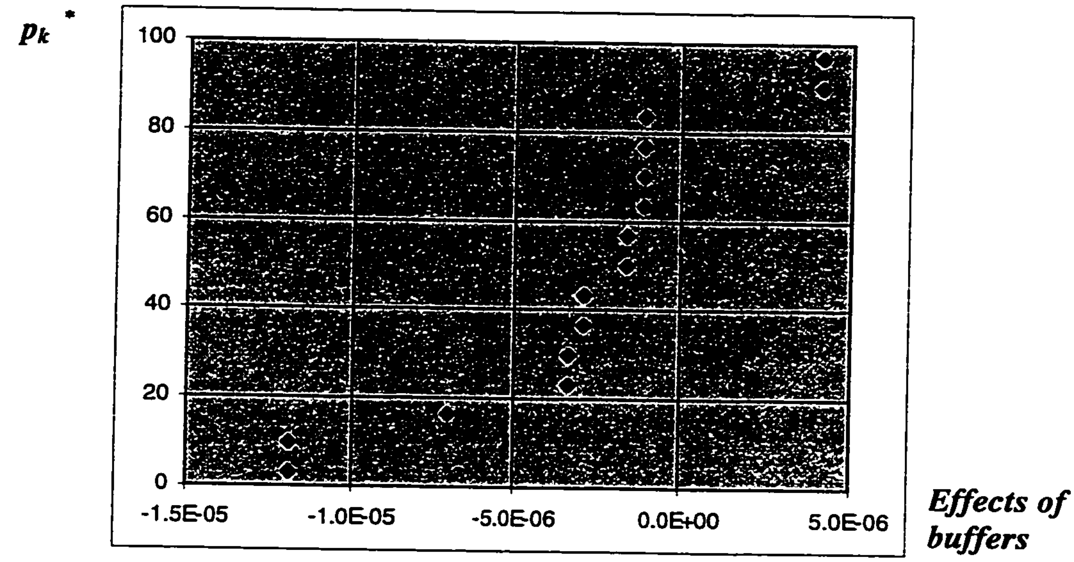
jam rates:

station	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
jam rates	3	3	0	5	0	0.5	0	3	0	0.5	0	0.5	0	0	0

Table 4.6.2. The optimal buffer ranges for Type 6 systems for the optimization with DoE (conclusion of 6th step)

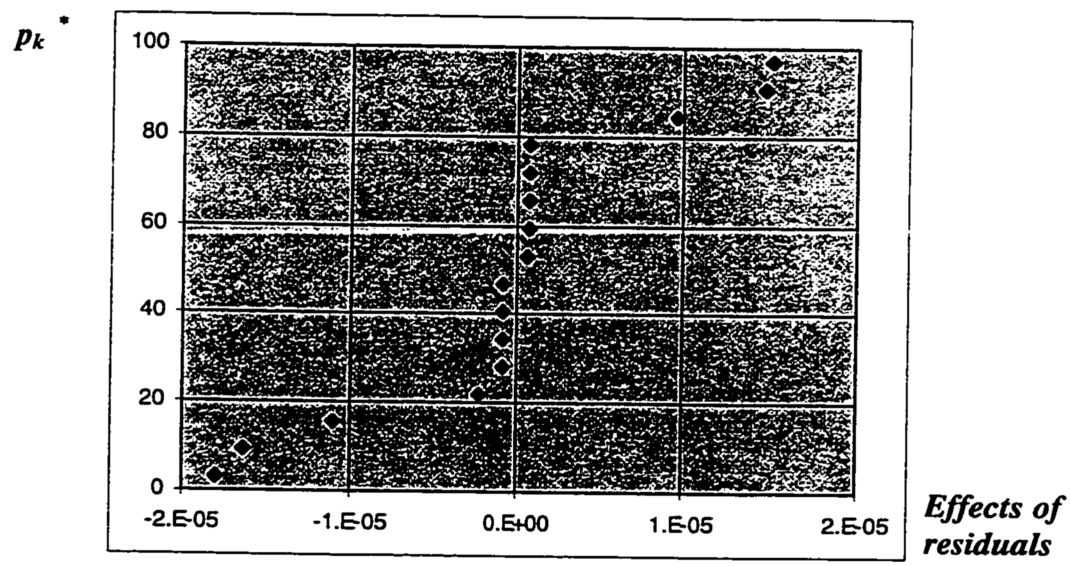
buffers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
-	16	12	12	8	8	6	6	5	5	1	1	3	3	2	2
+	17	13	13	9	9	7	7	6	6	2	2	4	4	3	3

Figure 4.6.1. The effects of buffers of Type 6 systems (conclusion; 6th step)



$l_{10}=l_{11}=-1.19*10^{-5}$

Figure 4.6.2. The residuals of buffers of Type 6 systems (conclusion; 6th step)



* $p_k = 100 * [(k-0.5)/k]$

CHAPTER 5

ROBUST DESIGN OF ASYNCHRONOUS ASSEMBLY SYSTEMS (AAS)

The idea of making a product or process insensitive to variation is the essence of robust design [45]. This research concentrates on manufacturing process design, which aims to find the optimal buffer specification to make the throughput insensitive to variation with respect to noise factors in the design phase of the asynchronous assembly systems.

The robust design method uses an established statistical tool (i.e., the design of experiments) to help solve an important engineering problem; reducing variability [45].

Statistically designed experiments have been used to improve industrial processes for decades, but most applications have focused on the mean values of process's functional characteristics. However, the yield of a manufacturing process (i.e., throughput) is more closely linked to the process's variability, and robust design is a method for reducing that variability without increasing process cost [45].

In this chapter, we present the experiment sets conducted for different systems and configurations. Next section (section 5.1.) discusses the need of a study for the robust design. Section 5.2. defines the problem and the system parameters. Section 5.3. reviews the methodology of the robust design briefly. Section 5.4. presents the studies conducted and the conclusions of the analyses. The systems studied and presented in sections 5.4.1. and 5.4.2. are the same systems that are discussed in sections 4.4.1. and 4.4.2., respectively. Finally, section 5.5. summarizes the studies conducted in this chapter and the conclusions.

5.1. THE NECESSITY OF THE ROBUST DESIGN

We propose the application of robust design to overcome one of the important shortcomings of previous studies; studying and reducing the effect of the uncontrollable parameters in assembly systems. The previous studies in optimization of buffer sizes in assembly systems kept some parameters fixed, then solved the optimization problem and proposed solutions accordingly. However, our experiences in the industry and theoretical work showed that some of these parameters that are kept fixed in previous studies may not be steady in reality. Yet, in previous optimization studies such as using the Stochastic Quasigradient methods (SQG) [55], the effects of these above mentioned parameters on the system response are ignored entirely. Consequently, the optimal results found in these previous studies may not give the anticipated improvement for the systems, because these potentially important effects are ignored. Therefore, a study on the effects of these above mentioned parameters and diminishing their effects by reducing the variance of the system response with respect to these parameters is necessary.

5.2. DEFINITION OF THE OBJECTIVE AND SYSTEM PARAMETERS

The objective of this chapter is to design the asynchronous assembly systems that are robust (insensitive) to noise factors (i.e., jam rates and jam clear times). For this purpose, we will identify the appropriate levels for the control factors (i.e., buffer sizes). First, we will review the objective of robust design, then describe the systems and common parameters.

5.2.1. THE OBJECTIVE OF ROBUST DESIGN AND REVIEW OF BASIC DEFINITIONS

In order to define the objective of the robust design more precisely, three concepts are needed, namely functional characteristics, control parameters, and source of noise[45].

Functional characteristics are basic, measurable quantities that determine how well the final product or process functions. In this research, the functional characteristic is the throughput of the asynchronous assembly systems.

Control parameters are the controllable process variables; their operating standards can be specified by the process engineers. In this research, the buffer sizes will be the controllable factors.

On the contrary, sources of noise are the variables that are impossible or expensive to control. In this research, the jam rates and jam clear times are considered as noise factors. They are assumed to be independent from each other and occur randomly.

The objective of the robust design is to find those control parameter settings where noise has a minimal effect on the functional characteristics. The key idea is to reduce functional characteristic sensitivity by making the process insensitive to noise rather than by controlling the sources of noise [45]. Therefore, our objective is *to find the appropriate levels for the control factors (i.e., buffer sizes) where the variance of the throughput with respect to noise factors (i.e., variance*$_{wrtnf}$*, as defined in section 3.4.) will be minimum.*

In view of the explanations above, the following section describes the systems and the common parameters.

5.2.2. AAS AND SYSTEMS PARAMETERS

The systems studied in this chapter are asynchronous assembly systems (AAS) which are closed sequences of automatic assembly workstations linked by an automatic transfer mechanism, as described in section 4.1. The type of the systems and many parameters are same as the systems that are described in Chapter 4, section 4.1. and 4.2. This section will describe the asynchronous assembly systems briefly and mention the common parameters for all systems studied in this chapter. Other parameters are described for each study independently.

In this research we consider three events that cause a station be "not operational"; the jams, the starvation and the blocking of the station. Consequently, the buffer and pallet specifications have important effects on the occurrences of these events.

The common parameters are as follows.

(1) The cycle time is deterministic and 5 time units (same for all systems).

(2) The transport time is 1 time unit per buffer unit (same for all systems).

(3) The mix of assembly types is assumed constant in any given time (same for all systems).

(4) The number of pallets are defined in each study.

(5) Jam rates.

(6) Jam clear times.

(7) Buffer sizes.

The jam rates and jam clear times are considered as *noise factors* in most of the studies (except the first study with Type 5 systems where only jam rates are considered as noise factors.) In each study, the levels of noise factors are defined accordingly. A range of $\pm 0.5\%$ for each jam rate and a range of ± 1 time unit (± 2, if indicated) of the mean of the geometric distribution of each jam clear time are used for defining the levels of noise factors. Although a change of $\pm 0.5\%$ or ± 1 time unit may seem very small, it is still a considerable amount, when contemplating the system as a total. The buffer sizes are the *decision variables (i.e., control factors)* in all studies and defined in two levels, as high and low levels.

Since the optimization of the buffer sizes where noise factors have already been studied in Chapter 4, we resume from this point and using these optimization results we will design the system that is robust to noise factors.

5.3. METHODOLOGY

In this research, we have followed a sequence that is similar to that described by Kacker and Shoemaker [45]. The methodology can be summarized as follows.

Our objective is to find the appropriate levels for the control factors (i.e., buffer sizes) where the variance of the throughput with respect to noise factors ($variance_{wrtnf}$) will be minimum. To attain this objective, the control factors and noise factors in an inner-outer array design are varied systematically. Then, the effect of noise is measured by calculating the variance of the throughput with respect to noise factors ($variance_{wrtnf}$) for each setting of control factors (i.e., each row of the inner array). Applying the data analysis techniques such as normal probability plotting and residual analysis, the effects of the control factors on the $variance_{wrtnf}$ are calculated. Finally, the appropriate levels of the control factors, hence the ranges of buffer sizes that will make the process insensitive to noise are predicted.

Consequently, we first decide the appropriate designs (see section 3.2.2.) for the inner-outer array design, and assign the buffer sizes as controllable factors to the inner array and jam rates and jam clear times as noise factors to the outer array. The levels of the buffer sizes are chosen as the optimal buffer ranges that were determined in the sub-sections of 4.4. The levels of noise factors are chosen separately in each study, however the change for each noise factor is considered in a small range.

Then, we conduct the experiments accordingly and analyze our results. For this purpose, we calculate the variance of the throughput with respect to noise factors ($variance_{wrtnf}$) as follows.

$$variance_{wrtnf(i)} = [\, \Sigma\, TP_{ij}^{\;2} - f(\Sigma\, TP_{ij})^2 \,] \,/\, [\, f^*(f-1)] \qquad , j : 1..f$$

where TP_{ij} is the number of units produced by the model for particular buffer size configuration, i (i.e., the configuration of the ith row of the inner array) , and noise factor configuration, j, and f is the total number of noise factor configurations (i.e., the number of columns in the outer array).

After calculating the $variance_{wrtnf}$ for each buffer configuration defined in the design of experiments, we calculate the effects of each buffer size on the $variance_{wrtnf}$. In other words, we determine how each buffer size affects the variance of the throughput with respect to noise factors. Then, we find the most important effects and choose the levels of these buffer sizes accordingly.

Choosing the levels of buffer sizes that have important effects and keeping them fixed at those levels allows us the freedom to choose other buffer sizes within the range. Clearly, the ability to choose the buffer sizes that do not have important effects at any of the two levels gives the flexibility that the design and manufacturing engineers may most likely need in practice. Thus, not only will we design the system that is robust but also will give the flexibility of choosing as many buffer sizes as possible within the range.

5.4. IMPLEMENTATION

We have designed systems that are robust to the noise factors. For this purpose, we have used the optimal buffer ranges that were determined in the sub-sections of 4.4., explored the robustness of this optimal area by using robust design approach, and finally re-defined these buffer ranges that give minimum $variance_{wrtnf}$. First section covers the systems that were studied using SQG methods. The second section discusses the systems that were studied using the DoE approach as optimization method.

Tables and Figures used in the next sections are listed in the following table 5.1.

Table 5.1. Tables and Figures used in the following studies:

section	5.4.1. (systems studied in section 4.4.1.)				5.4.2.(systems studied in section 4.4.2.)		
system	Type 1	Type 2	Type 3	Type 4	Type 5	Type 5 (2nd ex.)	Type 6
Tables & Figures:							
designs for buffers and noise factors	2^{10-5} and 2^2	L_{12} (2^{11}) and L_8 (2^7)	L_{12} (2^{11}) and L_8 (2^7)	L_{12} (2^{11}) and $L_9'(2^{21})$	2^5 and 2^5	2_V^{5-1} and 2_{III}^{10-6}	L_{16} (2^{15}) and L_{16} (2^{15})
ranges for buffers and noise factors	Table 5.1.1.	Table 5.2.1.	Table 5.3.1.	Table 5.4.1.	Table 5.5.1.	Table 5.6.1.	Table 5.7.1.
buffer ranges that make the system robust	*Table 5.1.2.*	*Table 5.2.2.*	*Table 5.3.2.*	*Table 5.4.2.*	*Table 5.5.2.*	*Table 5.6.2.*	*Table 5.7.2.*
graphical results of the analyses	Figure 5.1.1 & 5.1.2.	Figure 5.2.1. & 5.2.2.	Figure 5.3.1. & 5.3.2.	Figure 5. 4.1. & 5.4.2.	Figure 5.5.1. & 5.5.2.	Figure 5.6.1. & 5.6.2.	Figure 5. 7.1. & 5. 7.2.
results of exp. runs	App., Table 3.1.1.	App., Table 3.2.1.	App., Table 3. 3.1.	App., Table 3. 4.1.	App., Table 3.5.1.	App., Table 3.6.1.	App., Table 3.7.1.
mean and *variance*$_{wrtnf}$ of the TP	App., Table 3.1.2.	App., Table 3.2.2	App., Table 3.3.2	App., Table 3.4.2	App., Table 3.5.2	App., Table 3.6.2	App., Table 3.7.2

App. : Appendix

5.4.1. ROBUST DESIGN OF THE SYSTEMS PREVIOUSLY STUDIED WITH THE SQG AS THE OPTIMIZATION METHOD

In this section, we have studied the systems that were previously examined by using the SQG as the optimization method. We have investigated four different systems. We have used the optimal buffer ranges that were identified in the studies discussed in Chapter 4 (see section 4.4.1.) and investigated the robustness of this optimal area (while the noise factors are considered as jam rates and jam clear times.) Finally, we have re-defined the ranges of buffers that not only give an optimal area but also make the system robust to the noise factors. Following presents the studies with these four systems.

Type 1 (Uniform Stations That Are Subject To Jam):

Because of the special configuration of these systems, that is the uniformity of the stations, we could simplify our design by having two noise factors (i.e., the jam rate and jam clear time), instead of having ten same jam rates and ten same jam clear times, therefore having many repetitions in the outer array.

The analyses and confirmatory experiments showed that although stations are uniform, buffers affected the variation of the TP against noise factors (i.e., $variance_{wrtnf}$) in different levels of importance. Hence, to design the system that is insensitive to noise factors (i.e., robust), some buffers must be chosen as determined and others can be chosen within the range. The conclusion of buffer sizes for engineering designs is presented in Table 5.1.2.

Type 2 (Stations 2, 3, and 7 Subject To Jam; With Same Jam Rates):

The analyses revealed that the buffers between the non-zero-jam-rate stations (with the exception of b_2, which has the largest buffer size) have important effect on the $variance_{wrtnf}$. Thus, the buffers between non-zero-jam-rate stations with small spaces must be chosen at the low levels in order to make the system robust to noise factors (Table 5.2.2.). The confirmatory experiment and experiment run 1, which support our conclusion, verified our conclusion. By following our conclusion, the $variance_{wrtnf}$ could be reduced to $1.17*10^{-5}$.

Type 3 (Stations 2, 4, and 6 Subject To Jam; With Same Jam Rates):

The analyses showed that almost all effects are distinguishable, with the exception of b_1 ,b_6, b_2, and b_3. All of these buffers are adjoining to a non-zero-jam-rate stations. In addition, among the stations adjoining to a non-zero-jam-rate station, these buffers have relatively smaller spaces. This result also supports the one observed in previous study. Thus, we can remark the effect of the buffers with relatively small spaces adjoining to a non-zero-jam-rate station has important effect on the variation of the throughput. Consequently, to make the system robust to noise factors, these buffers must be chosen as specified in our conclusion (Table 5.3.2.).

Type 4 (All Stations Are Subject To Jam):

Analyses revealed that although all stations are subject to jam, the buffers with large spaces adjoining to high-jam-rate stations are more likely to affect the TP. The confirmatory experiment following our conclusion also indicated the same (Table 5.4.2.).

5.4.2. ROBUST DESIGN OF THE SYSTEMS PREVIOUSLY STUDIED WITH THE DoE APPROACH AS THE OPTIMIZATION METHOD

This section presents the systems that were studied in the design of experiments (DoE) approach as the optimization method and the optimal buffer ranges were identified accordingly (see section 4.4.2.). For the purpose of making these systems robust to noise factors, we have re-investigated an optimal area found in section 4.4.2. and re-defined the buffer ranges that give the minimum $variance_{wrtnf}$ for each system. Two types of AAS are studied, namely Type 5 systems that have all stations subject to jam and Type 6 systems that have some stations subject to jam. Type 5 systems (i.e., systems with all stations are subject to jam) are examined in two different design; the first one includes only the jam rates as the noise factors and uses a full-factorial design (2^5 by 2^5), while the second one considers the jam rates and jam clear times as noise factors and uses fractional factorial designs (2_V^{5-1} by 2_{III}^{10-6}). Type 6 systems are studied when jam rates and jam clear times are considered as noise factors, with the design of L_{16} (2^{15}) orthogonal array for both control factors and noise factors.

Type 5 (All Stations Are Subject To Jam) And Jam Rates As Noise Factors :

In this section, we have considered the jam rates as noise factors while keeping the jam clear times as fixed (i.e., a geometric distribution with a mean of 20 time units).

Analyses showed that four buffers had important effect on the variation of the TP against noise factors (i.e., $variance_{wrtnf}$). Hence, we do not have much flexibility in choosing buffer sizes .

As seen in Table 5.5.1., the $variance_{wrtnf}$ of the experimental run 24, which has the suggested configuration of the conclusion, has the smallest $variance_{wrtnf}$, thus supports our conclusion (Table 5.5.2.).

Type 5 (All Stations Are Subject To Jam) And Jam Rates And Jam Clear Times As Noise Factors (2nd Study With Type6 Systems):

We have studied the Type 5 systems where jam clear times are also considered as noise factors. For the 2_V^{5-1} design, we have used the following generator:

I = 12345 ,where, 5=1234.

Analyses revealed that all effects were negative, as in the previous section. However, only the smaller buffer size adjoining to the high-jam-rate station has the important effect on the TP. In other words, when jam rates and jam clear times are considered as noise factors, the flexibility of choosing buffer levels increased. However, because all buffers have still considerable effect on the $variance_{wrtnf}$, choosing as many buffers as possible at high levels is suggested. The confirmatory experiment verifies this conclusion, where all buffers are chosen at high levels (Table 5.6.2.).

Type 6 (Some Stations Are Subject To Jam) And Jam Rates And Jam Clear Times As Noise Factors:

Type 6 systems have some stations that are subject to jam and some stations are jam free. For the robust design, we have considered the jam rates and jam clear times as noise factors.

Analyses showed that many buffers adjoining to a non-zero-jam-rate station have relatively important effects on the variance with respect to noise factors. Yet, one can still choose the levels of eight buffers freely, which is a considerable amount of flexibility. Experimental runs 3 and 1, which have the configurations suggested in the conclusion, have the smallest values of the $variance_{wrtnf}$, hence they also verify our conclusion (Table 5.7.2.).

5.5. CONCLUSION

We have studied several systems and designed them to be robust (insensitive, unchanging) to noise factors. The analyses showed that noise factors could play an important role on the outcome of the system response. Hence, a study on the robustness of an optimal area, i.e., making the system response (TP) unchanging to uncontrollable system parameters, is necessary.

For instance, studies on systems with uniform stations revealed that noise factors affect the variability of the TP considerably, thus the robustness study becomes essential.

Similar conclusions are reached in systems with some non-zero-jam-rate stations and some jam-free stations, and with all stations subject to jam. In all cases, a considerable number of the buffers in systems were found to be important to reduce the $variance_{wrtnf}$. Consequently, robustness study in such systems are also needed.

Studies on systems previously optimized using the DoE approach also indicated the need of the robust design study in such systems.

Table 5.1.1. The levels of control factors (buffers) and noise factors (jam rates and jam clear times) for the inner-outer array design of Type 1 systems

control factors (buffers) of the inner array:

buffers	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}
-	2	2	2	2	2	2	2	2	2	2
+	3	3	3	3	3	3	3	3	3	3

noise factors (jam rates and jam clear times) of the outer array:

noise factors	jam rates (%)	jam clear times (time)
-	0.5	17
+	1.5	19

notation: jr_i : jam rate of *i*th station, jct_i : jam clear time of *i*th station

number of pallets: 20 pallets

the neutral levels of jam rates:

station	1	2	3	4	5	6	7	8	9	10
jam rate	1	1	1	1	1	1	1	1	1	1

Table 5.1.2. The buffer ranges that minimize the variation of the TP with respect to noise factors (*$variance_{wrtnf}$*) and the confirmatory experiments of Type 1 systems

The conclusion of buffer configurations for optimal area:

buffer	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
-	2	3	3	3	2	3	3	3	2	3
+	3	3	3	3	3	3	3	3	3	3

confirmatory experiments:

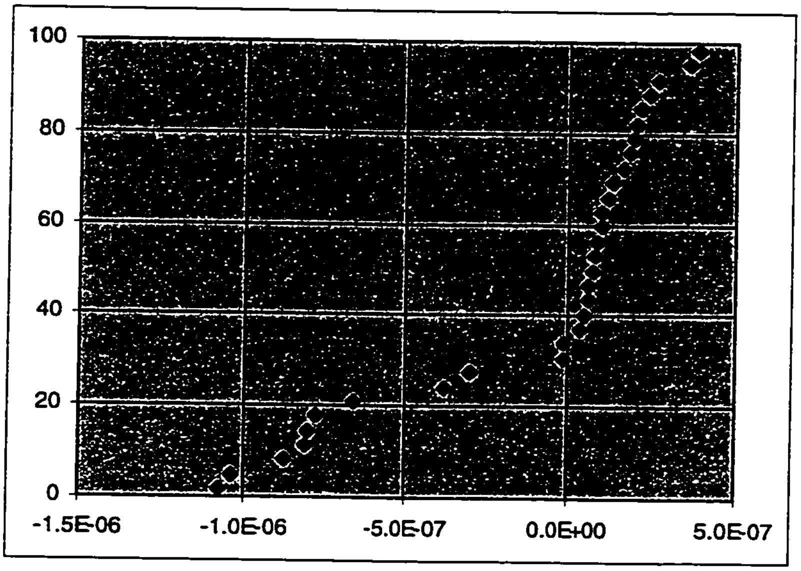
buffer configuration	**jam clear time**	**jam rate**	**TP**	**variance (10^{-5})**
2,3,3,3,2,3,3,3,2,3	17	0.5	.152733	6.8901
	19	0.5	.150946	8.0481
	17	1.5	.137830	14.7853
	19	1.5	.134158	15.8268

average TP = .143917

the variance of the TP with respect to noise factors: $\boldsymbol{variance_{wrtnf} = 8.65 * 10^{-5}}$

Figure 5.1.1. The effects of the buffers on the variation of the TP with respect to noise factors (*variance*$_{wrtnf}$) for Type 1 systems

p_k^*

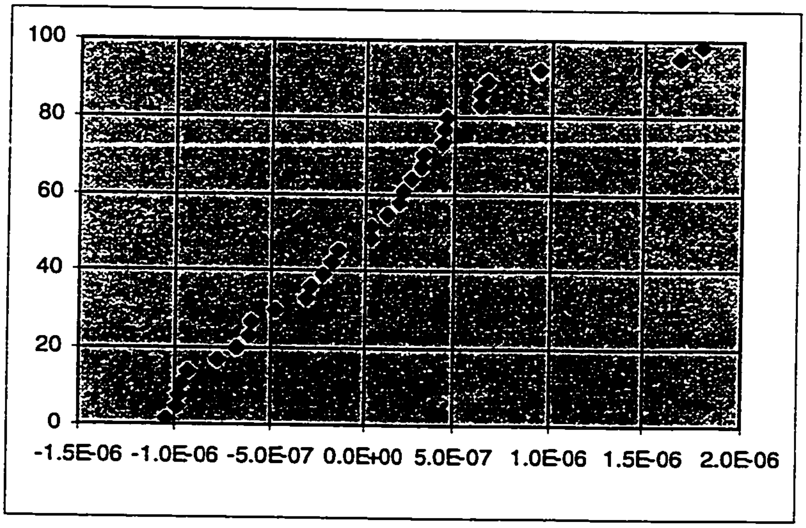


Effects of buffers

l_8=-1.07*10^{-6},l_4=-1.04*10^{-6},l_3=-1.88*10^{-6},l_2=l_6=-0.81*10^{-6},l_{10}=-0.78*10^{-6},l_7=-0.66*10^{-6}

Figure 5.1.2. The residuals of the buffers on the variation of the TP with respect to noise factors (*variance*$_{wrtnf}$) for Type 1 systems

p_k^*



Effects of residuals

* p_k = 100 * [(k-0.5)/k]

Table 5.2.1. The levels of control factors (buffers) and noise factors (jam rates and jam clear times) for the inner-outer array design of Type 2 systems

control factors (buffers) of the inner array:

buffers	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}
-	5	16	5	4	4	4	5	4	4	4
+	6	17	6	5	5	5	6	5	5	5

noise factors (jam rates and jam clear times) of the outer array:

noise factors	$jr_2(\%)$	$jr_3(\%)$	$jr_7(\%)$	$jct_2(t)$	$jct_3(t)$	$jct_7(t)$
-	2.5	2.5	2.5	34	34	34
+	3.5	3.5	3.5	38	38	38

notation: jr_i : jam rate of *i*th station, jct_i : jam clear time of *i*th station

number of pallets: 40 pallets

the neutral levels of jam rates:

station	1	2	3	4	5	6	7	8	9	10
jam rate	0	3	3	0	0	0	3	0	0	0

Table 5.2.2. The buffer ranges that minimize the variation of the TP with respect to noise factors ($variance_{wrtnf}$) and the confirmatory experiments of Type 2 systems

The conclusion of buffer configurations for optimal area:

buffer	1	2	3	4	5	6	7	8	9	10
-	5	16	5	4	4	4	5	4	4	4
+	6	17	5	4	4	4	6	5	5	5

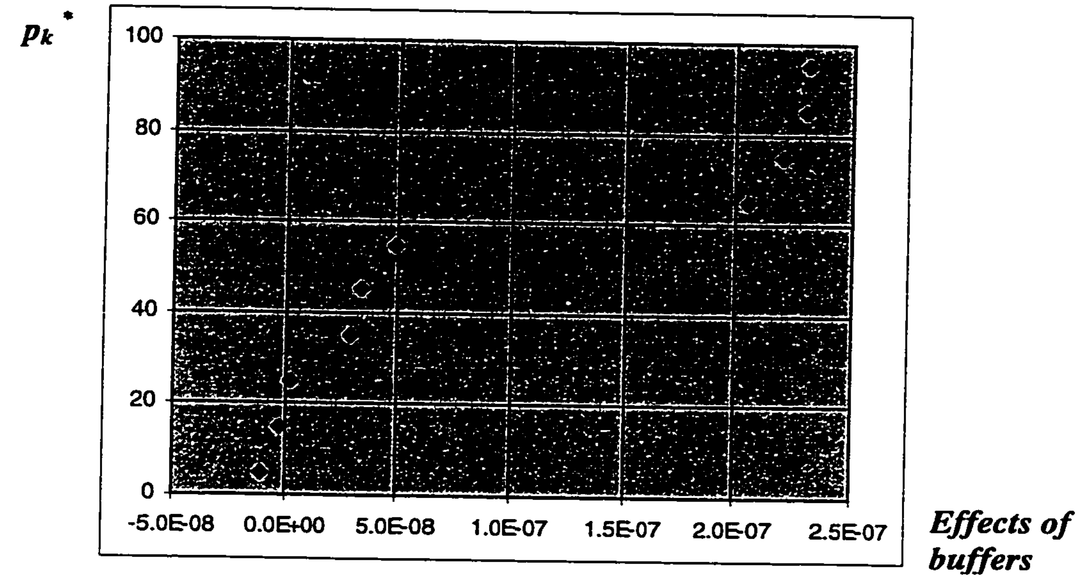
confirmatory experiments:

buffer configurations	TP	$variance_{wrtnf}$ (10^{-5})	TP	$variance_{wrtnf}$ (10^{-5})
5,17,5,4,4,4,6,4,5,4	.136396	1.59745	.129074	2.72056
	.132744	1.52409	.127260	2.90240
	.129460	1.10880	.126586	1.81434
	.127865	1.51378	.126707	2.02662

average TP = .129512

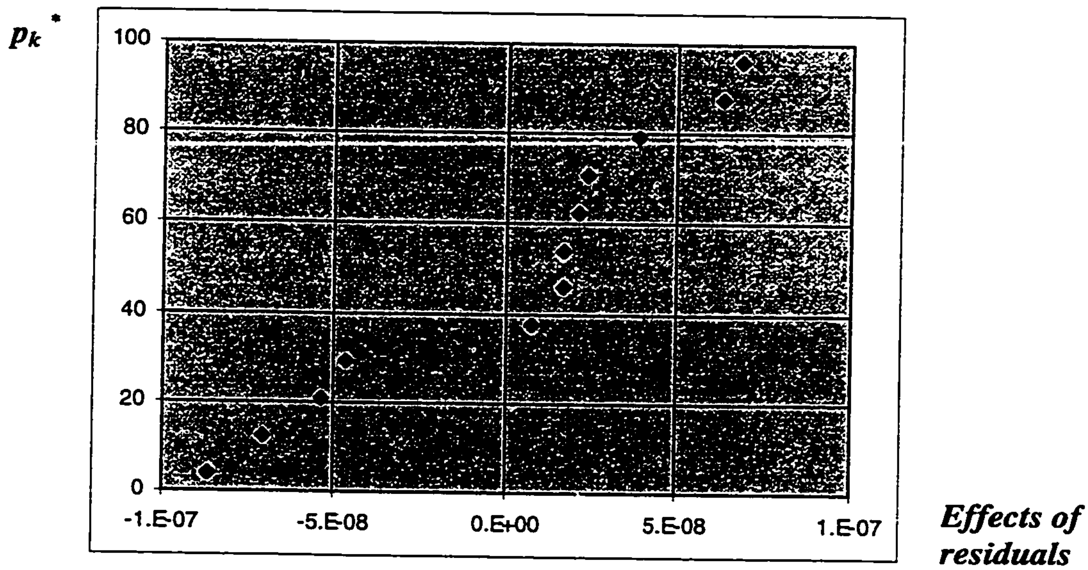
the variance of the TP with respect to noise factors: $variance_{wrtnf} = 1.17*10^{-5}$

Figure 5.2.1. The effects of the buffers on the variation of the TP with respect to noise factors ($variance_{wrtnf}$) for Type 2 systems



l_5=-2.3*10^{-7},l_6=2.3*10^{-7},l_3=2.2*10^{-6},l_4=2.06*10^{-7}

Figure 5.2.2. The residuals of the buffers on the variation of the TP with respect to noise factors ($variance_{wrtnf}$) for Type 2 systems



* $p_k = 100 * [(k-0.5)/k]$

Table 5.3.1. The levels of control factors (buffers) and noise factors (jam rates and jam clear times) for the inner-outer array design of Type 3 systems

control factors (buffers) of the inner array:

buffers	**b_1**	**b_2**	**b_3**	**b_4**	**b_5**	**b_6**	**b_7**	**b_8**	**b_9**	**b_{10}**
-	4	9	10	11	11	4	4	4	4	4
+	5	10	11	12	12	5	5	5	5	5

noise factors (jam rates and jam clear times) of the outer array:

noise factors	**jr_2(%)**	**jr_4(%)**	**jr_6(%)**	**jct_2(t)**	**jct_4(t)**	**jct_6(t)**
-	2.5	2.5	2.5	34	34	34
+	3.5	3.5	3.5	38	38	38

notation: jr_i : jam rate of *i*th station, jct_i : jam clear time of *i*th station

number of pallets: 40 pallets

the neutral levels of jam rates:

station	1	2	3	4	5	6	7	8	9	10
jam rate	0	3	0	3	0	3	0	0	0	0

Table 5.3.2. The buffer ranges that minimize the variation of the TP with respect to noise factors (*variance*$_{wrtnf}$) and the confirmatory experiments of Type 3 systems

The conclusion of buffer configurations for optimal area:

buffer	1	2	3	4	5	6	7	8	9	10
-	4	9	10	11	11	5	4	4	4	4
+	4	9	10	12	12	5	5	5	5	5

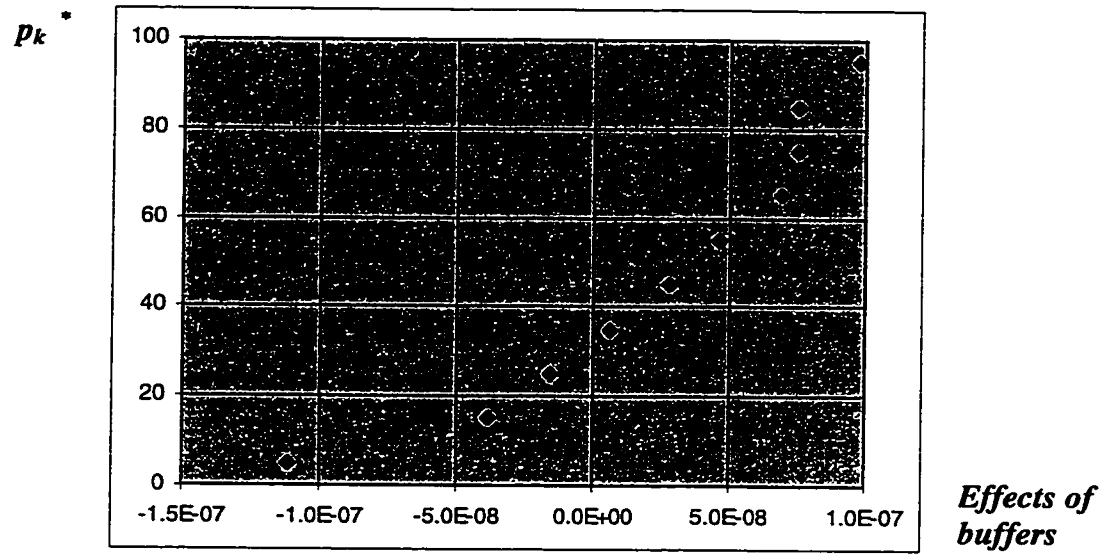
confirmatory experiments:

buffer configuration	TP	*variance*$_{wrtnf}$ (10^{-10})	TP	*variance*$_{wrtnf}$ (10^{-10})
4,9,10,11,11,5,5,5,5,5	.136289	310500	.128453	394405
	.132682	345064	.125865	355984
	.128009	343895	.127412	453523
	.127184	347300	.127754	486531

average TP = .129206

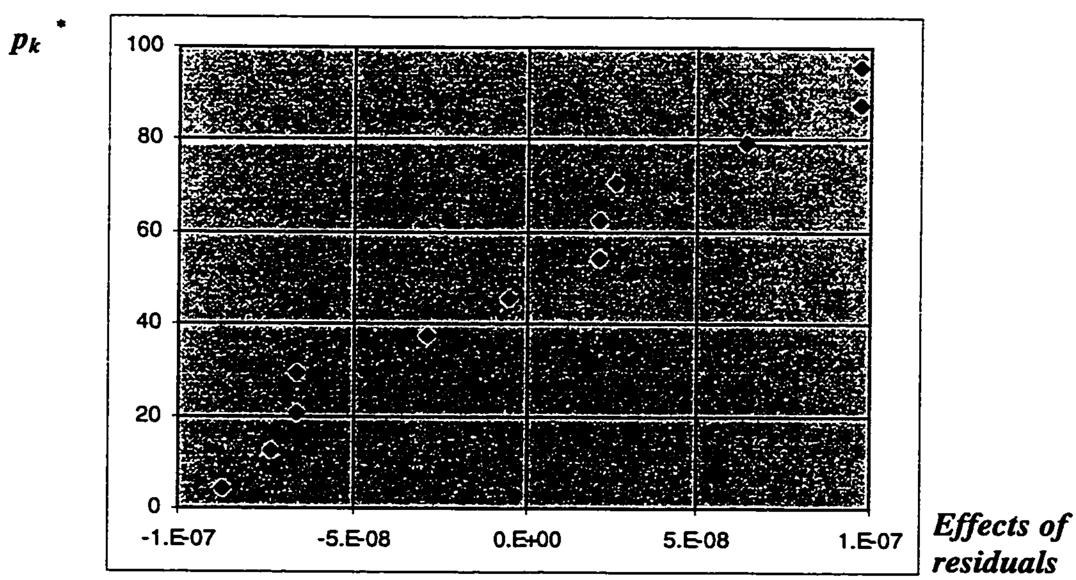
the variance of the TP with respect to noise factors: ***variance*$_{wrtnf}$ = 1.21*10^{-5}**

Figure 5.3.1. The effects of the buffers on the variation of the TP with respect to noise factors (*$variance_{wrtnf}$*) for Type 3 systems



$l_6=-1.12*10^{-7}, l_1=0.98*10^{-7}, l_2=0.75*10^{-7}, l_3=0.75*10^{-7}$

Figure 5.3.2. The residuals of the buffers on the variation of the TP with respect to noise factors (*$variance_{wrtnf}$*) for Type 3 systems



* $p_k = 100 * [(k-0.5)/k]$

Table 5.4.1. The levels of control factors (buffers) and noise factors (jam rates and jam clear times) for the inner-outer array design of Type 4 systems

control factors (buffers) of the inner array:

buffers	**b_1**	**b_2**	**b_3**	**b_4**	**b_5**	**b_6**	**b_7**	**b_8**	**b_9**	**b_{10}**
-	11	14	5	6	6	11	11	5	7	3
+	12	15	6	7	7	12	12	6	8	4

noise factors (jam rates and jam clear times) of the outer array:

noise factors	jr_1	jr_2	jr_3	jr_4	jr_5	jr_6	jr_7	jr_8	jr_9	jr_{10}
-	0	2.5	0	0	0	0	2.5	0	0	0
+	1	3.5	1	1	1	1	3.5	1	1	1

noise factors	jct_1	jct_2	jct_3	jct_4	jct_5	jct_6	jct_7	jct_8	jct_9	jct_{10}
-	17	17	17	17	17	17	17	17	17	17
+	19	19	19	19	19	19	19	19	19	19

notation: jr_i : jam rate of *i*th station, jct_i : jam clear time of *i*th station

number of pallets: 50 pallets

the neutral levels of jam rates:

station	1	2	3	4	5	6	7	8	9	10
jam rate	0.5	3	0.5	0.5	0.5	0.5	3	0.5	0.5	0.5

Table 5.4.2. The buffer ranges that minimize the variation of the TP with respect to noise factors (*variance*$_{wrtnf}$) and the confirmatory experiments of Type 4 systems

The conclusion of buffer configurations for optimal area:

buffer	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
-	11	15	5	6	6	11	12	6	7	3
+	11	15	6	7	7	12	12	6	8	4

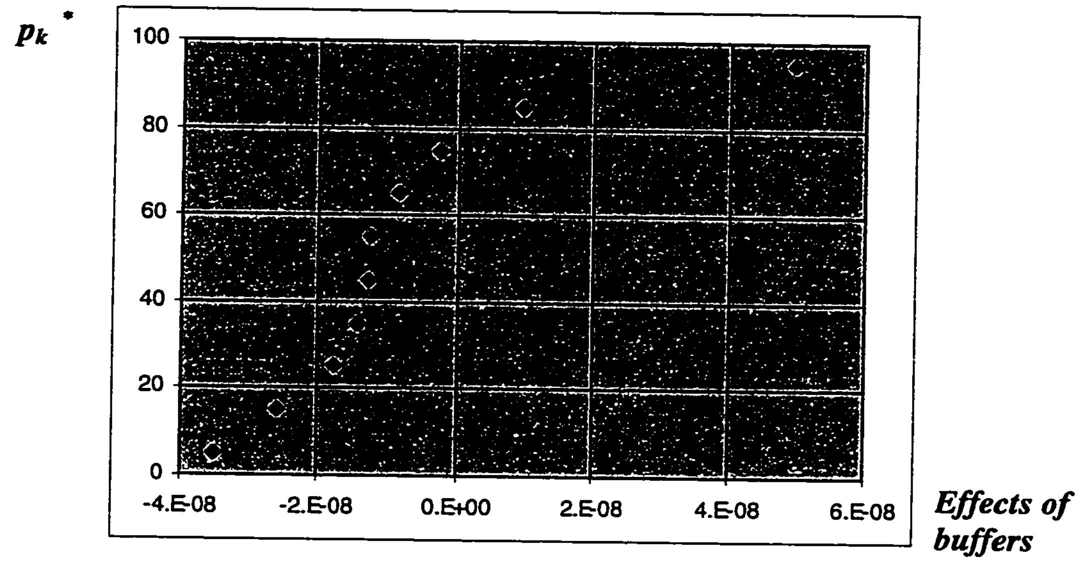
confirmatory experiments:

buffer configurations	**TP**	***variance*$_{wrtnf}$ (10^{-10})**	**TP**	***variance*$_{wrtnf}$ (10^{-10})**
11,15,5,7,7,11,12,6,7,3	.155105	59508	.149172	141492
	.153298	82239	.150649	63852
	.150195	45625	.150733	62070
	.150440	107713	.153237	85218
	.149818	132335		

average TP = .151405

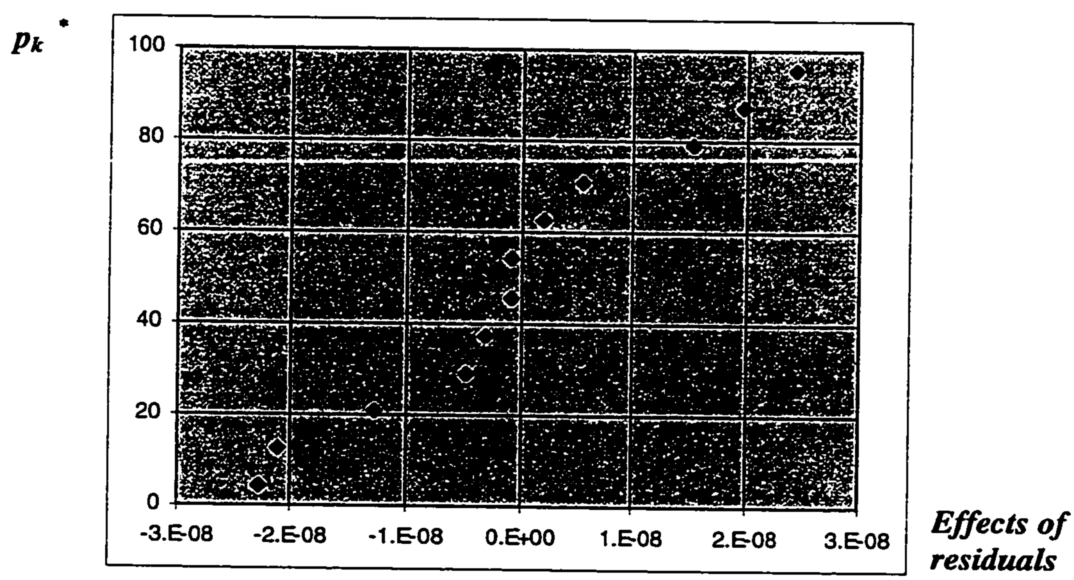
the variance of the TP with respect to noise factors: ***variance*$_{wrtnf}$ = $3.94*10^{-6}$**

Figure 5.4.1. The effects of the buffers on the variation of the TP with respect to noise factors ($variance_{wrtnf}$) for Type 4 systems



$l_1=4.95*10^{-8}, l_2=-3.5*10^{-8}, l_8=-2.59*10^{-8}$

Figure 5.4.2. The residuals of the buffers on the variation of the TP with respect to noise factors ($variance_{wrtnf}$) for Type 4 systems



* $p_k = 100 * [(k-0.5)/k]$

Table 5.5.1. The levels of control factors (buffers) and noise factors (jam rates) for the inner-outer array design of Type 5 systems of DoE optimization

control factors (buffers) of the inner array:

buffers	b_1	b_2	b_3	b_4	b_5
-	3	6	8	9	3
+	4	7	9	10	4

noise factors (jam rates) of the outer array:

noise factors	jr_1	jr_2	jr_3	jr_4	jr_5
-	0	2.5	0	4.5	0
+	1	3.5	1	5.5	1

notation: jr_i : jam rate of *i*th station,

number of pallets: 20 pallets

the neutral levels of jam rates:

station	1	2	3	4	5
jam rates	0.5	3	0.5	5	0.5

Table 5.5.2. The buffer ranges that minimize the variation of the TP with respect to noise factors (*$variance_{wrtnf}$*) and the confirmatory experiments of Type 5 systems of DoE optimization

The conclusion of buffer configurations for optimal area:

buffers	b_1	b_2	b_3	b_4	b_5
-	4	7	9	9	4
+	4	7	9	10	4

confirmatory experiments:

the buffer configuration: 4,7,9,9,4.

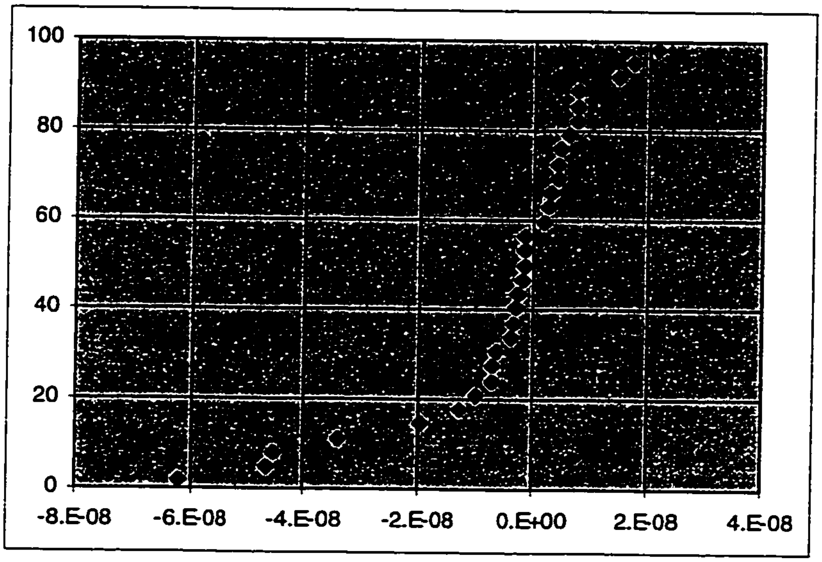
TP	variance (10^{-6})	TP	variance (10^{-6})	TP	variance (10^{-6})	TP	variance (10^{-6})
0.143460	4.0817	0.139702	5.9918	0.142695	3.7975	0.139961	6.3704
0.142409	2.8156	0.138670	5.4906	0.141539	2.1499	0.137975	5.3825
0.141725	6.7110	0.138482	6.5583	0.140837	4.8476	0.137640	5.3193
0.140761	3.7580	0.137482	4.5210	0.139651	2.2305	0.136747	3.4493
0.142067	9.2902	0.138409	10.1606	0.141179	8.3020	0.137753	9.9253
0.141035	8.0694	0.137404	9.8063	0.140077	6.9506	0.136853	8.7177
0.140368	8.6717	0.137009	9.3050	0.139412	7.2895	0.136358	8.0768
0.139209	6.6558	0.136047	7.6364	0.138128	4.6102	0.135446	6.1801

average TP = 0.139265

the variance of the TP with respect to noise factors: ***$variance_{wrtnf}$* = 4.50 *10^{-6}**

Figure 5.5.1. The effects of the buffers on the variation of the TP with respect to noise factors (*variance$_{wrtnf}$*) for Type 5 systems

p_k *

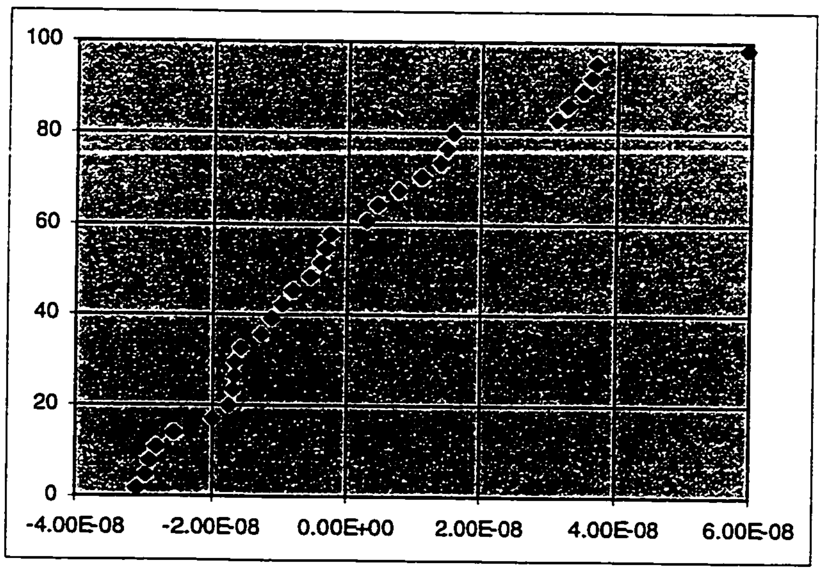


Effects of buffers

$l_3=-6.21*10^{-8}, l_5=-4.65*10^{-8}, l_1=-4.53*10^{-8}, l_2=-3.43*10^{-8}$

Figure 5.5.2. The residuals of the buffers on the variation of the TP with respect to noise factors (*variance$_{wrtnf}$*) for Type 5 systems

p_k *



Effects of residuals

* $p_k = 100 * [(k-0.5)/k]$

Table 5.6.1. The levels of control factors (buffers) and noise factors (jam rates and jam clear times) for the inner-outer array design of Type 5 systems of DoE optimization (2nd study)

control factors (buffers) of the inner array:

buffers	b_1	b_2	b_3	b_4	b_5
-	3	6	8	9	3
+	4	7	9	10	4

noise factors (jam rates and jam clear times) of the outer array:

noise factors	jr_1	jr_2	jr_3	jr_4	jr_5	jct_1	jct_2	jct_3	jct_4	jct_5
-	0	2.5	0	4.5	0	19	19	19	19	19
+	1	3.5	1	5.5	1	21	21	21	21	21

notation: jr_i : jam rate of *i*th station, jct_i : jam clear time of *i*th station

number of pallets: 20 pallets

the neutral levels of jam rates:

station	1	2	3	4	5
jam rates	0.5	3	0.5	5	0.5

Table 5.6.2. The buffer configurations that minimize the variation of the TP with respect to noise factors ($variance_{wrtnf}$) and the confirmatory experiments of Type 5 of DoE optimization (2nd study)

The conclusion of buffer configurations for optimal area:

buffers	1	2	3	4	5
-	3	6	9	9	3
+	4	7	9	10	4

confirmatory experiments:

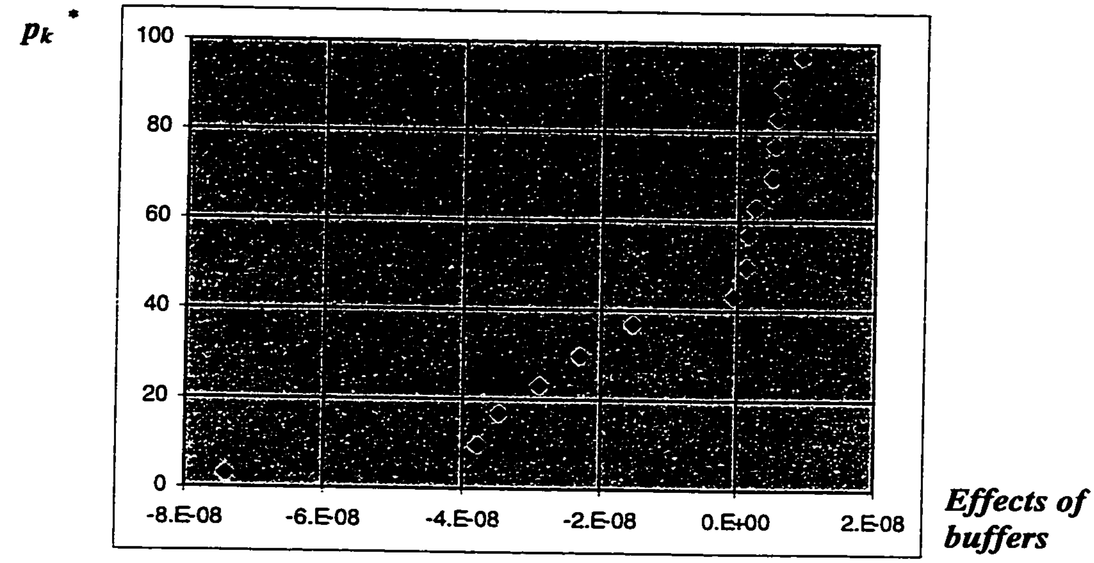
the buffer configuration: 4,7,9,10,4

TP	variance (10^{-6})	TP	variance (10^{-6})	TP	variance (10^{-6})	TP	variance (10^{-6})
.144630	3.6268	.138695	8.8288	.140621	76509	.137209	6.2181
.139802	4.0753	.139095	5.4722	.140174	35657	.136314	9.3330
.141960	2.5137	.138368	0.93125	.139733	93594	.138226	6.5782
.140449	8.7639	.138196	4.6434	.139342	59724	.133893	6.4517

the average TP = .139169

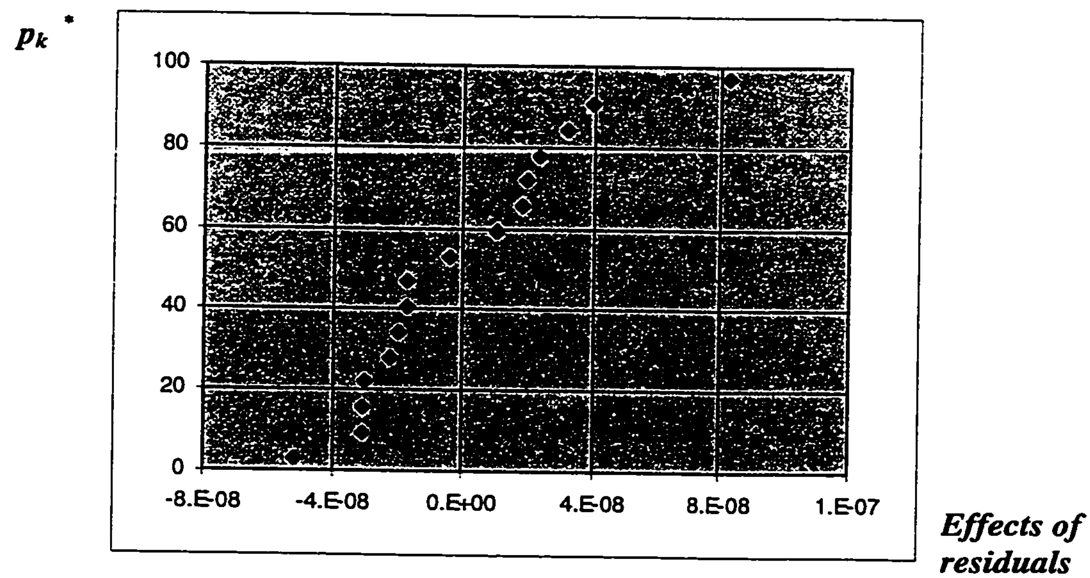
the variance of the TP with respect to noise factors: $variance_{wrtnf}$ **= 5.71 *10^{-6}**

Figure 5.6.1. The effects of the buffers on the variation of the TP with respect to noise factors (*variance*$_{wrtnf}$) for Type 5 systems (2[nd] study)



l_3=-7.42*10^{-8}

Figure 5.6.2. The residuals of the buffers on the variation of the TP with respect to noise factors (*variance*$_{wrtnf}$) for Type 5 systems (2[nd] study)



* $p_k = 100 * [(k-0.5)/k]$

Table 5.7.1. The levels of control factors (buffers) and noise factors (jam rates and jam clear times) for the inner-outer array design of Type 6 systems of DoE optimization

control factors (buffers) of the inner array:

buffers	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}	b_{11}	b_{12}	b_{13}	b_{14}	b_{15}
-	16	12	12	8	8	6	6	5	5	1	1	3	3	2	2
+	17	13	13	9	9	7	7	6	6	2	2	4	4	3	3

noise factors (jam rates and jam clear times) of the outer array:

noise	jr_1	jr_2	jr_4	jr_6	jr_8	jr_{10}	jr_{12}	jct_1	jct_2	jct_4	jct_6	jct_8	jct_{10}	jct_{12}
-	2.5	2.5	4.5	0	2.5	0	0	19	19	19	19	19	19	19
+	3.5	3.5	5.5	1	3.5	1	1	21	21	21	21	21	21	21

notation: jr_i : jam rate of *i*th station, jct_i : jam clear time of *i*th station

number of pallets: 60 pallets

the neutral levels of jam rates:

stations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
jam rates	3	3	0	5	0	0.5	0	3	0	0.5	0	0.5	0	0	0

Table 5.7.2. The buffer configurations that minimize the variation of the TP with respect to noise factors (*$variance_{wrtnf}$*) and the confirmatory experiments of Type 6 of DoE optimization

The conclusion of buffer configurations for optimal area:

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

confirmatory experiments:

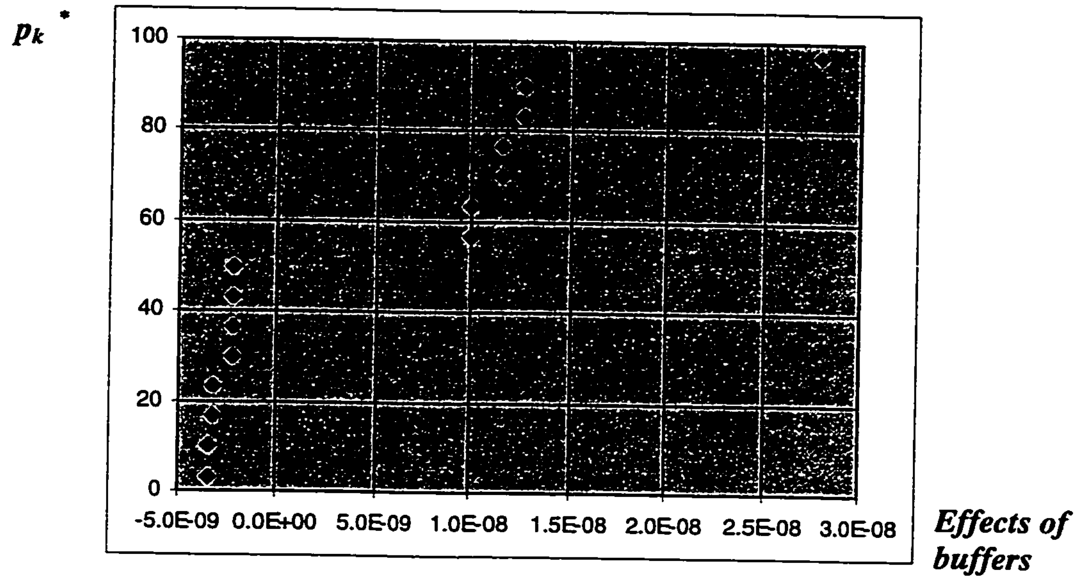
the buffer configuration: 16,12,12,8,9,7,6,5,5,1,1,4,3,2,3

TP	variance (10^{-6})	TP	variance (10^{-6})	TP	variance (10^{-6})	TP	variance (10^{-6})
.145754	7.7830	.140511	6.0030	.141319	7.2762	.141323	7.4373
.143440	9.3160	.141035	5.3492	.139298	8.0830	.141735	8.3610
.142374	5.9289	.139747	4.7340	.141288	6.8628	.141558	5.6608
.141711	9.2483	.141151	5.7821	.139574	9.0611	.142414	8.5901

average TP = .141515

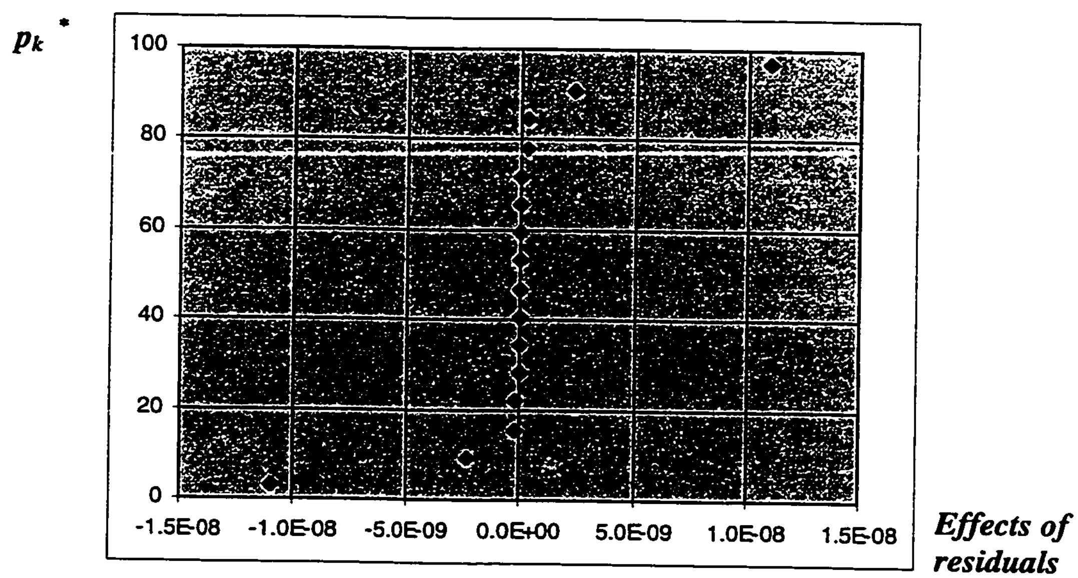
the variance of the TP with respect to noise factors: $\boldsymbol{variance_{wrtnf} = 2.44 * 10^{-6}}$

Figure 5.7.1. The effects of the buffers on the variation of the TP with respect to noise factors ($variance_{wrtnf}$) for Type 6 systems



l_1=-2.79*10^{-8},l_2=l_3=1.25*10^{-8},l_8=l_9=1.14*10^{-8},l_{10}=l_{11}=0.99*10^{-8}

Figure 5.7.2. The residuals of the buffers on the variation of the TP with respect to noise factors ($variance_{wrtnf}$) for Type 6 systems



* p_k = 100 * [(k-0.5)/k]

CHAPTER 6

CONCLUSION AND RECOMMENDATIONS FOR FURTHER STUDY

In this research, we have determined an optimal area of buffer sizes in AAS and designed robust AAS against noise factors. To determine an optimal area of buffers, we have studied the effects of buffers on the throughput and identified the important effects. By choosing the buffers with important effects at their appropriate level, we have provided the design engineer a flexibility to choose other buffers within a range. Studies for robust design of AAS indicated the need for studying robustness in AAS design phase. For these purposes we have used the DoE approach and a discrete-event simulation program written in TURBOPASCAL code.

DoE approach proved to be an effective tool to determine an optimal area of buffer sizes. In addition, it has also indicated that it can be used as a practical optimization tool. Especially when little known about the system to be designed, using the DoE approach to optimize the buffers can also provide a considerable amount of information on the system. Moreover, in an attempt to study its effect, we have considered the number of pallets as a decision variable and investigated a number of systems accordingly. Analyses showed that the number of pallets had significant effect on the throughput.

Robust design study of AAS proved to be essential. Several types of the AAS were studied and all cases indicated the necessity of the robust design. In all cases, the analyses revealed that a considerable number of buffers had important effect on the variance of the throughput with respect to noise factors. Hence, the robustness of AAS is necessary in order to design a more reliable system.

Consequently, our conclusion can be outlined as follows.

- Robust design of AAS is essential.
- Determining an optimal area of buffer sizes provides the design engineer the much needed flexibility to choose buffers within a range.
- Use of DoE approach also provides substantial information about the system, thus enables design engineer to design the system with a better understanding.
- Use of DoE approach to determine buffers proves to be an effective methodology.
- DoE approach can be used to optimize buffer sizes especially when little known about the system.
- We have also integrated the number of pallets into decision variables in an attempt to study its effect and the analyses revealed a significant effect on the throughput.

This research also revealed several interesting research issues. Some of these issues have been partially addressed by the studies described in this research and others are uncovered. Further study can apply the robust design to other optimization studies and use the robust design and optimization simultaneously. In addition, by using the DoE approach, other decision variables' effects on the throughput as well as on other system responses can be studied. Furthermore, the use of the DoE approach can be extended to other design problems of AAS.

Further study with an emphasis on the application of robust design on several AAS design problems may also serve as informing researchers on the necessity of the robust design and determining an optimal area to provide design engineer the flexibility much needed. In addition, cases in industry can be studied by applying both the DoE approach as the optimization tool and robust design simultaneously. Studying and improving the theoretical foundations of the DoE approach and its use as the optimization method are also research areas to be explored.

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INTRODUCTION TO APPENDICES

Appendix 1 covers the statistical techniques and definitions referred in the research. First section describes the resolution levels in designs. Section 1.2. discusses the statistical techniques used in the analysis phase of the design of experiments approach. The definitions, the hypothesis testings, the calculations of effects demonstrated by an example, normal probability plotting, and residual analysis are discusses in sections 1.2.1, 1.2.2, 1.2.3, 1.2.4, and 1.2.5, respectively. The statistical techniques used in robust design are discussed in section 1.3.

Appendix 2 provides detailed information on the experiments conducted to determine an optimal area in AAS. Section 2.1. covers the studies previously discussed in Chapter 4, section 4.4.1. (systems previously optimized by using SQG methods). The designs selected, the methodology followed, and the conclusion of the Design 2 studies where the effect of the number of pallets were studied are discussed. Section 2.2. covers the studies previously discussed in Chapter 4, section 4.4.2. (DoE optimization). The steps of optimization studies are discussed. The results of experimental runs and graphical results of analyses are also presented.

Appendix 3 covers the robust design studies in AAS. The results of experimental runs and calculated mean and $variance_{wrtnf}$ are presented.

APPENDIX 1

STATISTICAL TECHNIQUES USED IN DoE AND ROBUST DESIGN

1.1. RESOLUTION LEVELS

There are mainly three alternatives for the level of the interactions chosen to be confounded with the main factors and/or the interaction of the fewer factors: the *resolutions* V, IV, and III. If an economical design with the most information possible is desired, the resolution V is recommended. In resolution V designs, the interactions of the four or more factors are confounded with some of the main factors. Hence, the effects of these columns can easily be attributed to the effects of the main factors. When more economical design with less information is required, the resolution IV may be a better alternative. The resolution IV designs have the interactions of three or more factors confounded with some of the main factors. Also in this case it is most likely that the importance comes from the main factors. If the economical and time concerns are the most important or some information on the interactions and/or main factors are available, then the resolution III can be chosen. In such design, the interactions of two or more factors are confounded with some of the main factors. Hence, it may not be as easy as in other resolutions to attribute the importance directly to the main factors. The main factors involved in the interactions should be studied carefully before reaching to a conclusion.

1.2. STATISTICAL TECHNIQUES USED FOR DATA ANALYSIS IN DoE

Following sections present the techniques used to analyze the results (throughputs) obtained from the experimental runs of the DoE. The first section presents some basic definitions. The second section discusses the hypothesis testings that are used to verify the results and the experimenting. The third section explains the normal probability technique to calculate the effects of the decision variables and to identify the important ones. The fourth section presents the residual analysis to verify the conclusion based on the normal probability plotting.

1.2.1. THE STATISTICAL INFERENCE (BASIC DEFINITIONS AND CONFIDENCE LEVELS)

A main purpose of the statistical methods we will use is to try to estimate or make statements about the parent population which is considered to be stable. The sample itself is not stable in the sense that if we sampled again we could obtain a different set of values.

As Logothesis and Wynn [56] describe, the most important characteristics of a population are the ones that describe the population's central tendency and dispersion, i.e., the variability. For this purpose, two measures are commonly used; the arithmetic mean and the variance. With respect to the sample, which is the throughput of the assembly systems we will study throughout this research, "the sample mean" and "the sample variance" are given by mean throughput : $m = \Sigma z_r / n$, r:1..n

variance : $v = [n\Sigma z_r^2 - (\Sigma z_r)^2] / [n(n-1)]$, r:1..n

where z_r is the number of units produced by the model for particular buffer configuration at the given replication r and n is the total number of replications.

Discrete event simulation is used to estimate the value of the production rate as a function of buffer sizes (and number of pallets, in certain cases). The expected value of each function estimate, $F(z_r)$: the throughput, is obtained by simulating the system around 10,000 time units, with 10 independent replications. For each replication, a warm-up time of 500 time units is set in order to remove the initial transient effects. Literature available [16,27,46] indicates that with the above mentioned sample size, warm-up time, and a number of replications, the estimates of the value of the objective function are reliable for engineering applications. The confidence interval (*CI*s) for the mean throughput obtained from the simulation results are determined as follows.

$$CI = m \pm [t(\mathrm{df};\alpha) * (v/n)^{-1/2}]$$

where $t = t(\mathrm{df};\alpha)$ is a value depending on the degrees of freedom (df=n-1) and on the "level of significance" α (i.e., α is taken as 5 per cent in this research) ; these t values can be found from the t-tables. However, while calculating the t values, we should also complete the F-test (see next section) to ensure that the variability of throughput is the same (i.e., the variance is homogeneous) in all populations representing the same parent population.

1.2.2. THE HYPOTHESIS TESTINGS

In order to be certain that the samples that we collect through the simulation and DoE approach are statistically valid, we have to do some hypothesis testings. First, we will ensure that the variability of the throughputs are same in all populations representing the same parent population by carrying out a significance test for the homogeneity of variance, called the *F*-test. Then, we will do the *t*-test to check if they really represent the same parent population. In other words, by doing these two significance tests, we will assure that the data we gather through the experiments are statistically reliable for the data analyses that are described in the next sections.

The F-test: Comparing variances

The *F*-test is conducted prior to calculation of the *t* values to assure their validity. The technique is very simple and concerns the variability in different sample groups that represent the same parent population. The hypothesizes are as follows.

Null hypothesis (H_0) : $v_i^2 = v_j^2$

Alternative hypothesis (H_1) : $v_i^2 \neq v_j^2$

The *F* (observed) value is calculated as follows.

F = (larger sample variance) / (smaller sample variance) = $v_i \;/\; v_j$

where v_i and v_j are the estimates of the variance of the results obtained in the runs i and j, respectively and $v_i > v_j$.

The critical value can be founded in the F-tables, depending on the degrees of freedom (df) of the larger sample variance as the numerator and the df of the smaller sample variance as the denominator, with the significance level, α, at the 5%. If

F (observed) < F (critical)

then, we cannot reject the null hypothesis of equal population variances at the 5% significance level, α. Hence, the assumption (i.e., the homogeneity of the variance) that is necessary for the calculation of the t values is satisfied.

The t-test

The validation of the results of experimental runs by t-test is necessary, in order to verify the interpretations we will make based on the normal probability plotting. The t-test enables us to be certain of the accuracy of the data we obtain from the experimental runs.

The t-test technique is a simple procedure that investigates the means of two different populations representing the same parent population. We use a standard hypothesis testing procedure. In order to check the validity of the results of runs, we test the equality of different runs' results. Since each run is replicated R times, we obtain a mean and a variance for each run. Our hypotheses are as follows.

$H_0 : m_i = m_j$

$H_1 : m_i \neq m_j$

Since the estimates of mean and variance of both runs are based on the same number, r replications, the pooled variance, and the standard error of the difference between the estimates of the means are calculated as:

pooled variance = $(v_i + v_j) / 2$

standard error of $(m_i - m_j) = [\,(2 * \text{pooled variance}) / r\,]^{-(1/2)}$

where v_i and v_j are the estimates of the variance of the results obtained in the runs i and j, and m_i and m_j are the estimates of the mean of the results obtained in the runs i and j, respectively.

Hence, t (observed) can be calculated as follows.

t (observed) = $(m_i - m_j)$ / standard error of $(m_i - m_j)$, and

degrees of freedom = $2 * r - 2$, r : replications

Depending on the significance level α,which is assumed as 5%, we compare the t (observed) to the value found in the t-test tables corresponding to this confidence level, t (critical). If

t (observed) < t (critical)

then, we cannot reject the null hypothesis (H_0) of equal population means at the α=5% level of significance. In other words, there is no evidence that there is a significant difference observed between the two estimates.

1.2.3. CALCULATION OF EFFECTS

The effect of a factor is the change in the response as we move from - to + version of that factor, which in this research is the low level of buffers (or number of pallets, or noise factors) to high level of buffers (or number of pallets, or noise factors) [13]. Consider the following example where the response and the sign columns of factors A, B, and their interaction A×B are given.

run	A	B	A×B	response
1	-	-	+	43
2	+	-	-	39
3	-	+	-	47
4	+	+	+	38

Consider the effect of factor A. In runs 1 and 3, A is at the low level and in runs 2 and 4, A is at the high level. Thus, we can calculate the effect of the factor A as follows.

$$effect_A = \tfrac{1}{2}\,[(A_1{*}response_1)+ (A_2{*}response_2)+ (A_3{*}response_3)+ (A_4 * response_4)]$$

$$= \tfrac{1}{2}\,[(-1){*}43 + (+1){*}39 + (-1){*}47 + (+1){*}38] = \mathbf{-6.5}$$

Similarly, the effect of B is calculated as:

$$effect_B = \tfrac{1}{2}\,[(B_1{*}response_1)+ (B_2{*}response_2)+ (B_3{*}response_3)+ (B_4 * response_4)]$$

$$= \tfrac{1}{2}\,[(-1){*}43 + (-1){*}39 + (+1){*}47 + (+1){*}38] = \mathbf{1.5}$$

The effect of interaction of A×B is calculated by following the same method:

$$effect_{A\times B} = \tfrac{1}{2}\,[(A{\times}B_1{*}response_1)+(A{\times}B_2{*}response_2)+(A{\times}B_3{*}response_3)+(A{\times}B_4{*}response_4)]$$

$$= \tfrac{1}{2}\,[(+1){*}43 + (-1){*}39 + (-1){*}47 + (+1){*}38] = \mathbf{-2.5}$$

1.2.4. THE NORMAL PROBABILITY PLOTTING

The normal probability plotting, developed by Daniel (1959), is a very effective technique to accurately analyze data. The steps of normal probability plotting are follows[13].

1. calculate the effect of the factor i:

   1.1. find the sign column that corresponds to the factor i,

   1.2. multiply each row of this sign column by each row of results column, get $l_{i(rowj)}$ for each row, where $rowj$: 1..n (n :total number of experimental runs),

   1.3. calculate the effect of the factor i, l_i such as:

   $l_i = \Sigma\, l_{i(rowj)} / (n/2)$, where n: total number of experimental runs

2. plot these effects in order of magnitude along the horizontal scale and then refer to the vertical axis which has a normal probability scale.

   The calculation of the interval values, p_k, for the vertical axis:

   $p_k = 100 * [(k - 0.5) / k]$

   where,

   k : the order number; k: 1..(n-1) , n: total number of experimental runs

   p_k : the probability of k.

The normal probability plotting technique is very effective because we can see the main effects as well as the interactions effects at the same time and more importantly, we can point out the important effects simply by looking at the graphics. Because the technique adjusts the effects such that they roughly plot a straight line, the effects that do not plot a line are considered as not easily explained chance occurrences, i.e., these effects can be explained by noise. However, to be certain that of this conclusion, conducting the residual analysis is necessary. When used with residual analysis, the normal probability plotting technique gives accurate and satisfactory information.

1.2.5. THE RESIDUAL ANALYSIS

In order the verify the validity of the system responses (throughput) obtained from the experimental runs and conclusions reached using normal probability plotting, which is described above, we use residual analysis. In other words, normal probability plotting of residuals provides a diagnostic check for any tentatively entertained model [13].

After plotting the effects of factors into normal probability paper and finding the most important effects, we now need to verify our results by diagnostic check. For example, let us assume that we found the effects of a, c, e, and the interaction of $c \times e$ important, using normal probability plotting data. In this case, the estimated result for the data are given at the vertices of the design by

$$y^* = y_{avg} + (l_a/2)*x_a + (l_c/2)*x_c + (l_e/2)*x_e + (l_{c\times e}/2)*(x_c \times x_e)$$

where y_{avg} : the mean of response, l_i: the effect of factor i, and x_a, x_c, x_e take the value (-1) or ($+1$) according to the columns of signs that correspond to factors.

Then, the values of y and y^* are calculated. Following, the residuals are calculated such as:

$residual_k = y_k - y_k^*$,

where k: the order, k :1..n, n: the total number of experimental runs

After these calculations are done, the model is checked by the normal probability plotting technique using the following equation for the calculation of the intervals, p_k^{res}, on the vertical axis.

$p_k^{res} = 100 * [(k - 0.5) / k]$

where,

k : the order number; k: 1..n , n: total number of experimental runs

p_k^{res} : the probability of k.

Unlike the original plot of the effects, all the points from this residual plot are expected to lie down close to a line, in order to confirm the conjecture that the effects that are not considered important can be explained by random noise. Hence, the residual analysis can provide assurance for both the validity of the data collected through the experimental runs and the accuracy of the interpretations of analysis of the normal probability plotting of the effects.

1.3. STATISTICAL TECHNIQUES USED IN ROBUST DESIGN

The following sections discuss the calculation of the $variance_{wrnf}$ and the modified normal probability plotting and other techniques.

1.3.1. CALCULATION OF THE VARIANCE WITH RESPECT TO NOISE FACTORS ($variance_{wrtnf}$)

We follow the methodology described in the study by Kacker and Shoemaker [45]. The variance with respect to noise factors ($variance_{wrtnf}$) is the measure of the variability of the throughput (TP) in the case of the changing noise factors (jam rates and/or jam clear times) and unchanging control factors (buffer sizes). In other words, the $variance_{wrtnf}$ measures the variability of the TP along the row of the inner-array which corresponds to the configuration of buffer sizes.

We will explain the calculation of the $variance_{wrtnf}$ with a demonstration. Considering the example of the inner-array design shown in **Figure 3.5.**, we will calculate the $variance_{wrtnf}$..

Let us calculate the $variance_{wrtnf(1)}$ which measures the variability of the TP when the configuration of control factor is (-,-,-,-,-,-) and the noise factors change. In this case, the $variance_{wrtnf(1)}$ is:

$$variance_{wrtnf(1)} = [f \Sigma TP_{1j}{}^2 - (\Sigma TP_{1j})^2] / [f*(f-1)] \qquad ,j: 1..f$$

where TP_{1j} is the system response (the throughput) for the configuration of control factors (-,-,-,-,-,-) and the noise factor configuration, j, and f is the total number of noise factor configurations, which is four, in this example.

Hence, in general, the $variance_{wrtnf(i)}$ is calculated as follows.

$$variance_{wrtnf(i)} = [f \Sigma TP_{ij}^{\ 2} - (\Sigma TP_{ij})^2] / [f*(f-1)] \qquad ,j: 1..f$$

where TP_{ij} is the number of units produced by the model for particular buffer configuration, i (i.e., the configuration of the ith row of the inner array) , and noise factor configuration, j, and f is the total number of noise factor configurations (i.e., the number of columns in the outer array).

1.3.2. THE MODIFIED NORMAL PROBABILITY PLOTTING

The normal plotting calculations and steps are fundamentally same as discussed in section Appendix, 1.2.4. However, the results column and the considered number of runs differ in this modified normal probability plotting. Instead of the throughputs (TP) which we obtain from the experimental runs, in the robust design we will use the $variance_{wrtnf}$ as the results column. The $variance_{wrtnf}$ columns is obtained by calculating the $variance_{wrtnf}$ for each buffer configuration specified in the inner array. After obtaining the $variance_{wrtnf}$ column as the results column, the remainder of the normal probability plotting process is conducted accordingly. Hence, the steps are as follows.

1. calculate the effect of the factor i:

   1.1. find the sign column that corresponds to the factor i,

   1.2. multiply each row of this sign column by each row of results column (i.e., the $variance_{wrtnf}$), get $l_{i(rowj)}$ for each row, where $rowj$:1..n (n :total number of experimental runs of only the inner array; in other words, the total number of rows of the inner array), 1.3. calculate the effect of the factor i, l_i such as:

$l_i = \Sigma\, l_{i(rowj)} / (n/2)$, where n: total number of experimental runs of the inner array.

2. plot these effects in order of magnitude along the horizontal scale and then refer to the vertical axis which has a normal probability scale.

The calculation of the interval values, p_k, for the vertical axis:

$p_k = 100 * [(k - 0.5) / k]$

where,

k : the order number; k: $1..(n-1)$, n: total number of experimental runs of the inner array,

p_k : the probability of k.

1.3.3. OTHER TECHNIQUES

The residual analysis is also modified accordingly. In robust design, the residual analysis is used to verify the validity of the calculated $variance_{wrtnf}$ and the conclusions about the important effects on the $variance_{wrtnf}$. However, the calculations and steps are same as discussed in section 1.2.5.

The F-test and the t-test are applied to the throughput in order to verify the validity of the system responses. Therefore, there is no modification in the application of these tests.

APPENDIX 2

Section 2.1. first describes the methodology followed in section 4.4.1. in detail, then discusses the conclusions of the studies on the effect of the number of pallets in AAS for each system (Design 2 studies). Finally, it lists the results of experimental runs conducted in section 4.4.1. Similarly, section 2.2. lists the experimental runs conducted in section 4.4.2. In addition, section 2.2. discusses the optimization steps briefly.

2.1. STUDIES CONDUCTED IN SECTION 4.4.1.

Methodology:

Our primary goal is to define the ranges, thus an optimal area, for buffer sizes between the stations. The decision variables are buffer sizes given a fixed number of pallets (Design 1). For studying the effect of the number of pallets in AAS, the decision variables are buffer sizes and number of pallets (Design 2).

Hence, we have two DoE settings for each system type. The first one (Design 1) studies only the effects of buffer configurations, while the second one (Design 2) studies the effects of both buffer configurations and number of pallets in the system.

For Design 1, we use a 2_{IV}^{10-5} fractional factorial design of experiments. The generator of the 2_{IV}^{10-5} DoE is as follows.

I = 12346=12357=12458=13459=234510

where, 6=1234, 7=1235, 8=1245, 9=1345, 10=2345,

the effects and buffer allocations assignments are:

$b_1 : l_1$, $b_2 : l_2$, b_3: l_3, b_4: l_4, b_5: l_5, b_6: l_6 (9=345), $b_7 : l_7$, $b_8 : l_8$ (10=2345), $b_9 : l_9$ (6=1234), $b_{10} : l_{10}$ (8 =1245)

For Design 2, we use a 2_{III}^{11-6} fractional factorial design of experiments. The generator of the 2_{III}^{11-6} DoE is as follows.

I = 1236 = 2347 = 3458 =1349 =34510=24511

where, 6=123, 7=234, 8=345, 9=134, 10=345, 11=245,

the assignments effects and buffer allocations are:

$b_1 : l_1$, $b_2 : l_2$ (6=123),b_3: l_3, b_4: l_4 (7=234), b_5: l_5 (column 2), b_6: l_6 (9=134), $b_7 : l_7$ (column 4), $b_8 : l_8$ (10=145), $b_9 : l_9$ (11=245), $b_{10} : l_{10}$ (8=345), effect of pallets (column 5) .

Before conducting the experiments, we have first verified the results of iterations listed in SQG approach by using these parameters in our simulation program. Then, we have applied the t-test for our results. We have found that all iterations are statistically not different at 95% confidence level for all systems. Next, we have chosen the buffer levels for the experiments according to the configurations that gave high TP among those iterations. We have then conducted the experiments and reached conclusions, as mentioned in section 4.4.1.

Conclusion of Design 2 studies (effects of number of pallets and buffers are studied for four type of systems):

We have found out that even a slightest change in the number of pallets in all types of systems affects the TP significantly. Because the effect of the number of pallets in the system is very large, the effects of buffers are ignored, when compared to the effect of number of pallets. The graphical results of the analyses of Design 2 studies are demonstrated in Figures 2.1.2. to 2.4.2.

Tables:

Table 2.1. compares the results obtained by SQG optimization approach and simulation program we use in this research. Tables 2.1.1. to 2.4.1. list the results of the experimental runs of Design 1 (only effects of buffers studied) of systems discussed in section 4.4.1. Similarly, Table 2.1.2. to 2.4.2. list the results of experimental runs of Design 2 (effects of buffers and number of pallets studied) of same systems.

2.2. STUDIES CONDUCTED IN SECTION 4.4.2. (DoE OPTIMIZATION)

Two types of systems studied for the optimization using the DoE approach. The methodology is as follows.

Initial buffer ranges are chosen and experiments are conducted, accordingly. Then, using the data analysis techniques (see Appendix 1, section 1.2.), the results of the experimental runs are investigated. The effects of buffers are calculated and results are plotted to the normal probability papers. Important effects (the ones that are distinguishable from other effects) are identified. Then, the buffer ranges are determined as follows. The buffer sizes for buffers with positive important effects on the throughput are increased and for buffers with negative important effects on the throughput are decreased (if there is not an important interaction effect; if there are important interaction effects, then their effects and signs are also considered when choosing the new buffer ranges). The buffer sizes for buffers with no important effects on the throughput are kept unchanged. Also, the variances of each pair of TPs ($variance_{anytwoTP}$) are calculated for verification. If buffers seem to have important effects, the next experimenting step is conducted by using the determined buffer ranges in this step as the initial buffer ranges. The optimization steps are terminated based on the satisfaction of the stopping criteria. The main stopping criterion is having small effects of buffers such that they are indistinguishable and/or small. In addition, we want the $variance_{anytwoTP}$ to be small enough. We reach an optimal area when these criteria are satisfied simultaneously. Following is a brief discussion of steps conducted for the optimization of each system.

2.2.1. Type 5 Systems (All Stations Are Subject to Jam)

The initial buffer ranges are chosen considering the conclusions of buffer allocations studies of section 4.4.1. Four steps are conducted to reach an optimal area.

Step 1:

The initial buffers are as follows.

Buffer	b_1	b_2	b_3	b_4	b_5
-	2	5	4	8	4
+	3	7	5	11	5

The results of the experimental runs of this step are listed in Appendix 2, Table 2.5.1.1. The effects of the buffers and residual analysis are calculated and shown in Appendix 2, Figure 2.5.1.1. and 2.5.1.2. The largest $variance_{anytwoTP}$ is calculated as $6.54*10^{-7}$ and all of the $variance_{anytwoTP}$ found in a range of $6.54*10^{-7}$ to $7.94*10^{-9}$. Since the effects are large enough, we will conduct a new set of experiments by using the conclusion of this set to choose the new levels of buffers (see Appendix 2, Table 2.5.1.2.).

Step 2:

The buffer levels are chosen accordingly (Appendix 2, Table 2.5.1.2.) The results of the experimental runs of this step are listed in Appendix 2, Table 2.5.2.1. The effects of the buffers and residual analysis are shown in Appendix 2, Figure 2.5.2.1. and 2.5.2.2. The largest $variance_{anytwoTP}$ is calculated as $6.14*10^{-9}$ and all of the $variance_{anytwoTP}$ found in a the range of $6.14*10^{-9}$ to $2*10^{-12}$. Although the $variance_{anytwoTP}$ is considerably smaller, the effects are still important. Hence, we will continue experimenting. The conclusion of this step is listed in Appendix 2, Table 2.5.2.2.

Step 3:

The buffer levels are chosen following the conclusion of the previous step (Appendix 2, Table 2.5.2.2.) The results of the experimental runs of this step are listed in Appendix 2, Table 2.5.3.1. The effects of the buffers and residual analysis are demonstrated in Appendix 2, Figure 2.5.3.1. and 2.5.3.2. The largest $variance_{anytwoTP}$ is calculated as $3.89*10^{-9}$ and all of the $variance_{anytwoTP}$ found in a the range of $3.89*10^{-9}$ to $2*10^{-12}$. Although the $variance_{anytwoTP}$ is considerably smaller, the effects may still be important. Hence, we will continue experimenting by using the conclusion of this step as listed in Appendix 2, Table 2.5.3.2.

Step 4:

The buffer levels are chosen accordingly (Appendix 2, Table 2.5.3.2.) The results of the experimental runs of this step are listed in Appendix 2, Table 2.5.4.1. The largest $variance_{anytwoTP}$ is calculated as $2.31*10^{-9}$ and all of the $variance_{anytwoTP}$ found in a the range of $2.31*10^{-9}$ to $5*10^{-13}$. At this step, we have found that the effects are almost indistinguishable. In addition, considering the smaller $variance_{anytwoTP}$ values calculated in this step and confirmatory experiments conducted, we have terminated the experimenting at this step. The effects of the buffers and residual analysis are demonstrated in Chapter 4, Figure 4.5.1. and 4.5.2. The conclusion of this step is listed in Chapter 4, Table 4.5.2.

2.2.2. Type 6 Systems (Some Stations Are Subject to Jam)

In this study, we have chosen the initial levels of the buffers randomly. Six steps are conducted to reach an optimal area.

Step 1:

The initial buffers are as follows.

buffers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
-	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
+	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6

The results of the experimental runs of this step are listed in Appendix 2, Table 2.6.1.1. The effects of the buffers and residual analysis are calculated and shown in Appendix 2, Figure 2.6.1.1. and 2.6.1.2. The largest $variance_{anytwoTP}$ is calculated as $1.37*10^{-7}$ and all of the $variance_{anytwoTP}$ found in a the range of $1.37*10^{-7}$ to $3.47*10^{-18}$. Since the effects are large, we will conduct a new set of experiments by using the conclusion of this set to choose the new levels of buffers (see Appendix 2, Table 2.6.1.2.)

Step 2:

The buffer levels are chosen accordingly (Appendix 2, Table 2.6.2.1.) The results of the experimental runs of this step are listed in Appendix 2, Table 2.6.2.1. The effects of the buffers and residual analysis are shown in Appendix 2, Figure 2.6.2.1. and 2.6.2.2.

The largest $variance_{anytwoTP}$ is calculated as $1.1*10^{-8}$ and all of the $variance_{anytwoTP}$ found in a the range of $1.1*10^{-8}$ to $4.5*10^{-12}$. Since effects of buffers are large, we will conduct the next step. The conclusion of this step is listed in Appendix 2, Table 2.6.2.2.

Step 3:

The buffer levels are chosen following the conclusion of the previous step (Appendix 2, Table 2.6.2.2.) The results of the experimental runs of this step are listed in Appendix 2, Table 2.6.3.1. The effects of the buffers and residual analysis are demonstrated in Appendix 2, Figure 2.6.3.1. and 2.6.3.2. The largest $variance_{anytwoTP}$ is calculated as $1.1*10^{-8}$ and all of the $variance_{anytwoTP}$ found in a the range of $1.1*10^{-8}$ to $3.47*10^{-18}$. The effects may seem important. Hence, we will continue experimenting by using the conclusion of this step as listed in Appendix 2, Table 2.6.3.2.

Step 4:

The buffer levels are chosen accordingly (Appendix 2, Table 2.6.3.2.). The results of the experimental runs of this step are listed in Appendix 2, Table 2.6.4.1. The effects of the buffers and residual analysis are shown in Appendix 2, Figure 2.6.4.1. and 2.6.4.2. The largest $variance_{anytwoTP}$ is calculated as $1.01*10^{-8}$ and all of the $variance_{anytwoTP}$ found in a the range of $1.01*10^{-8}$ to $2.78*10^{-18}$. Some effects may still seem important, thus we will conduct the next step. The conclusion of this step is listed in Appendix 2, Table 2.6.4.2.

Step 5:

The buffer levels are chosen following the conclusion of the previous step (Appendix 2, Table 2.6.4.2.) The results of the experimental runs of this step are listed in Appendix 2, Table 2.6.1.5. The largest $variance_{anytwoTP}$ is calculated as $2.66*10^{-9}$ and all of the $variance_{anytwoTP}$ found in a the range of $2.66*10^{-9}$ to $1.52*10^{-10}$. The effects of the buffers and residual analysis are demonstrated in Appendix 2, Figure 2.6.5.1. and 2.6.5.2. We have found that some effects had large values.. Hence, we will continue experimenting by using the conclusion of this step as listed in Appendix 2, Table 2.6.5.2.

Step 6:

The buffer levels are chosen accordingly (Appendix 2, Table 2.6.5.2.) The results of the experimental runs of this step are listed in Appendix 2, Table 2.6.1.6. The largest $variance_{anytwoTP}$ is calculated as $6.13*10^{-10}$ and all of the $variance_{anytwoTP}$ found in a the range of $6.13*10^{-10}$ to $2.78*10^{-18}$. At this step, we have found that the effects may be considered as indistinguishable. To verify that, we have run some confirmatory experiments and concluded that the effects are indeed indistinguishable, thus we have terminated the experimenting at this step. The effects of the buffers and residual analysis are demonstrated in Chapter 4, Figure 4.6.1. and 4.6.2. The conclusion of this step is listed in Chapter 4, Table 4.6.2.

Table 2.1. The comparison of the results of SQG optimization approach and the discrete-event simulation program used in this research

nomenclature:

iter : iteration number of the SQG optimization approach,

b_i : the size of the buffer between station i and station i+1, i:1..10,

TP : Throughput (production rate),

TP_1 : TP of SQG optimization approach,

TP_2 : TP of the experimental runs obtained from the simulation program we used,

var_2: variance of experimental runs obtained from the simulation program we used,

jr : jam rate at station i, i:1..10,

jct: jam clear time

repl. : replications

Type (1) systems :

iter	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}	TP_1	TP_2	var_2 (10^{-10})
a	2	2	2	2	2	2	2	2	2	2	.1435	.142442	141966
b	3	3	3	3	3	3	3	3	3	3	.1440	.143123	118864
c	4	4	4	4	4	4	4	4	4	4	.1429	141802	082289
jr	1	1	1	1	1	1	1	1	1	1	jct:18	10repl.	20pallet

Type (2) systems:

iter	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}	TP_1	TP_2	var_2 (10^{-10})
a	6	9	6	6	6	6	6	6	6	6	.1201	.127923	228282
b	4	15	4	4	4	4	4	4	4	4	.1206	.128882	181452
c	5	16	5	5	5	5	5	5	5	5	.1212	.129854	200433
d	5	17	5	5	5	5	5	5	5	5	.1214	.130028	195530
e	4	18	4	4	4	4	4	4	4	4	.1210	.129582	172274
jr	0	3	3	0	0	0	3	0	0	0	jct:36	10repl.	40pallet

Type (3) systems:

iter	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}	TP_1	TP_2	var_2 (10^{-10})
a	6	11	11	9	9	6	6	6	6	6	.1231	.128484	458754
b	6	10	10	11	11	5	5	5	5	5	.1235	.128672	462235
c	5	10	10	10	10	5	5	5	5	5	.1234	.128753	460000
d	5	9	10	12	12	4	4	4	4	4	.1236	.128879	449504
e	4	9	9	11	11	4	4	4	4	4	.1235	.128826	463270
f	4	10	11	12	12	4	4	4	4	4	.1236	.129028	445386
g	4	10	10	11	11	3	3	3	3	3	.1230	.128704	459431
h	4	10	10	12	12	4	4	4	4	4	.1237	.128956	447717
i	4	9	10	11	11	3	3	3	3	3	.1229	.128628	458248
jr	0	3	0	3	0	3	0	0	0	0	jct:36	10repl.	40pallet

Type (4) systems:

iter	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}	TP_1	TP_2	var_2 (10^{-10})
a	12	13	6	7	7	10	12	7	8	4	.1455	.150575	121490
b	12	14	6	7	7	11	12	6	8	3	.1456	.150586	124354
c	11	15	6	7	7	12	11	6	8	2	.1454	.150525	128161
d	11	15	6	6	6	12	11	6	7	4	.1457	.150619	125606
jr	.5	3	.5	.5	.5	.5	3	.5	.5	.5	jct:18	10repl.	50pallet

Table 2.1.1. The results of experimental runs of Design 1 of Type 1 systems

buffer range: (-) : 2 and (+) : 3 for all stations

number of pallets: 20, 10 replications for each run

experimental run order	TP (Throughput)	variance (10^{-10})
1	.143084	128459
2	.142802	126292
3	.142858	126897
4	.143011	122378
5	.142825	123807
6	.143063	122762
7	.143140	131989
8	.143021	120081
9	.142888	135926
10	.143098	119975
11	.143189	128640
12	.143151	125233
13	.143205	128910
14	.143126	121554
15	.143121	119979
16	.143054	124004
17	.142870	129511
18	.143028	117917
19	.143121	127571
20	.143182	126108
21	.143056	126871
22	.143130	123277
23	.143114	120883
24	.143042	121622
25	.143167	120633
26	.143307	124216
27	.143261	123599
28	.143114	115511
29	.143226	118020
30	.143109	112633
31	.143172	120003
32	.143123	118864

Table 2.1.2. The results of experimental runs of Design 2 of Type 1 systems

buffer range: (-) : 2 and (+) : 3 for all stations

pallet range: (-): 20 and (+): 21, 10 replications for each run

experimental run order	TP (Throughput)	variance (10^{-10})
1	.142442	141966
2	.143014	121745
3	.143196	122290
4	.143289	121116
5	.143068	118981
6	.143063	120669
7	.143088	120105
8	.143125	124800
9	.143189	129135
10	.143130	124668
11	.143128	125201
12	.143018	119879
13	.143140	131989
14	.143063	122762
15	.143154	122174
16	.143095	114639
17	.143328	132514
18	.143626	121394
19	.143881	125190
20	.143795	121361
21	.143935	131148
22	.143591	132080
23	.143546	133941
24	.143547	127710
25	.143346	139405
26	.143746	130990
27	.143777	132899
28	.143712	133242
29	.143596	129134
30	.143777	122862
31	.143949	124403
32	.144047	121862

Figure 2.1.1. The effects of buffers and number of pallets of Type 1 systems (Design 2)

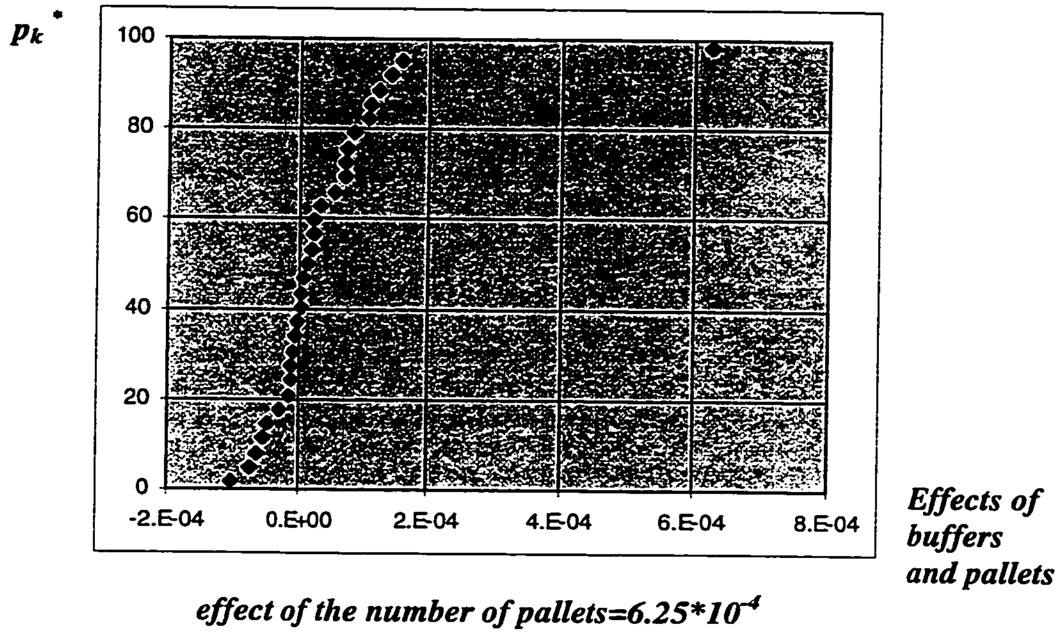
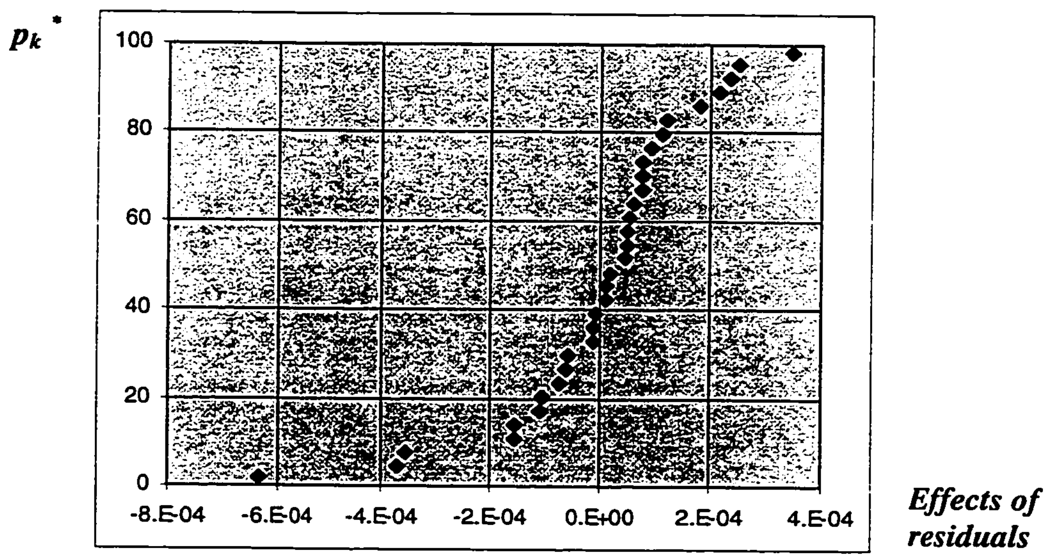


Figure 2.1.2. The residuals of Type 1 systems (Design 2)



* $p_k = 100 * [(k-0.5)/k]$

Table 2.2.1. The results of experimental runs of Design 1 of Type 2 systems

buffer range: (-) : 5,16,5,4,4,4,5,4,4,4 and (+) : 6,17,6,5,5,5,6,5,5,5

number of pallets: 40, 10 replications for each run

experimental run order	TP (Throughput)	variance (10^{-9})
1	.129789	199983
2	.129668	190576
3	.129886	190773
4	.129821	185847
5	.129770	197725
6	.129837	202276
7	.129972	194978
8	.130002	197281
9	.129770	197725
10	.129837	202276
11	.129972	194978
12	.130002	197281
13	.129847	200309
14	.129830	202830
15	.130030	195149
16	.130000	197004
17	.129770	197725
18	.129837	202276
19	.129972	194978
20	.130002	197281
21	.129847	200309
22	.129830	202830
23	.130030	195149
24	.130000	197004
25	.129847	200309
26	.129830	202830
27	.130030	195149
28	.130000	197004
29	.129854	200433
30	.129875	202260
31	.130019	195062
32	.130009	198767

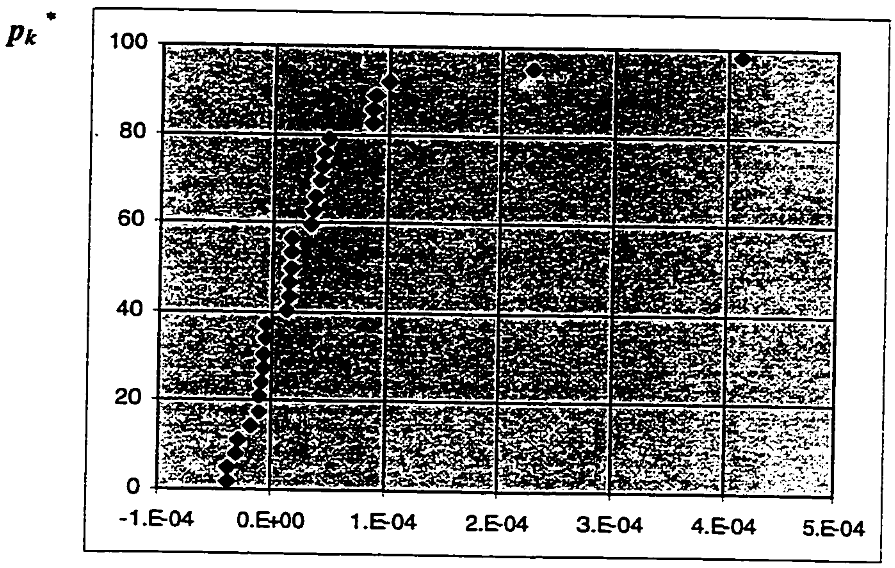
Table 2.2.2. The results of experimental runs of Design 2 of Type 2 systems

buffer range: (-) : 5,16,5,4,4,4,5,4,4,4 and (+) : 6,17,6,5,5,5,6,5,5,5

pallet range: (-): 40 and (+): 45, 10 replications for each run

experimental run order	TP (Throughput)	variance (10 [illegible])
1	.129582	185006
2	.129961	196279
3	.129988	194666
4	.129860	202542
5	.130019	195062
6	.129837	202276
7	.129847	200309
8	.129989	197965
9	.129823	200781
10	.129958	197595
11	.130005	195337
12	.129807	201380
13	.129972	194978
14	.129837	202276
15	.129847	200309
16	.130051	197189
17	.129770	200305
18	.130370	197016
19	.130458	195349
20	.130304	203948
21	.130523	195876
22	.130177	201993
23	.130258	201040
24	.130389	195274
25	.130105	199009
26	.130370	197016
27	.130458	195349
28	.130167	203622
29	.130307	195024
30	.130270	204997
31	.130353	203697
32	.130700	196514

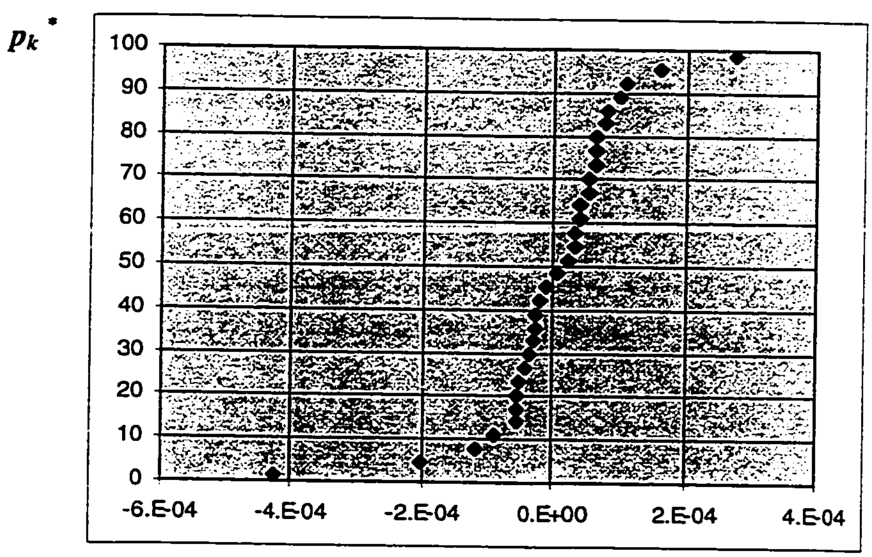
Figure 2.2.1. The effects of buffers and number of pallets of Type 2 systems (Design 2)



Effects of buffers and pallets

*effect of the number of pallets=4.12*10⁻⁴, l_2=2.3*10⁻⁴*

Figure 2.2.2. The residuals of Type 2 systems (Design 2)



Effects of residuals

$^*p_k = 100 * [(k\text{-}0.5)/k]$

Table 2.3.1. The results of experimental runs of Design 1 of Type 3 systems

buffer range: (-) : 4,9,10,11,11,4,4,4,4,4 and (+) : 5,10,11,12,12,5,5,5,5,5

number of pallets: 40, 10 replications for each run

experimental run order	TP (Throughput)	variance (10^{-9})
1	.128798	463921
2	.128865	463741
3	.128912	461201
4	.128807	462643
5	.128912	461201
6	.128807	462643
7	.128940	460157
8	.128872	461907
9	.128914	452462
10	.128830	450068
11	.128914	448315
12	.128856	448582
13	.128914	448315
14	.128856	448582
15	.128981	447035
16	.128965	446873
17	.128914	452462
18	.128830	450068
19	.128914	448315
20	.128856	448582
21	.128914	448315
22	.128856	448582
23	.128981	447035
24	.128965	446873
25	.128874	448575
26	.128825	447717
27	.128904	446202
28	.128891	446010
29	.128904	446202
30	.128891	446010
31	.129014	444803
32	.128863	445503

Table 2.3.2. The results of experimental runs of Design 2 of Type 3 systems

buffer range: (-) : 4,9,10,11,11,4,4,4,4,4 and (+) : 5,10,11,12,12,5,5,5,5,5

pallet range: (-): 40 and (+): 45, 10 replications for each run

experimental run order	TP (Throughput)	variance (10^{-10})
1	.128826	463270
2	[illegible]	450042
3	.128814	462973
4	.128795	449855
5	.128928	448867
6	.128851	450425
7	.128879	450940
8	.128856	448582
9	.128804	452776
10	.128830	450068
11	.128868	449676
12	.128816	454152
13	.128870	461101
14	.128786	463569
15	.128888	449094
16	.128870	446361
17	.129393	464525
18	.129489	463503
19	.129686	441969
20	.129540	439651
21	.129739	444781
22	.129565	444197
23	.129609	446966
24	.129633	441503
25	.129440	442489
26	.129612	448391
27	.129651	449937
28	.129504	446595
29	.129561	458473
30	.129519	465416
31	.129704	440251
32	.129758	429546

Figure 2.3.1. The effects of buffers and number of pallets of Type 3 systems (Design 2)

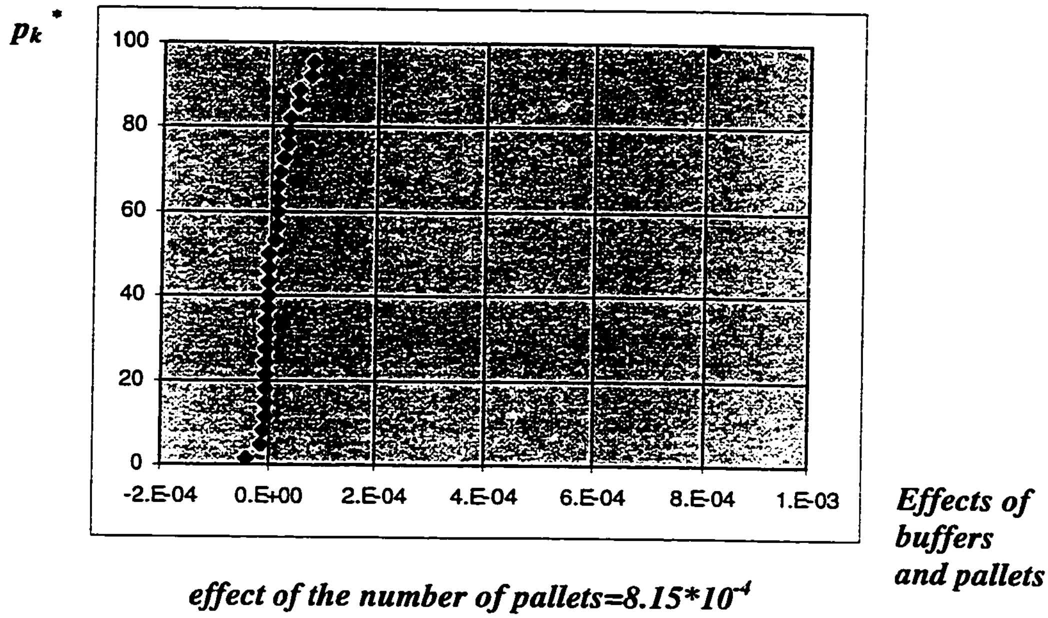
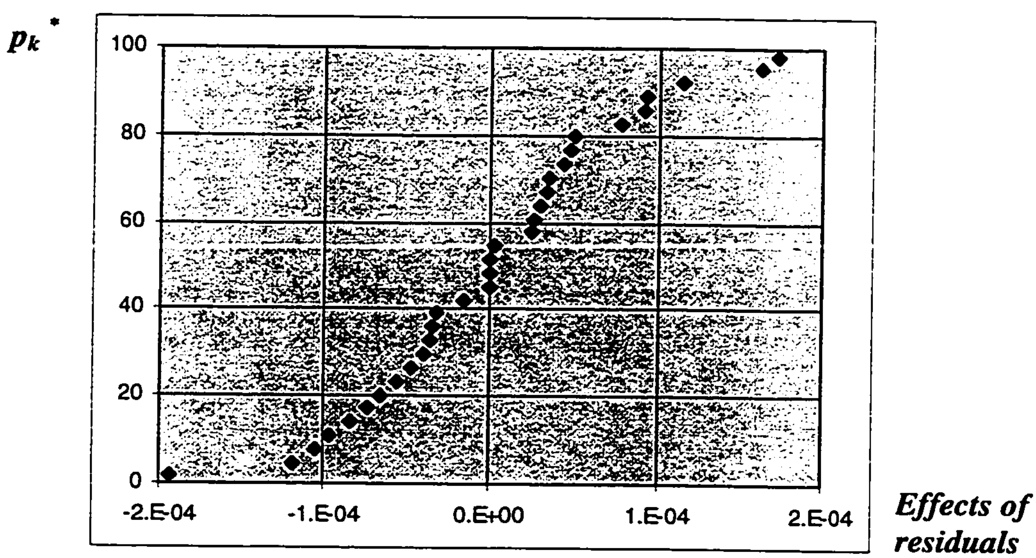


Figure 2.3.2. The residuals of Type 3 systems (Design 2)



$^* p_k = 100 * [(k\text{-}0.5)/k]$

Table 2.4.1. The results of experimental runs of Design 1 of Type 4 systems

buffer range: (-) : 11,14,56,6,11,11,5,7,3 and (+) : 12,15,6,7,7,12,12,6,8,4

number of pallets: 50, 10 replications for each run

experimental run order	TP (Throughput)	variance (10^{-10})
1	.150598	127262
2	.150632	123802
3	.150602	126123
4	.150654	119371
5	.150591	125307
6	.150618	125158
7	.150600	126532
8	.150665	120677
9	.150561	126628
10	.150633	121309
11	.150609	124565
12	.150632	124042
13	.150568	128207
14	.150618	120988
15	.150595	125531
16	.150623	122431
17	.150574	126553
18	.150639	121549
19	.150612	124929
20	.150644	123921
21	.150575	128632
22	.150630	120871
23	.150605	125280
24	.150628	122671
25	.150581	126627
26	.150596	124268
27	.150581	126785
28	.150644	118856
29	.150565	125926
30	.150596	124424
31	.150577	125655
32	.150612	120655

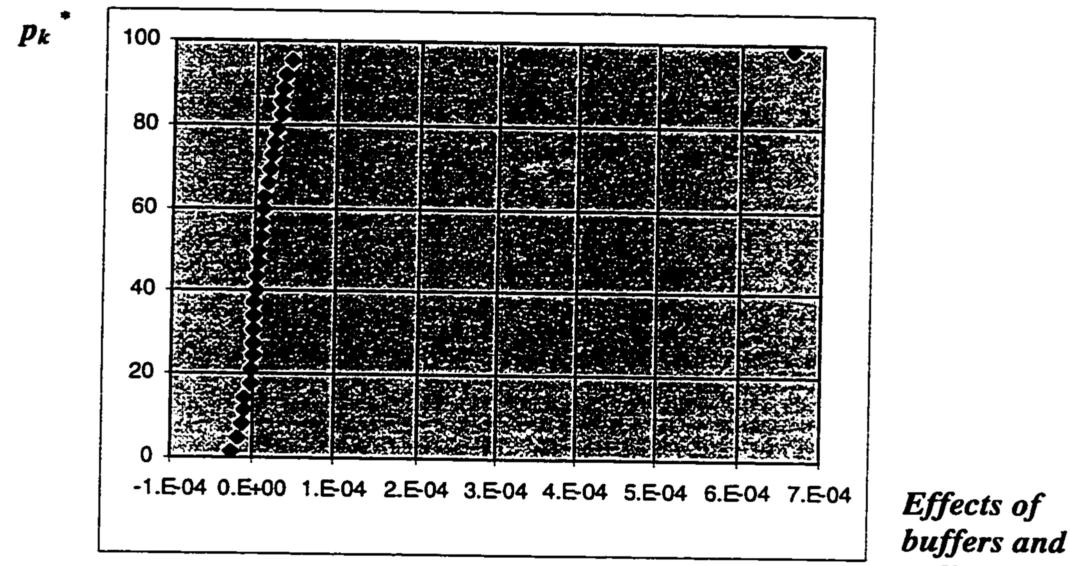
Table 2.4.2. The results of experimental runs of Design 2 of Type 4 systems

buffer range: (-) : 11,14,56,6,11,11,5,7,3 and (+) : 12,15,6,7,7,12,12,6,8,4

pallet range: (-): 50 and (+): 60, 10 replications for each run

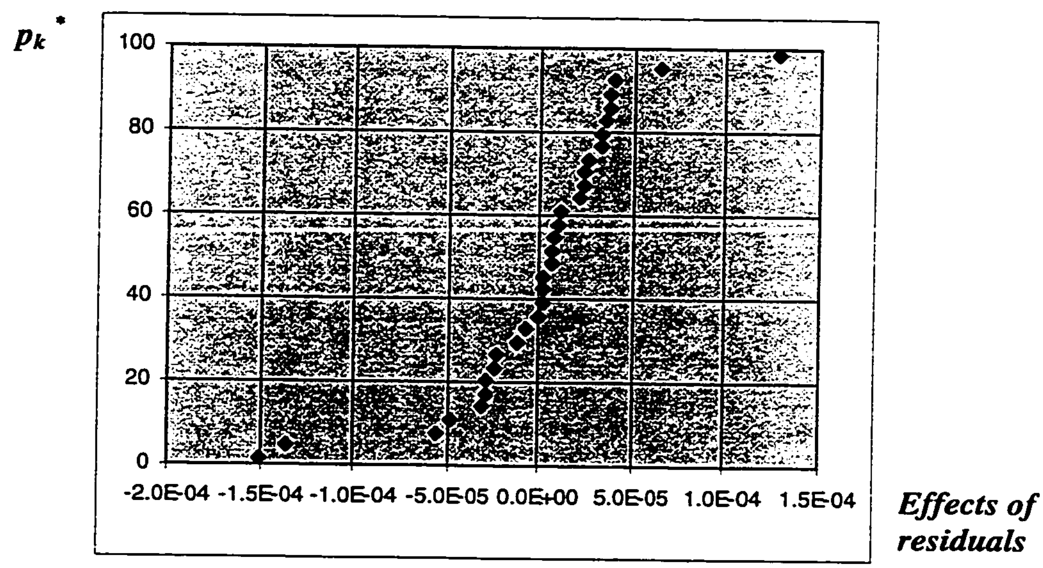
experimental run order	TP (Throughput)	variance ($10^{[illegible]}$)
1	.150577	126168
2	.1506[illegible]	1248[illegible]
3	.150579	125199
4	.150608	125070
5	.150596	124981
6	.150636	120723
7	.150584	126536
8	.150644	119683
9	.150579	127123
10	.150639	119361
11	.150614	125909
12	.150639	120485
13	.150600	126532
14	.150618	125158
15	.150558	127519
16	.150614	123780
17	.151177	129888
18	.151132	128673
19	.151289	131003
20	.151304	130041
21	.151270	133584
22	.151307	128924
23	.151244	135299
24	.151302	129036
25	.151211	135068
26	.151270	131303
27	.151267	133574
28	.151275	131123
29	.151277	131277
30	.151333	131197
31	.151291	132419
32	.151395	129334

Figure 2.4.1. The effects of buffers and number of pallets of Type 4 systems (Design 2)



*effect of the number of pallets=6.61*10⁻⁴*

Figure 2.4.2. The residuals of Type 4 systems (Design 2)



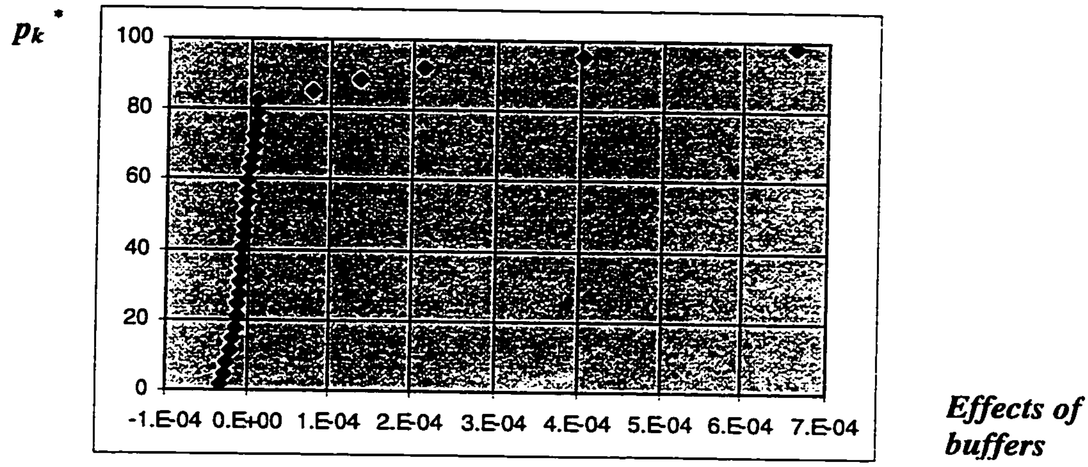
* $p_k = 100 * [(k-0.5)/k]$

Table 2.5.1.1. The results of experimental runs of optimization of AAS (Type 5) using DoE approach, 1st experiment set (1st step)

buffer range: (-) : 2,5,4,8,4 and (+) : 3,7,5,11,5; number of pallets: 20; 10 replications

experimental run order	TP (Throughput)	variance (10^{-10})
1	.137639	29747
2	.137886	30120
3	.138277	25584
4	.138589	30829
5	.138056	24742
6	.138288	26084
7	.138735	25814
8	.138963	31332
9	.137835	29144
10	.138011	28565
11	.138518	26985
12	.138728	30877
13	.138232	23275
14	.138495	26967
15	.138911	27001
16	.139063	31955
17	.137768	29380
18	.137958	29364
19	.137768	29380
20	.137958	29364
21	.138160	24262
22	.138416	26819
23	.138860	27053
24	.139032	31391
25	.137888	29577
26	.138063	29137
27	.138570	27753
28	.138751	30961
29	.138293	23873
30	.138540	27593
31	.138944	27764
32	.139070	27764

Figure 2.5.1.1. The effects of buffers of Type 5 systems using DoE optimization method (1st step)



$l_2=6.63*10^{-4}$, $l_3=4.04*10^{-4}$, $l_1=2.12*10^{-4}$, $l_4=1.35*10^{-4}$

Figure 2.5.1.2. The residuals of buffers of Type 5 systems using DoE optimization method (1st step)

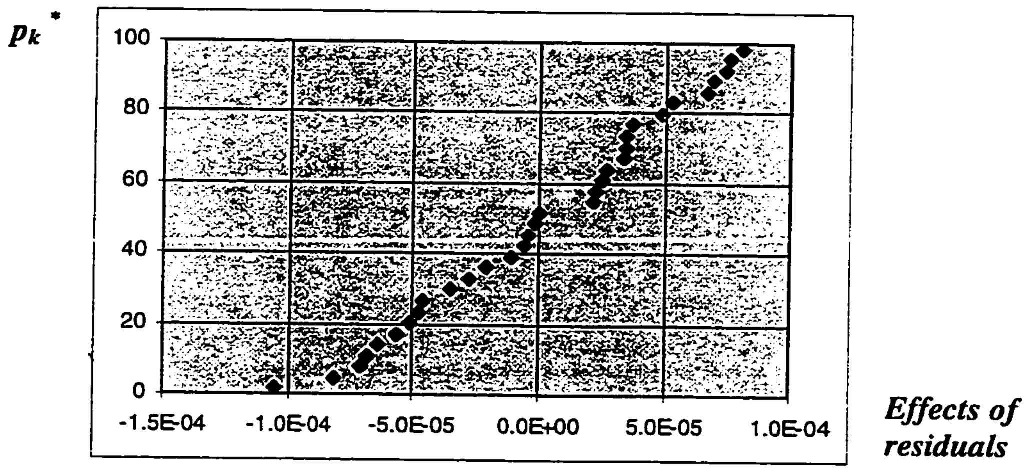


Table 2.5.1.2. The conclusion of 1st step

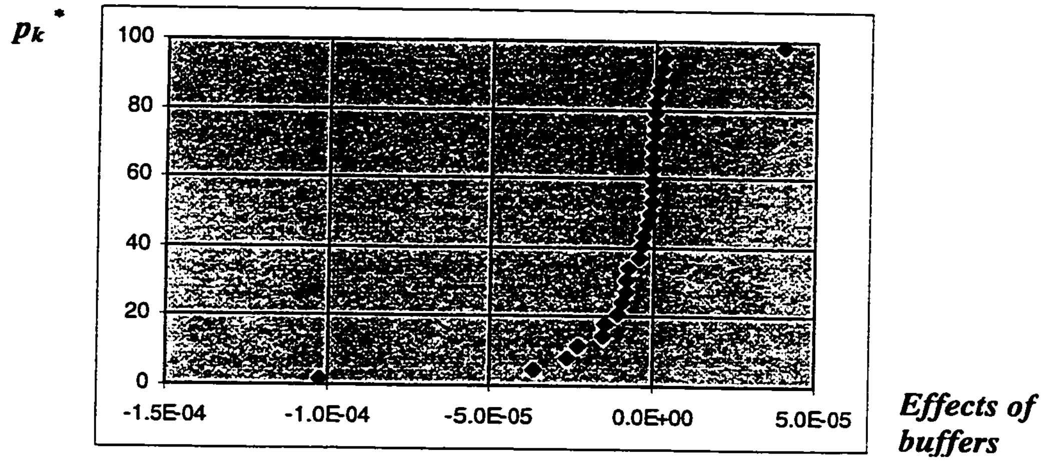
buffers	b_1	b_2	b_3	b_4	b_5
-	3	7	6	9	4
+	4	8	8	12	5

Table 2.5.2.1. The results of experimental runs of optimization of AAS (Type 5) using DoE approach, 2nd experiment set (2nd step)

buffer range: (-) : 3,7,6,9,4 and (+) : 4,8,8,12,5; number of pallets: 20; 10 replications

experimental run order	TP (Throughput)	variance (x1[illegible])
1	.139163	32658
2	.139175	34528
3	.139165	34896
4	.139150	36379
5	.139251	31034
6	.139261	31832
7	.139228	31864
8	.139216	31965
9	.139121	32772
10	.139107	34319
11	.139093	33772
12	.139068	34734
13	.139158	31238
14	.139140	31511
15	.139104	31176
16	.139074	31068
17	.139165	32815
18	.139167	34829
19	.139160	35023
20	.139142	36390
21	.139244	31310
22	.139237	32009
23	.139204	31689
24	.139181	31715
25	.139098	32201
26	.139084	33735
27	.139074	33209
28	.139046	34253
29	.139125	30975
30	.139098	31293
31	.139067	30784
32	.139030	30674

Figure 2.5.2.1. The effects of buffers of Type 5 systems using DoE optimization method (2nd step)



l_4=-1.02*10^{-4}, l_3=0.40*10^{-4}, l_2=-0.36*10^{-4}, l_{34}=-0.27*10^{-4}, l_5=-0.23*10^{-4}

Figure 2.5.2.2. The residuals of buffers of Type 5 systems using DoE optimization method (2nd step)

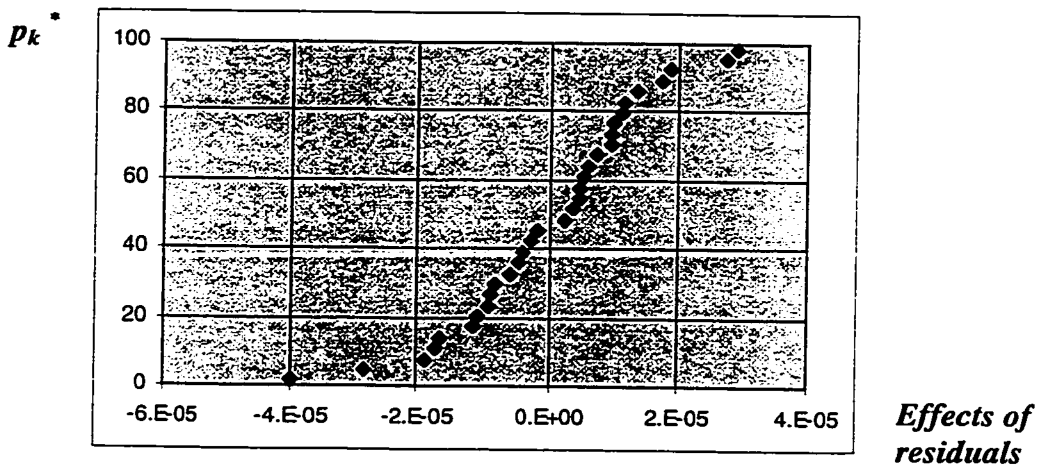


Table 2.5.2.2. The conclusion of 2nd step

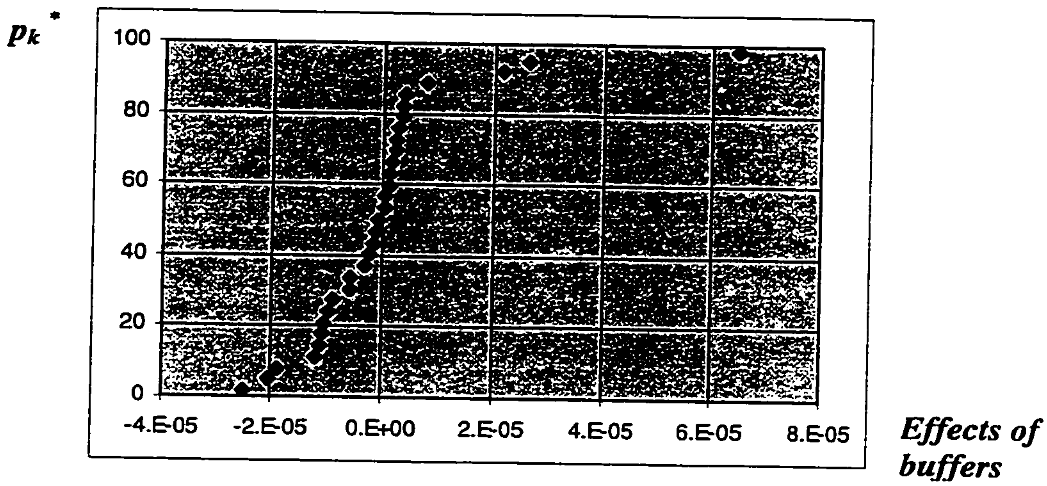
buffers	b_1	b_2	b_3	b_4	b_5
-	3	6	7	8	3
+	4	7	9	10	4

Table 2.5.3.1. The results of experimental runs of optimization of AAS (Type 5) using DoE approach, 3rd experiment set (3rd step)

buffer range: (-) : 3,6,7,8,3 and (+) : 4,7,9,10,4; number of pallets: 20; 10 replications

experimental run order	TP (Throughput)	variance (10^{-10})
1	.139119	29694
2	[illegible]	[illegible]
3	.139147	31737
4	.139223	[illegible]
5	.139242	29979
6	.139298	30907
7	.139232	30484
8	.139277	31184
9	.139191	30302
10	.139235	31295
11	.139200	31821
12	.139230	32541
13	.139274	29633
14	.139302	30516
15	.139256	30221
16	.139267	30772
17	.139209	29984
18	.139244	30864
19	.139230	31609
20	.139247	32266
21	.139307	29506
22	.139319	30142
23	.139291	30158
24	.139261	31832
25	.139209	30380
26	.139228	31624
27	.139216	31944
28	.139218	32691
29	.139279	29774
30	.139284	30592
31	.139254	30462
32	.139239	30541

Figure 2.5.3.1. The effects of buffers of Type 5 systems using DoE optimization method (3rd step)



$l_3=6.48*10^{-5}$, $l_1=2.6*10^{-5}$, $l_2=-0.95*10^{-5}$, $l_4=0.23*10^{-5}$, $l_5=-2.14*10^{-5}$, $l_{15}=-2.04*10^{-5}$, $l_{23}=-1.9*10^{-5}$, $l_{45}=-2.49*10^{-5}$

Figure 2.5.3.2. The residuals of buffers of Type 5 systems using DoE optimization method (3rd step)

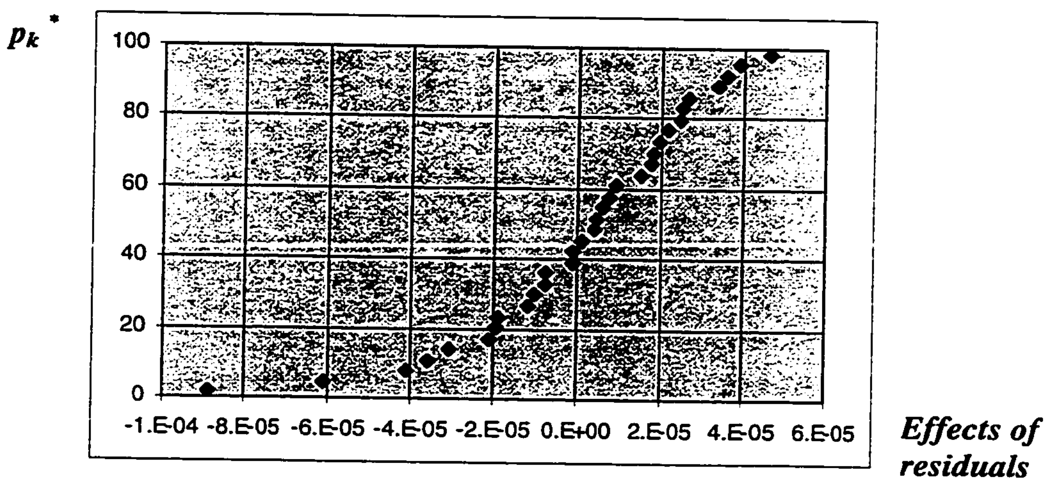


Table 2.5.3.2. The conclusion of 3rd step

buffers	b_1	b_2	b_3	b_4	b_5
-	3	6	8	9	3
+	4	7	9	10	4

Table 2.5.4.1. The results of experimental runs of optimization of AAS (Type 5) using DoE approach, 4th experiment set (4th step)

buffer range: (-) : 3,6,8,9,3 and (+) : 4,7,9,10,4; number of pallets: 20; 10 replications

experimental run order	TP (Throughput)	variance (10^{-6})
1	.139249	030454
2	.139286	031026
3	.139237	030996
4	.139268	031610
5	.139282	029636
6	.1392[illegible]	030252
7	.139268	030153
8	.139288	030606
9	.139244	030425
10	.139274	031145
11	.139228	031043
12	.139256	031931
13	.139274	029633
14	.139302	030516
15	.139256	030221
16	.139267	030772
17	.139268	030271
18	.139279	031046
19	.139251	031034
20	.139261	031832
21	.139296	029635
22	.139307	030412
23	.139227	030065
24	.139272	030670
25	.139253	030487
26	.139261	031240
27	.139239	031399
28	.139237	032009
29	.139279	029774
30	.139284	030592
31	.139254	030462
32	.139239	035041

Table 2.6.1.1. The results of experimental runs of optimization of AAS (Type 6) using DoE approach, 1st experiment set (1st step)

initial levels of buffers:

buffers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
-	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
+	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
jam rate	3	3	0	5	0	0.5	0	3	0	0.5	0	0.5	0	0	0

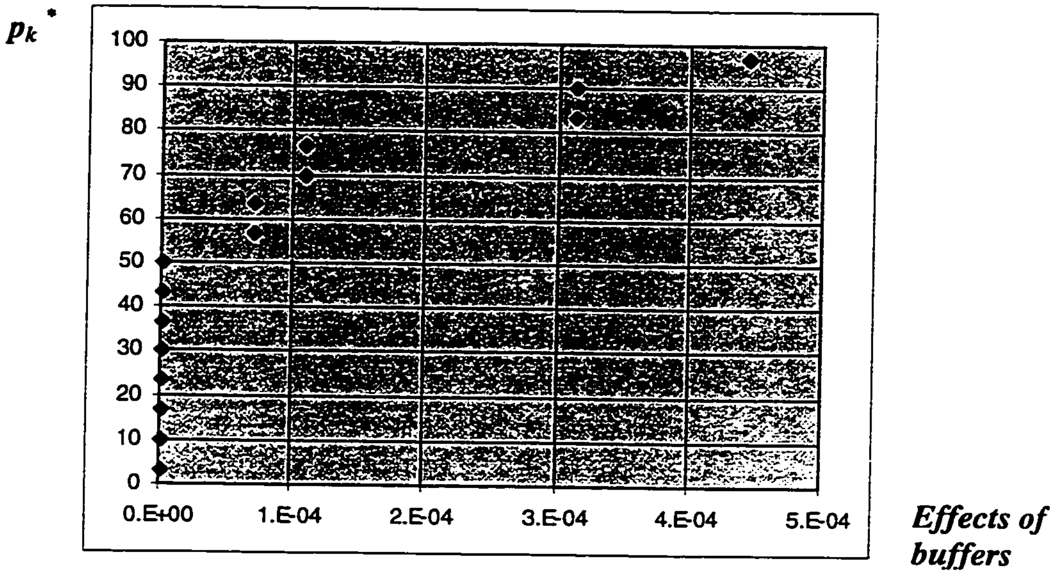
number of pallets : 60, jam clear time : 20 time units, cycle time : 5 time units

experimental run order	TP	variance (10[illegible])
1	.137165	110175
2	.137179	110345
3	.137533	108821
4	.137533	108821
5	.137939	103891
6	.137939	103891
7	.138016	100915
8	.138016	100915
9	.138109	106214
10	.138109	106214
11	.138109	106214
12	.138109	106214
13	.138109	106214
14	.138109	106214
15	.138109	106214
16	.138109	106214

Table 2.6.1.2. The conclusion of 1st step

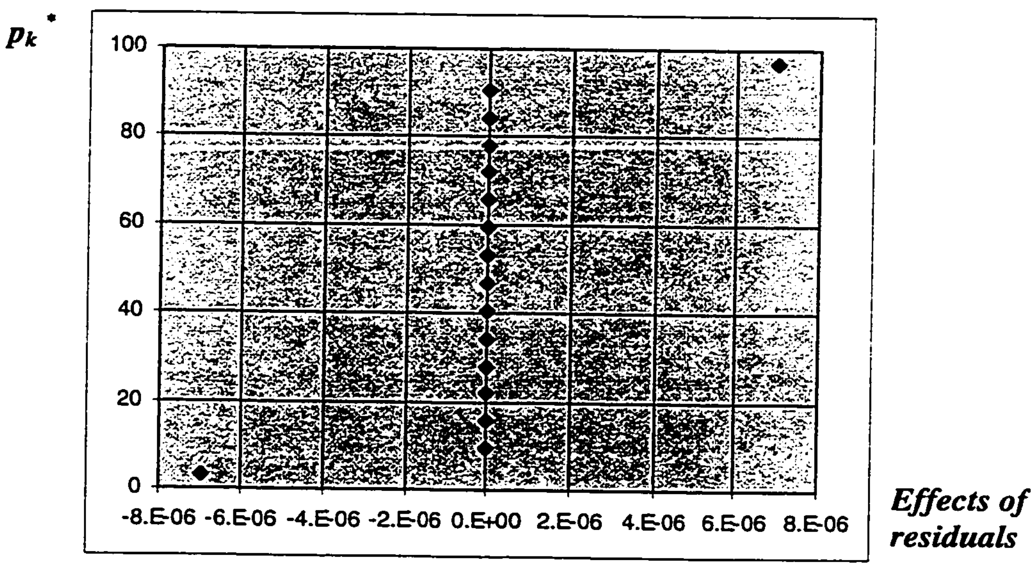
buffers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
-	11	9	9	8	8	7	7	5	5	5	5	5	5	5	5
+	12	10	10	9	9	8	8	6	6	6	6	6	6	6	6

Figure 2.6.1.1. The effects of buffers of Type 6 systems using DoE optimization method (1st step)



$l_1=4.44*10^{-4}$, $l_2=l_3=3.13*10^{-4}$, $l_4=l_5=1.1*10^{-4}$, $l_6=l_7=0.71*10^{-4}$

Figure 2.6.1.2. The residuals of buffers of Type 6 systems using DoE optimization method (1st step)



* $p_k = 100 * [(k-0.5)/k]$

Table 2.6.2.1. The results of experimental runs of optimization of AAS (Type 6) using DoE approach, 2nd experiment set (2nd step)

initial levels of buffers:

buffers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
-	11	9	9	8	8	7	7	5	5	5	5	5	5	5	5
+	12	10	10	9	9	8	8	6	6	6	6	6	6	6	6
jam rate	3	3	0	5	0	0.5	0	3	0	0.5	0	0.5	0	0	0

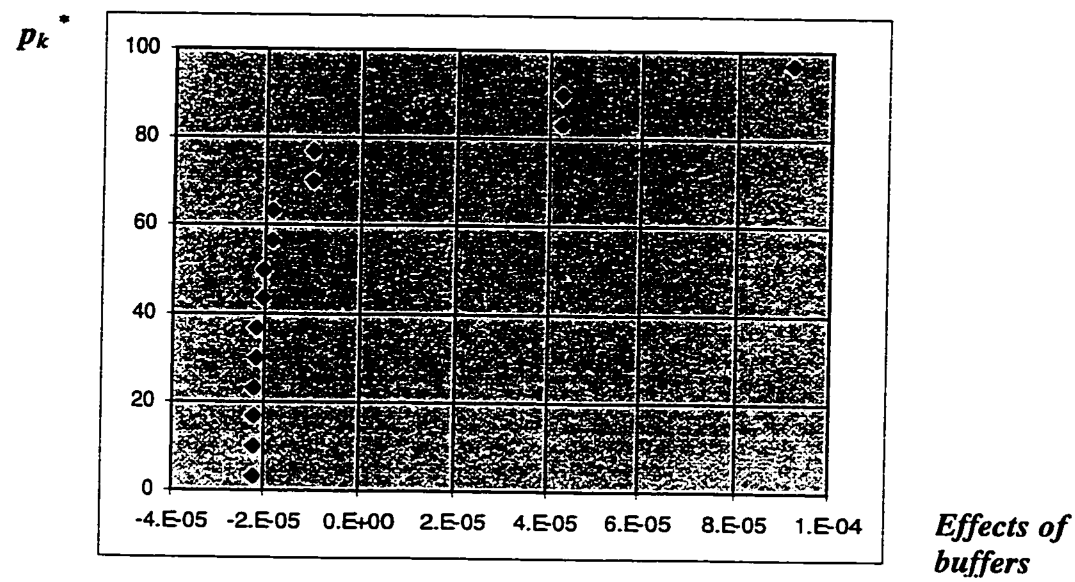
number of pallets : 60, jam clear time : 20 time units, cycle time : 5 time units

experimental run order	TP	variance (10^{-10})
1	.141074	72958
2	.140926	73861
3	.140923	71396
4	.140958	73960
5	.141032	67256
6	.141067	69742
7	.141049	67261
8	.141084	69733
9	.141107	68020
10	.141107	68020
11	.141107	68020
12	.141107	68020
13	.141107	68020
14	.141107	68020
15	.141107	68020
16	.141107	68020

Table 2.6.2.2. The conclusion of 2nd step

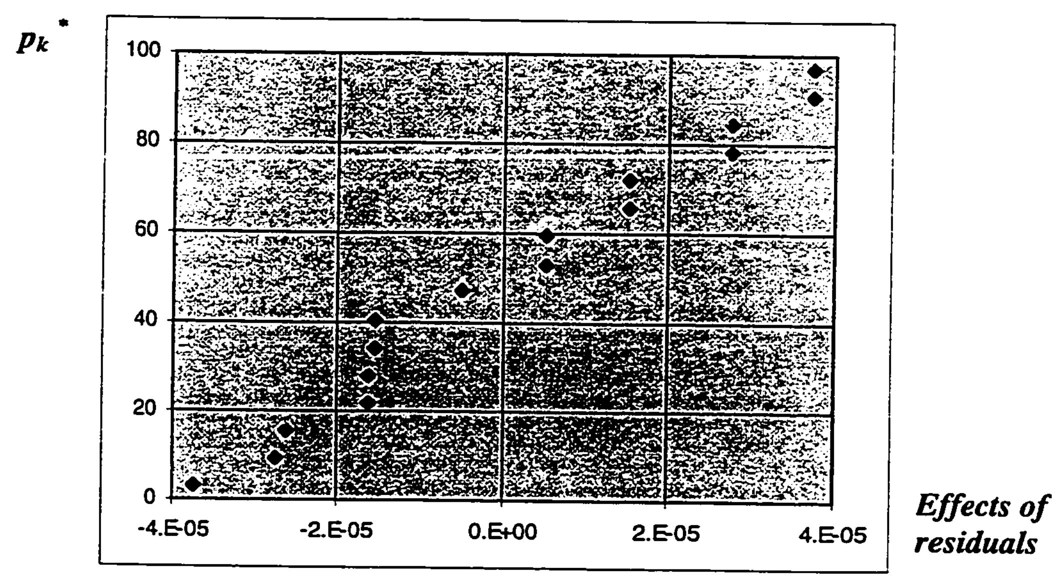
buffers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
-	13	10	10	8	8	6	6	5	5	4	4	4	4	4	4
+	14	11	11	9	9	7	7	6	6	5	5	5	5	5	5

Figure 2.6.2.1. The effects of buffers of Type 6 systems using DoE optimization method (2nd step)



$l_1=9.29*10^{-5}, l_2=l_3=4.39*10^{-5}, l_{10}=l_{11}=l_{12}=l_{13}=l_{14}=l_{15}=-2.29*10^{-5}, l_6=l_7=-1.91*10^5$

Figure 2.6.2.2. The residuals of buffers of Type 6 systems using DoE optimization method (2nd step)



$^* p_k = 100 * [(k\text{-}0.5)/k]$

Table 2.6.3.1. The results of experimental runs of optimization of AAS (Type 6) using DoE approach, 3rd experiment set (3rd step)

initial levels of buffers:

buffers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
-	13	10	10	8	8	6	6	5	5	4	4	4	4	4	4
+	14	11	11	9	9	7	7	6	6	5	5	5	5	5	5
jam rate	3	3	0	5	0	0.5	0	3	0	0.5	0	0.5	0	0	0

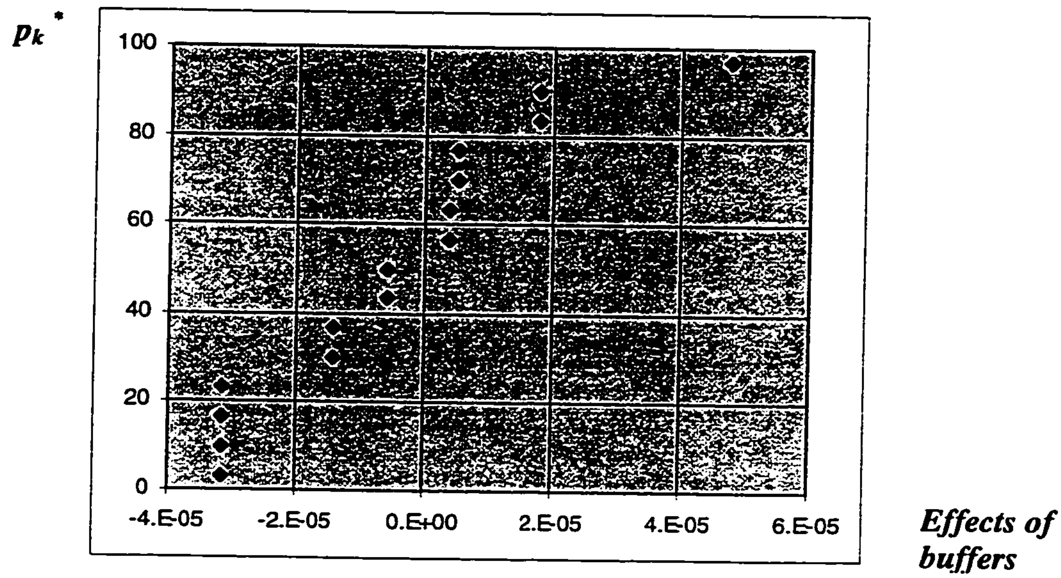
number of pallets : 60, jam clear time : 20 time units, cycle time : 5 time units

experimental run order	TP	variance (10^{-10})
1	.141423	66817
2	.141275	67964
3	.141330	64859
4	.141365	67263
5	.141321	66727
6	.141426	65882
7	.141377	63703
8	.141412	66070
9	.141414	63987
10	.141414	63987
11	.141414	63987
12	.141414	63987
13	.141414	63987
14	.141414	63987
15	.141414	63987
16	.141414	63987

Table 2.6.3.2. The conclusion of 3rd step

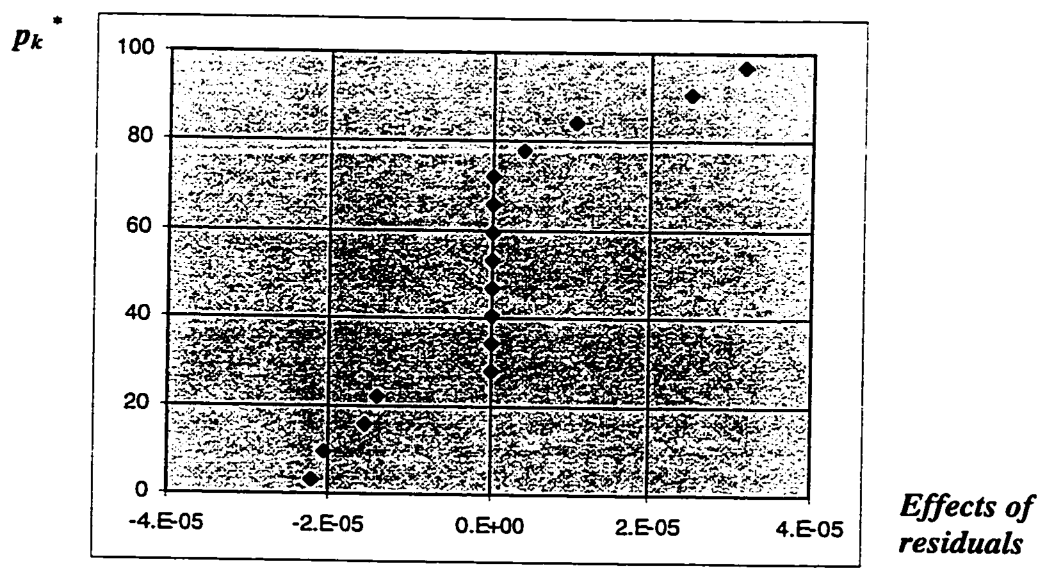
buffers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
-	14	10	10	8	8	6	6	5	5	3	3	4	4	3	3
+	15	11	11	9	9	7	7	6	6	4	4	5	5	4	4

Figure 2.6.3.1. The effects of buffers of Type 6 systems using DoE optimization method (3rd step)



$l_1=4.79*10^{-5}, l_{10}=l_{11}=l_{14}=l_{15}=-3.16*10^{-5}$

Figure 2.6.3.2. The residuals of buffers of Type 6 systems using DoE optimization method (3rd step)



$^{*}p_k = 100 * [(k-0.5)/k]$

Table 2.6.4.1. The results of experimental runs of optimization of AAS (Type 6) using DoE approach, 4th experiment set (4th step)

initial levels of buffers:

buffers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
-	14	10	10	8	8	6	6	5	5	3	3	4	4	3	3
+	15	11	11	9	9	7	7	6	6	4	4	5	5	4	4
jam rate	3	3	0	5	0	0.5	0	3	0	0.5	0	0.5	0	0	0

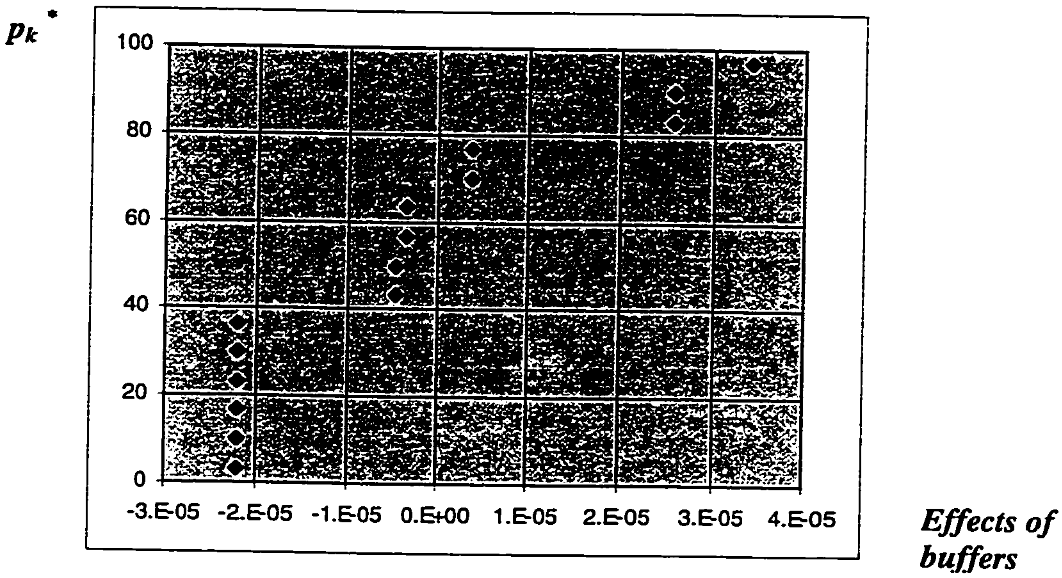
number of pallets : 60, jam clear time : 20 time units, cycle time : 5 time units

experimental run order	TP	Variance (10^{-10})
1	.141558	66143
2	.141416	67144
3	.141470	64009
4	.141505	66378
5	.141528	62785
6	.141563	65110
7	.141514	62973
8	.141549	65308
9	.141547	63707
10	.141547	63707
11	.141547	63707
12	.141547	63707
13	.141547	63707
14	.141547	63707
15	.141547	63707
16	.141547	63707

Table 2.6.4.2. The conclusion of 4th step

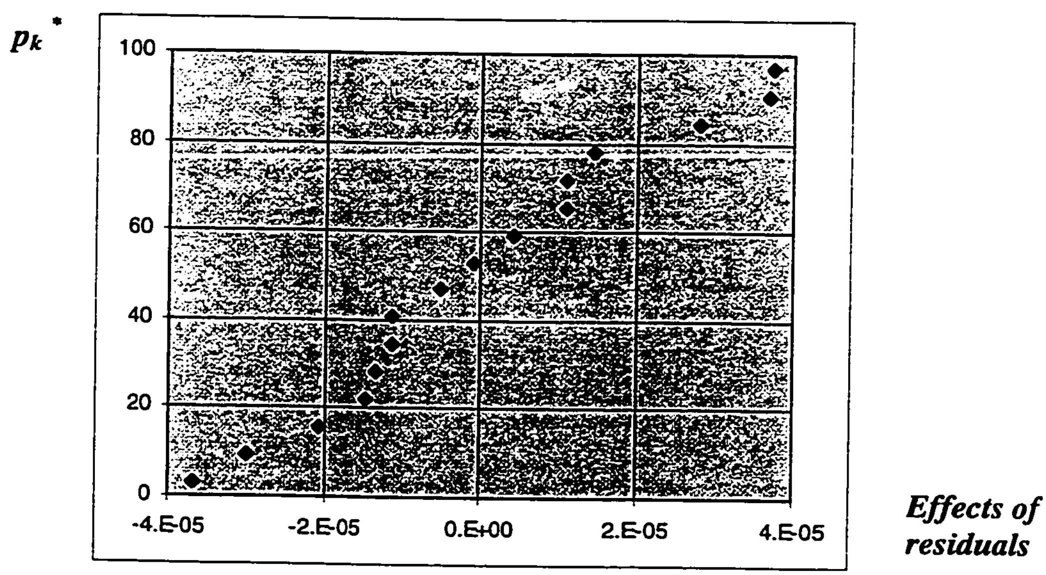
buffers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
-	15	11	11	8	8	6	6	5	5	2	2	3	3	2	2
+	16	12	12	9	9	7	7	6	6	3	3	4	4	3	3

Figure 2.6.4.1. The effects of buffers of Type 6 systems using DoE optimization method (4th step)



$l_1=3.41*10^{-5}$, $l_2=l_3=2.56*10^{-5}$, $l_{10}=l_{11}=l_{12}=l_{13}=l_{14}=l_{15}=-2.21*10^{-5}$

Figure 2.6.4.2. The residuals of buffers of Type 6 systems using DoE optimization method (4th step)



$^{*}p_k = 100 * [(k-0.5)/k]$

Table 2.6.5.1. The results of experimental runs of optimization of AAS (Type 6) using DoE approach, 5th experiment set (5th step)

initial levels of buffers:

buffers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
-	15	11	11	8	8	6	6	5	5	2	2	3	3	2	2
+	16	12	12	9	9	7	7	6	6	3	3	4	4	3	3
jam rate	3	3	0	5	0	0.5	0	3	0	0.5	0	0.5	0	0	0

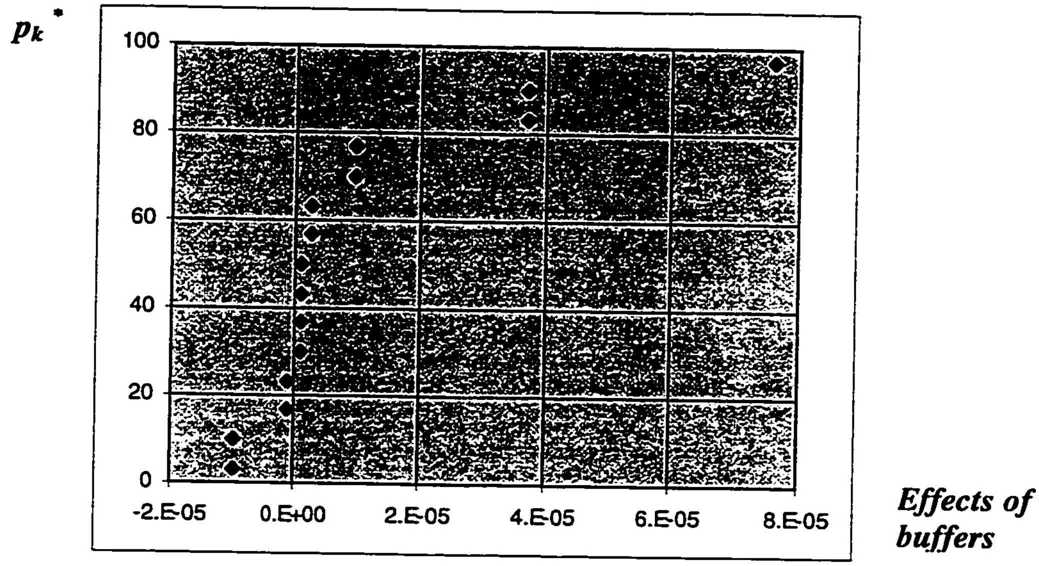
number of pallets : 60, jam clear time : 20 time units, cycle time : 5 time units

experimental run order	m	variance (10[illegible])
1	.141658	58433
2	.141639	65570
3	.141686	62086
4	.141660	59444
5	.141733	63334
6	.141751	64105
7	.141719	63553
8	.141737	64329
9	.141774	61212
10	.141774	61212
11	.141774	61212
12	.141774	61212
13	.141774	61212
14	.141774	61212
15	.141774	61212
16	.141774	61212

Table 2.6.5.2. The conclusion of 5th step

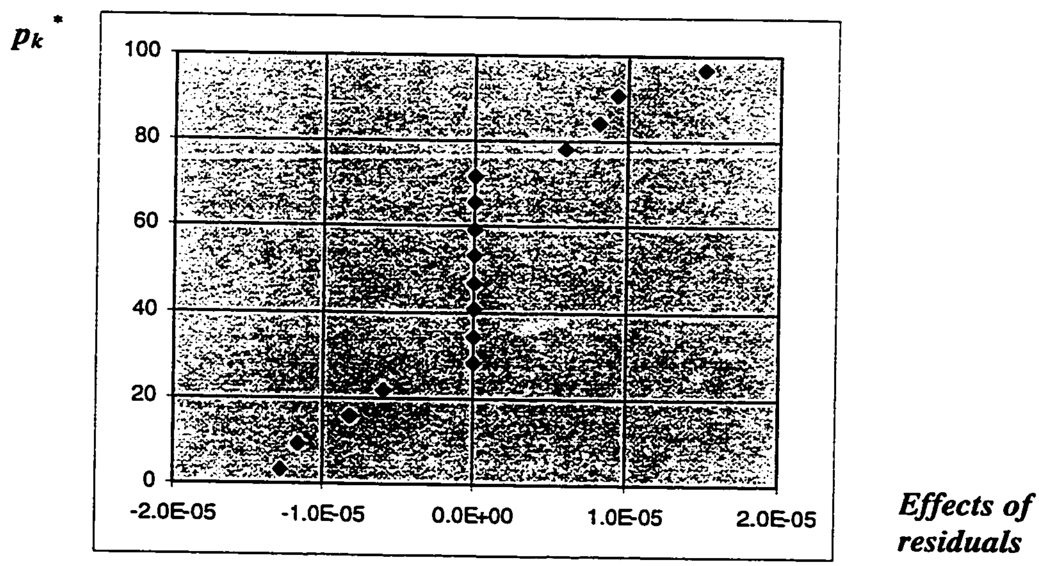
buffers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
-	16	12	12	8	8	6	6	5	5	1	1	3	3	2	2
+	17	13	13	9	9	7	7	6	6	2	2	4	4	3	3

Figure 2.6.5.1. The effects of buffers of Type 6 systems using DoE optimization method (5th step)



$l_1=7.61*10^{-5}, l_2=l_3=3.71*10^{-5}, l_{10}=l_{11}=-1.01*10^{-5}$

Figure 2.6.5.2. The residuals of buffers of Type 6 systems using DoE optimization method (5th step)



* $p_k = 100 * [(k-0.5)/k]$

Table 2.6.6.1. The results of experimental runs of optimization of AAS (Type 6) using DoE approach, 6th experiment set (6th step)

buffers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
-	16	12	12	8	8	6	6	5	5	1	1	3	3	2	2
+	17	13	13	9	9	7	7	6	6	2	2	4	4	3	3
jam rates	3	3	0	5	0	0.5	0	3	0	0.5	0	0.5	0	0	0

number of pallets : 60, jam clear time : 20 time units, cycle time : 5 time units

experimental run order	TP	variance (10^{-10})
1	.141774	55005
2	.141739	64578
3	.141772	59536
4	.141746	57170
5	.141753	60462
6	.141770	61212
7	.141739	60708
8	.141756	61463
9	.141749	61241
10	.141749	61241
11	.141749	61241
12	.141749	61241
13	.141749	61241
14	.141749	61241
15	.141749	61241
16	.141749	61241

Table 3.1.1. The experimental runs for the Type 1 systems and jam rates and jam clear times as noise factors

[illegible]	[illegible]		[illegible]		[illegible]		[illegible]	
[illegible]	[illegible]		[illegible]		[illegible]		[illegible]	
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	.152726	71934	.150888	85817	.137618	143810	.133877	158239
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	.152651	67124	.150837	82687	.137372	149005	.133656	158208
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	.152696	68819	.150867	84347	.137393	139348	.133614	155945
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	.152777	66087	.150947	81259	.137747	153100	.134002	166337
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	.152628	67452	.150798	79104	.137249	159642	.133567	167409
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	.152849	67480	.151005	82901	.137809	143064	.134093	155867
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
13	.152747	68143	.150926	82506	.137730	153049	.133986	165215
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
15	.152760	66744	.150967	80560	.137779	144697	.134126	156094
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
17	.152733	68651	.150874	84286	.137304	147106	.133567	157385
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
19	.152811	65376	.150967	81610	.137744	144332	.134004	158852
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
21	.152670	65987	.150835	80149	.137540	165166	.133877	167104
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
23	.152884	65529	.151053	83423	.137770	142798	.134082	154268
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
25	.152760	67390	.150923	82330	.137751	140202	.133970	157636
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
27	.152781	63064	.150953	80795	.137730	147442	.133995	162670
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
29	.152795	64224	.150977	80724	.137804	137272	.134030	154251
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
31	.152765	62449	.150926	77661	.137707	152141	.134035	166751
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Table 3.1.2. The mean of the TP and $variance_{wrtnf}$ for each buffer configuration (i.e., the row of inner array) of Type 1 systems

[illegible]	[illegible]	[illegible]
1	0.143777	8.89
2	[illegible]	[illegible]
3	0.143629	9.07
4	[illegible]	[illegible]
5	0.143643	9.13
6	[illegible]	[illegible]
7	0.143868	8.81
8	[illegible]	[illegible]
9	0.143561	9.14
10	[illegible]	[illegible]
11	0.143939	8.79
12	[illegible]	[illegible]
13	0.143847	8.8
14	[illegible]	[illegible]
15	0.143908	8.71
16	[illegible]	[illegible]
17	0.143620	9.22
18	[illegible]	[illegible]
19	0.143882	8.84
20	[illegible]	[illegible]
21	0.143731	8.86
22	[illegible]	[illegible]
23	0.143947	8.85
24	[illegible]	[illegible]
25	0.143851	8.81
26	[illegible]	[illegible]
27	0.143865	8.83
28	[illegible]	[illegible]
29	0.143902	8.79
30	[illegible]	[illegible]
31	0.143858	8.79
32	[illegible]	[illegible]

Table 3.2.1. The experimental runs for the Type 2 systems and jam rates and jam clear times as noise factors

[illegible]	[illegible]							
	[illegible]		[illegible]		[illegible]		[illegible]	
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	.136158	159641	.132484	148987	.129296	111433	.127675	152453
2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	.136570	175358	.133030	166595	.129630	120817	.128060	156446
4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	.136705	171796	.133163	168567	.129709	117093	.128179	155218
6	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	.136488	172211	.132911	162907	.129477	112892	.127946	154249
8	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	.136567	173749	.133044	165639	.129593	118813	.128051	154575
10	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	.136635	171193	.133058	166178	.129572	110938	.128081	152713
12	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

[illegible]	[illegible]							
	[illegible]		[illegible]		[illegible]		[illegible]	
[illegible]	TP	[illegible]	TP	[illegible]	TP	[illegible]	TP	[illegible]
1	.128818	273474	.126902	300763	.126411	175901	.126530	213100
2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	.129051	288868	.127114	297067	.126568	191092	.126646	218927
4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	.129182	288448	.127304	291724	.126719	185011	.126800	207397
6	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	.129128	283498	.127230	290931	.126505	187115	.126598	217360
8	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	.129130	287821	.127247	292356	.126561	189407	.126616	217182
10	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	.129137	285275	.127279	290731	.126709	183376	.126765	207088
12	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Table 3.2.2. The mean of the TP and $variance_{wrtnf}$ for each buffer configuration (i.e., the row of inner array) of Type 2 systems

[illegible]	[illegible]	[illegible]
1	0.129284	1.17E-05
2	[illegible]	[illegible]
3	0.129584	1.24E-05
4	[illegible]	[illegible]
5	0.12972	1.24E-05
6	[illegible]	[illegible]
7	0.129535	1.22E-05
8	[illegible]	[illegible]
9	0.129601	1.24E-05
10	[illegible]	[illegible]
11	0.129655	1.22E-05
12	[illegible]	[illegible]

Table 3.3.1. The experimental runs for the Type 3 systems and jam rates and jam clear times as noise factors

[illegible]	[illegible]							
[illegible]	[illegible]		[illegible]		[illegible]		[illegible]	
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	.136432	313605	.132775	346765	.128035	364886	.127288	355686
2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	.136468	313228	.132884	342399	.128107	333586	.127284	340360
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	.136479	301036	.132940	327671	.128067	333380	.127346	330496
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	.136347	306010	.132802	334610	.128023	334653	.127193	336514
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	.136323	320120	.132718	355505	.128039	335551	.127168	343763
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	.136375	306626	.132826	332838	.128047	334625	.127212	339155
12	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

[illegible]	[illegible]							
[illegible]	[illegible]		[illegible]		[illegible]		[illegible]	
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	.128509	401568	.125960	366348	.127584	455927	.127926	491252
2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	.128511	397970	.125923	359993	.127516	447532	.127851	481416
4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	.128479	395194	.125882	357489	.127544	442518	.128870	474590
6	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	.128439	396078	.125821	355326	.127426	446898	.127802	480023
8	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	.128428	299415	.125807	358077	.127388	451650	.127725	489115
10	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	.128463	396333	.125872	356476	.127460	447993	.127835	481163
12	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Table 3.3.2. The mean of the TP and $variance_{wrtnf}$ for each buffer configuration (i.e., the row of inner array) of Type 3 systems

[illegible]	[illegible]	[illegible]
1	0.129314	1.22E-05
[illegible]	[illegible]	[illegible]
3	0.129318	1.24E-05
[illegible]	[illegible]	[illegible]
5	0.129451	1.22E-05
6	[illegible]	[illegible]
7	0.129232	1.24E-05
8	[illegible]	[illegible]
9	0.1292	1.23E-05
10	[illegible]	[illegible]
11	0.129261	1.23E-05
12	[illegible]	1.24E-05

Table 3.4.1. The experimental runs for the Type 4 systems and jam rates and jam clear times as noise factors

[illegible]	[illegible]								
[illegible]	[illegible]		[illegible]		[illegible]		[illegible]		[illegible]
exp run	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	.155142	61270	.153314	80674	.150039	45502	.150419	107760	.149854
2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	.155105	59508	.153342	80872	.150111	44531	.150391	103950	.149828
4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	.155098	59160	.153333	80892	.150160	45930	.150437	105419	.149821
6	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	.155128	58309	.153382	80302	.150161	46426	.150439	106100	.149881
8	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	.155128	58309	.153325	81114	.150153	44778	.150428	105181	.149839
10	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	.155137	58522	.153372	78543	.150107	44476	.150428	104908	.149835
12	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

[illegible]	[illegible]								
[illegible]	[illegible]	[illegible]		[illegible]		[illegible]		[illegible]	
exp run	var	TP	var	TP	var	TP	var	TP	var
1	131181	.149184	143287	.150639	61791	.150725	61645	.153256	86378
2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	128063	.149154	143026	.150642	63120	.150721	60007	.153219	85109
4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	127052	.149175	141618	.150649	64092	.150744	60904	.153216	84215
6	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	126584	.149135	143587	.150660	62943	.150788	59346	.153288	83646
8	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	130210	.149118	143510	.150675	64192	.150767	61653	.153267	83360
10	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	123273	.149167	142040	.150670	62843	.150760	59912	.153298	82635
12	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Table 3.4.2. The mean of the TP and *variance$_{wrtnf}$* for each buffer configuration (i.e., the row of inner array) of Type 4 systems

[illegible]	[illegible]	[illegible]
1	0.151397	4.03E-06
2	[illegible]	[illegible]
3	0.15139	4E-06
4	[illegible]	[illegible]
5	0.151404	3.95E-06
6	[illegible]	[illegible]
7	0.151429	4.03E-06
8	[illegible]	[illegible]
9	0.151411	4.02E-06
10	[illegible]	4E-06
11	0.151419	4.06E-06
12	[illegible]	4.01E-06

Table 3.5.1. The experimental runs for the Type 5 systems and jam rates as noise factors (sets 1 to 4)

[illegible]	[illegible]							
	[illegible]		[illegible]		[illegible]		[illegible]	
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	0.143602	40673	0.142496	27317	0.141956	66480	0.140716	37053
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	0.143598	40604	0.142493	27763	0.141900	67022	0.140665	36963
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	0.143551	40604	0.142493	27763	0.141900	67022	0.140665	36963
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	0.143560	40729	0.142446	27787	0.141839	67064	0.140609	36783
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	0.143549	40922	0.142481	27631	0.141921	67906	0.140709	37917
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	0.143549	40698	0.142461	28093	0.141860	67955	0.140644	37622
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
13	0.143504	40698	0.142461	28093	0.141860	67955	0.140644	37622
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
15	0.143566	40853	0.142409	28017	0.141800	67728	0.140577	36667
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
17	0.143549	40922	0.142481	27631	0.141921	67906	0.140709	37917
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
19	0.143549	40698	0.142461	28093	0.141860	67955	0.140644	37622
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
21	0.143549	40698	0.142461	28093	0.141860	67955	0.140577	37622
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
23	0.143504	40853	0.142409	28017	0.141800	67728	0.140651	36667
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
25	0.143516	41036	0.142432	27572	0.141860	67955	0.140582	37554
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
27	0.143504	40853	0.142411	27991	0.141800	67728	0.140582	36616
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
29	0.143504	40853	0.142411	27991	0.141800	67728	0.140582	36616
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
31	0.143468	41155	0.142356	27963	0.141740	67310	0.140509	35770
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Table 3.5.1. The experimental runs for the Type 5 systems and jam rates as noise factors (continued; sets 5 to 8)

[illegible]	[illegible]							
[illegible]	[illegible]		[illegible]		[illegible]		[illegible]	
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	0.142025	101040	0.140823	87207	0.140442	91586	0.139072	71838
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	0.142089	99172	0.140911	86437	0.140453	92274	0.139118	71985
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	0.142144	97668	0.140932	85449	0.140518	85990	0.139160	68678
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	0.142168	94602	0.140977	82827	0.140505	86547	0.139163	68111
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	0.141982	100988	0.140821	87441	0.140402	91304	0.139065	71391
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	0.142040	99135	0.140895	86702	0.140414	92500	0.139089	71819
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
13	0.142095	97637	0.140919	85748	0.140474	86013	0.139132	68404
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
15	0.142118	94665	0.140944	82721	0.140460	86912	0.139121	67733
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
17	0.141982	100988	0.140821	87441	0.140402	91304	0.139065	71391
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
19	0.142040	99135	0.140895	86702	0.140414	92500	0.139089	71819
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
21	0.142095	97637	0.140919	85748	0.140474	86013	0.139132	68404
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
23	0.142118	94665	0.140944	82721	0.140460	86912	0.139121	67733
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
25	0.141940	100828	0.140781	87131	0.140353	90914	0.139011	70533
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
27	0.141993	99235	0.140842	86199	0.140351	92032	0.139018	70815
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
29	0.142046	977313	0.140865	85195	0.140411	85549	0.139060	67372
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
31	0.142068	94858	0.140886	82239	0.140398	86613	0.139046	66901
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Table 3.5.1. The experimental runs for the Type 5 systems and jam rates as noise factors (continued; sets 9 to 12)

[illegible]	[illegible]							
	[illegible]		[illegible]		[illegible]		[illegible]	
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	0.139849	64646	0.138751	57190	0.138551	68349	0.137526	47027
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	0.139830	63634	0.138723	56151	0.138526	66918	0.137489	46032
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	0.139830	63634	0.138723	55059	0.138526	66918	0.137489	46032
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	0.139805	62517	0.138693	56105	0.138500	65620	0.137456	44821
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	0.139812	64306	0.138732	55271	0.138560	67753	0.137547	47093
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	0.139788	63159	0.138695	55271	0.138530	66405	0.137500	45891
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
13	0.139788	63159	0.138695	55271	0.138530	66405	0.137500	46304
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
15	0.139765	62220	0.138661	54394	0.138500	65408	0.137453	44742
16	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
17	0.139812	64306	0.138732	56105	0.138560	67753	0.137547	47093
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
19	0.139788	63159	0.138695	55271	0.138530	66405	0.137500	45891
20	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
21	0.139788	63159	0.138695	55271	0.138530	66405	0.137500	45891
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
23	0.139765	62220	0.138661	54394	0.138560	67753	0.137453	44742
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
25	0.139711	61640	0.138700	55245	0.138521	66886	0.137504	46091
26	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
27	0.139748	62861	0.138663	54415	0.138493	65781	0.137454	44883
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
29	0.139747	62861	0.138663	54415	0.138493	65781	0.137454	44883
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
31	0.139718	61405	0.138626	53636	0.138451	64273	0.137404	43819
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Table 3.5.1. The experimental runs for the Type 5 systems and jam rates as noise factors (continued; sets 13 to 16)

[illegible]	[illegible]							
	[illegible]		[illegible]		[illegible]		[illegible]	
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	0.138368	120083	0.137226	110326	0.136984	99913	0.135853	77759
2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	0.138396	116136	0.137353	106566	0.137025	99425	0.135912	78384
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	0.138491	110230	0.137419	102811	0.136984	99913	0.135933	74781
6	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	0.138509	106595	0.137442	99206	0.136944	103812	0.135986	75754
8	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	0.138326	118928	0.137307	109535	0.136975	99973	0.135872	78903
10	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	0.138353	115249	0.137330	105865	0.137014	99763	0.135919	79455
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
13	0.138446	109374	0.137391	102098	0.137060	94611	0.135940	75763
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
15	0.138465	105981	0.137411	98639	0.137105	95573	0.135984	76691
16	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
17	0.138326	118928	0.137307	109535	0.136975	99973	0.135872	78903
18	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
19	0.138353	115249	0.137330	109865	0.137014	99763	0.135919	79455
20	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
21	0.138446	109374	0.137391	102098	0.137060	94611	0.135940	75763
22	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
23	0.138465	105981	0.137411	98639	0.137105	95573	0.135984	76697
24	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
25	0.138286	118053	0.137279	109155	0.136935	99640	0.135828	78561
26	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
27	0.138311	114597	0.137302	105587	0.136972	99567	0.135868	78986
28	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
29	0.138402	108748	0.137354	101636	0.137011	94011	0.135889	75300
30	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
31	0.138416	104715	0.137377	98220	0.137051	94840	0.135926	76388
32	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Table 3.5.1. The experimental runs for the Type 5 systems and jam rates as noise factors (continued; sets 17 to 20)

[redacted]	[redacted]							
[redacted]	[redacted]		[redacted]		[redacted]		[redacted]	
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
1	0.142688	36691	0.141412	18940	0.140998	46638	0.139591	22390
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
3	0.142693	37008	0.141405	19771	0.140951	46514	0.139547	21984
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
5	0.142693	37008	0.141405	19771	0.140951	46514	0.139547	21984
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
7	0.142663	37146	0.141360	19712	0.140898	46429	0.139498	21709
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
9	0.142714	37308	0.141467	18333	0.141000	48071	0.139625	22454
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
11	0.142723	37589	0.141442	19236	0.140949	47806	0.139565	22048
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
13	0.142723	37589	0.141442	19236	0.140949	48806	0.139565	22048
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
15	0.142689	37605	0.141382	19299	0.140896	47639	0.139493	21805
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
17	0.142732	37985	0.141528	20160	0.140986	47641	0.139651	22098
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
19	0.142740	38116	0.141504	21012	0.140935	47375	0.139588	21746
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
21	0.142740	38116	0.141504	21012	0.140935	47375	0.139588	21746
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
23	0.142702	37874	0.141440	20994	0.140881	47255	0.139516	21455
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
25	0.142753	38158	0.141512	19799	0.140974	48646	0.139642	22159
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
27	0.142758	38181	0.141481	20602	0.140928	48486	0.139568	21870
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
29	0.142758	38181	0.141481	20602	0.140928	48486	0.139568	21870
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
31	0.142751	37927	0.141414	20625	0.140872	48306	0.139488	21693
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]

Table 3.5.1. The experimental runs for the Type 5 systems and jam rates as noise factors (continued; sets 21 to 24)

[illegible]	[illegible]							
	[illegible]		[illegible]		[illegible]		[illegible]	
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	0.141040	85669	0.139779	74097	0.139435	70465	0.137893	49450
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	0.141107	84831	0.139854	73613	0.139463	71667	0.137925	49881
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	0.141153	83000	0.139877	72031	0.139519	66174	0.137963	47415
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	0.141189	80936	0.139914	69283	0.139526	66481	0.137981	46696
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	0.141058	85612	0.139816	72876	0.139426	71107	0.137905	49165
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	0.141123	85291	0.139867	72355	0.139449	71997	0.137928	49693
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
13	0.141174	83540	0.139889	70900	0.139507	66504	0.137963	46985
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
15	0.141205	81514	0.139912	68223	0.139509	71246	0.137965	46449
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
17	0.141058	87631	0.139867	75904	0.139416	72387	0.137926	49149
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
19	0.141119	87363	0.139916	75388	0.139430	66606	0.137939	49939
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
21	0.141168	85413	0.139940	73872	0.139495	67445	0.137981	46957
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
23	0.141198	83414	0.139958	71000	0.139488	71684	0.137974	46728
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
25	0.141077	87957	0.139842	74563	0.139405	72986	0.137914	49133
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
27	0.141130	87527	0.139886	73987	0.139412	67145	0.137921	50109
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
29	0.141184	85763	0.139909	72445	0.139479	67028	0.138130	46097
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
31	0.141209	83675	0.139925	69756	0.139465	68306	0.137951	47073
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Table 3.5.1. The experimental runs for the Type 5 systems and jam rates as noise factors (continued; sets 25 to 28)

[illegible]	[illegible]							
	[illegible]		[illegible]		[illegible]		[illegible]	
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	0.139018	63511	0.137937	50775	0.137682	53098	0.136642	33099
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	0.139007	63498	0.137912	49874	0.137679	55249	0.136639	32885
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	0.139007	63498	0.137912	49874	0.137679	55249	0.136639	32885
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	0.139989	63054	0.137884	49044	0.137640	55249	0.136609	32106
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	0.139016	64436	0.137960	50597	0.137756	53299	0.136718	33459
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	0.139998	63882	0.137925	49779	0.137739	54505	0.136704	33003
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
13	0.139998	63882	0.137925	49779	0.137679	55249	0.136704	33003
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
15	0.139975	633065	0.137891	49017	0.137700	53961	0.136653	32376
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
17	0.139026	65886	0.137988	53021	0.137749	53355	0.136747	33592
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
19	0.139007	65279	0.137954	52211	0.137732	54565	0.136732	33220
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
21	0.139007	65279	0.137954	52211	0.137732	54565	0.136732	33220
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
23	0.139984	64445	0.137923	51451	0.137693	54023	0.136688	32657
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
25	0.139011	65706	0.137989	52965	0.137772	53545	0.136760	33741
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
27	0.139988	64864	0.137954	52133	0.137746	54182	0.136728	33386
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
29	0.139988	64864	0.137954	52133	0.137746	54182	0.136728	33386
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
31	0.139958	63560	0.137916	51212	0.137698	53110	0.136677	32759
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Table 3.5.1. The experimental runs for the Type 5 systems and jam rates as noise factors (continued; sets 29 to 32)

[illegible]	[illegible]							
	[illegible]		[illegible]		[illegible]		[illegible]	
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	0.137619	112876	0.136642	94000	0.136182	80038	0.135163	58114
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	0.137667	109026	0.136675	90211	0.136256	82124	0.135235	58398
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	0.137733	103246	0.136725	86347	0.136291	78472	0.135246	55854
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	0.137774	100131	0.136754	82826	0.136342	79106	0.135274	56387
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	0.137614	112134	0.136656	92513	0.136249	81855	0.135235	59352
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	0.137653	108614	0.136681	89023	0.136309	83445	0.135286	59921
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
13	0.137719	102852	0.136730	85317	0.136328	79256	0.135296	57264
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
15	0.137751	99360	0.136756	81770	0.136379	80112	0.135314	57912
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
17	0.137632	114611	0.136689	96012	0.136267	82581	0.135279	61114
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
19	0.137670	111041	0.136721	92524	0.136323	84404	0.135330	61690
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
21	0.137737	105216	0.136763	88649	0.136356	79858	0.135340	59012
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
23	0.137768	101682	0.136791	85030	0.136402	81283	0.135358	59680
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
25	0.137609	113669	0.136672	95072	0.136270	83637	0.135277	62116
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
27	0.137644	109983	0.136702	91514	0.136284	85338	0.135311	62876
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
29	0.137709	104181	0.136744	87942	0.136337	80219	0.135325	60051
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
31	0.137733	100102	0.136772	84235	0.136375	81132	0.135333	60906
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Table 3.5.2. The mean of the TP and $variance_{wrtnf}$ **for each buffer configuration (i.e., the row of inner array) of Type 5 systems**

[illegible]	[illegible]	[illegible]
1	0.139186	4.76
[illegible]	[illegible]	[illegible]
3	0.139203	4.70
[illegible]	[illegible]	[illegible]
5	0.139222	4.68
[illegible]	[illegible]	[illegible]
7	0.139247	4.65
[illegible]	[illegible]	[illegible]
9	0.139196	4.68
[illegible]	[illegible]	[illegible]
11	0.139232	4.65
[illegible]	[illegible]	[illegible]
13	0.139251	4.63
[illegible]	[illegible]	[illegible]
15	0.139244	4.58
[illegible]	[illegible]	[illegible]
17	0.139206	4.66
[illegible]	[illegible]	[illegible]
19	0.139210	4.62
[illegible]	[illegible]	[illegible]
21	0.139231	4.59
[illegible]	[illegible]	[illegible]
23	0.139255	4.55
[illegible]	[illegible]	[illegible]
25	0.139179	4.63
[illegible]	[illegible]	[illegible]
27	0.139211	4.63
[illegible]	[illegible]	[illegible]
29	0.139239	4.59
[illegible]	[illegible]	[illegible]
31	0.139218	4.55
[illegible]	[illegible]	[illegible]

Table 3.6.1. The experimental runs for the Type 5 systems and jam rates and jam clear times as noise factors (2nd study)

[illegible]	[illegible]		[illegible]		[illegible]		[illegible]	
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	.144761	36215	.139672	44759	.141986	22676	.140533	90064
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	.144798	36050	.139675	44838	.141858	23023	.140607	91143
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	.144798	36260	.139689	43693	.141858	23023	.140670	84932
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	.144721	36543	.139719	42026	.141896	23980	.140616	86175
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	.144761	36215	.139637	45348	.141907	21614	.140533	90064
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	.144721	36543	.139663	44638	.141926	23985	.140505	91866
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
13	.144721	36543	.139689	42846	.141926	23985	.140554	85023
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
15	.144721	36543	.139688	42291	.141821	22985	.140616	86175
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

[illegible]	[illegible]		[illegible]		[illegible]		[illegible]	
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	.138649	98420	.139218	54047	.138312	108398	.138304	46682
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	.138684	96395	.139153	54620	.138353	104040	.138258	45949
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	.138744	94085	.139153	54620	.138430	098466	.138258	45949
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	.138718	89159	.139142	54336	.138430	96190	.138214	46473
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	.138649	98420	.139219	54212	.138288	107017	.138304	46682
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	.138633	93846	.139186	54895	.138295	103742	.138216	46782
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
13	.138688	91685	.139177	54790	.138368	098617	.138216	46782
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
15	.138718	89159	.139139	54550	.138412	094801	.138214	46473
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Table 3.6.1. The experimental runs for the Type 5 systems and jam rates and jam clear times as noise factors (2nd study) (continued)

[illegible]	[illegible]		[illegible]		[illegible]		[illegible]	
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	.140533	82540	.140221	36773	.139582	103316	.139533	56623
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	.140542	80409	.140193	36202	.139640	101832	.139489	55461
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	.140612	75747	.140193	36202	.139670	100126	.139489	55461
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	.140625	77196	.140119	35430	.139700	96864	.139414	57504
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	.140544	79852	.140221	36773	.139582	103316	.139560	56195
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	.140574	83193	.140126	35339	.139596	102242	.139470	57697
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
13	.140649	78415	.140126	35339	.139625	100408	.139470	57697
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
15	.140649	74614	.140119	35430	.139700	96864	.139437	56930
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

	SE 15		SE 16		SE 17		SE 18	
Expt. no.	TP	Variance (10^{-11})	TP	Variance (10^{-11})	TP	Variance (10^{-11})	TP	Variance (10^{-11})
1	.137235	62024	.136365	101561	.138416	70330	.133753	61648
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	.137158	58790	.136416	100207	.138433	69604	.133714	58454
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	.137158	58790	.136481	94944	.138433	69604	.133746	55085
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	.137196	60139	.136470	94222	.138361	67916	.133818	60088
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	.137207	59665	.136365	101561	.138416	70330	.133723	59468
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	.137219	61115	.136340	99568	.138344	68607	.133782	63175
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
13	.137219	61115	.136451	94827	.138344	68607	.133811	59695
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
15	.137165	57746	.136470	94222	.138361	67916	.133796	57526
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Table 3.6.2. The mean of the TP and *variance$_{wrtnf}$* for each buffer configuration (i.e., the row of inner array) of Type 5 systems (2nd study)

[illegible]	[illegible]	[illegible]
1	0.139192	5.8560
[illegible]	[illegible]	[illegible]
3	0.139186	5.8765
[illegible]	[illegible]	[illegible]
5	0.139211	5.8448
[illegible]	[illegible]	[illegible]
7	0.139197	5.7423
[illegible]	[illegible]	[illegible]
9	0.139182	5.8600
[illegible]	[illegible]	[illegible]
11	0.139162	5.8055
[illegible]	[illegible]	[illegible]
13	0.139190	5.7582
[illegible]	[illegible]	[illegible]
15	0.139189	5.7449
[illegible]	[illegible]	[illegible]

Table 3.7.1. The experimental runs for the Type 6 systems and jam rates and jam clear times as noise factors

[illegible]	[illegible]		[illegible]		[illegible]		[illegible]	
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	.145805	84024	.143475	95143	.142337	61152	.141705	90750
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	.145686	79438	.143377	92089	.142377	56722	.141682	93589
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	.145749	76429	.143428	89780	.142523	57960	.141781	96294
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	.145749	76429	.143428	89780	.142523	57960	.141781	96294
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	.145770	77424	.143412	91031	.142519	58034	.141753	97000
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	.145770	77424	.143412	91031	.142519	58034	.141753	97000
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
13	.145770	77424	.143412	91031	.142519	58034	.141753	97000
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
15	.145770	77424	.143412	91031	.142519	58034	.141753	97000
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

[illegible]	set5		set6		set7		set8	
exp. no	TP	variance [illegible]	TP	variance [illegible]	TP	variance [illegible]	TP	variance [illegible]
1	.140507	60173	.140998	53919	.139719	46661	.141184	58723
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	.140475	58482	.141049	52296	.139732	48192	.141093	56955
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	.140581	62206	.141163	56160	.139721	47200	.141135	57464
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	.140581	62206	.141163	56160	.139721	47200	.141135	57464
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	.140558	61954	.141147	54370	.139725	47366	.141126	57434
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	.140558	61954	.141147	54370	.139725	47366	.141126	57434
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
13	.140558	61954	.141147	54370	.139725	47366	.141126	57434
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
15	.140558	61954	.141147	54370	.139725	47366	.141126	57434
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Table 3.7.1. The experimental runs for the Type 6 systems and jam rates and jam clear times as noise factors (continued)

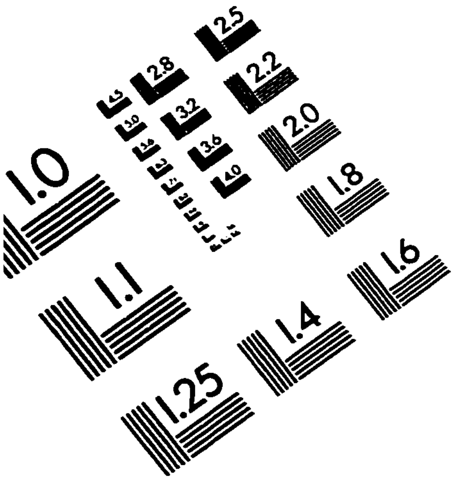
[illegible]	[illegible]		[illegible]		[illegible]		[illegible]	
exp. no.	TP	variance (10^{-5})	TP	variance (10^{-5})	TP	variance (10^{-5})	TP	variance (10^{-5})
1	.141353	72183	.139304	90260	.141386	69174	.139640	91557
2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	.141270	73371	.139228	90041	.141189	67516	.139496	89857
4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	.141291	74290	.139228	90041	.141189	67516	.139496	89857
6	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	.141291	74290	.139228	90041	.141189	67516	.139496	89857
8	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	.141291	74113	.139230	90003	.141189	67750	.139489	90611
10	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	.141291	74113	.139230	90003	.141189	67750	.139489	90611
12	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
13	.141291	74113	.139230	90003	.141189	67750	.139489	90611
14	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
15	.141291	74113	.139230	90003	.141189	67750	.139489	90611
16	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

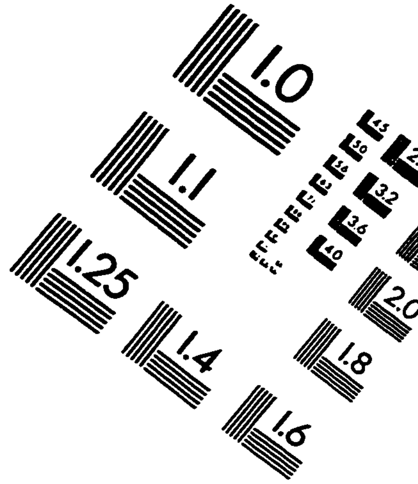
[illegible]	[illegible]		[illegible]		[illegible]		[illegible]	
exp. no.	TP	variance (10^{-5})	TP	variance (10^{-5})	TP	variance (10^{-5})	TP	variance (10^{-5})
1	.141330	76016	.141702	83187	.141549	54722	.142398	84464
2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	.141309	72552	.141754	84627	.141514	57392	.142356	85360
4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	.141395	73103	.141775	83671	.141640	58614	.142404	86507
6	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	.141395	73103	.141775	83671	.141658	58785	.142405	86506
8	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	.141396	74934	.141839	81901	.141646	60032	.142435	85649
10	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	.141396	74934	.141839	81901	.141646	60032	.142435	85649
12	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
13	.141396	74934	.141839	81901	.141646	60032	.142435	85649
14	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
15	.141396	74934	.141839	81901	.141646	60032	.142435	85649
16	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

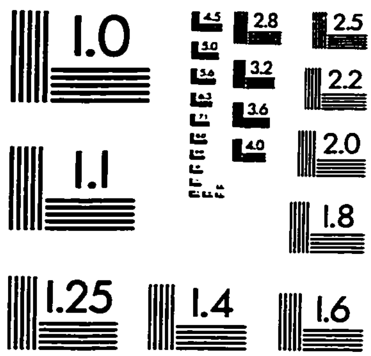
Table 3.7.2. The mean of the TP and $variance_{wrtnf}$ for each buffer configuration (i.e., the row of inner array) of Type 6 systems

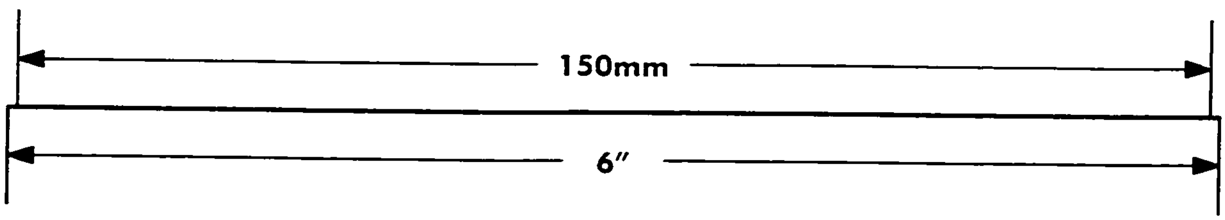
[illegible]	[illegible]	[illegible]
1	0.141525	2.458E-06
[illegible]	[illegible]	[illegible]
3	0.141474	2.436E-06
[illegible]	[illegible]	[illegible]
5	0.141531	2.492E-06
[illegible]	[illegible]	[illegible]
7	0.141532	2.492E-06
[illegible]	[illegible]	[illegible]
9	0.141533	2.509E-06
10	[illegible]	2.509E-06
11	0.141533	2.509E-06
12	[illegible]	2.509E-06
13	0.141533	2.509E-06
14	[illegible]	2.509E-06
15	0.141533	2.509E-06
16	[illegible]	2.509E-06

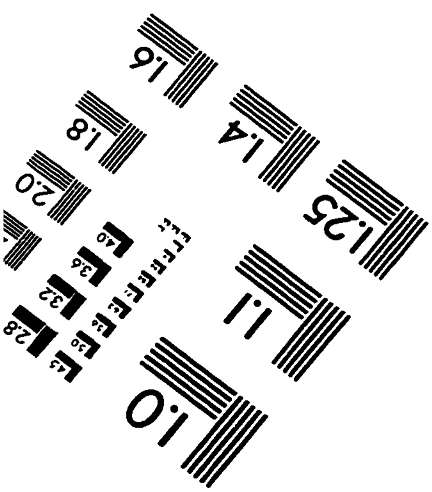
IMAGE EVALUATION
TEST TARGET (QA-3)

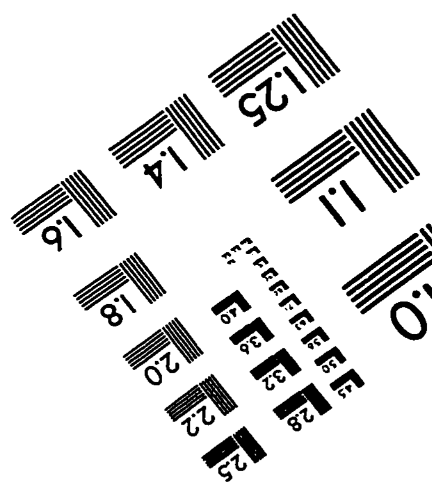












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