A ROBUST PRODUCTION SYSTEM DESIGN USING ROBUST ENGINEERING METHODOLOGY

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ABSTRACT

A Robust Production System Design Using Robust Engineering Methodology

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Traditional production system design approaches have concentrated on feasibility, meeting volume requirements, and minimizing cost. In the competitive environment of today's industries, effective and robust production systems are required. In order to be responsive to changing external requirements and internal disturbances, productions systems must be robust and design approaches must involve more than meeting volume requirements and minimizing cost.

A robust production system can handle planned as well as unplanned changes. It is well understood that the robustness can be achieved during the design process more easily and with lower costs, than during the operation phase when most system parameters are already set. There is a need to improve strategies to develop production systems which are designed from the standpoint of robustness and quality. The system robustness should be made during the design phase and not during operation when most system parameters cannot be changed with ease.

Also, there has been limited research in the area of robustness and quality for production system design in the literature. The objective of this research is to demonstrate a method for the design of robust production systems with the aid of computer simulation and to optimize a production process through simulation to make the system robust to noise factors. It has been emphasized in this research to use robust design techniques, also known as Taguchi's methods to achieve robust production systems.

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CHAPTER 1

INTRODUCTION

1.1 CONCEPT OF ROBUST ENGINEERING

Robust Engineering is an engineering optimization strategy, ideally used for the development of new technologies and for improving the quality in the areas of product and process design. Robust Engineering was developed by Dr. Genichi Taguchi to provide companies with more efficiency in development leading to a more competitive position (Phadke, 1989). Taguchi defines robustness as "the state where the technology, product, or process performance is minimally sensitive to factors causing variability and aging at the lowest unit manufacturing cost." According to Taguchi, "we measure the quality of a product or process, in terms of total loss to society due to functional variation and harmful side effects." For ideal quality, the loss would be zero. The greater the loss, the lower is the quality (Wadsworth *et al.,* 2002; Phadke, 1989).

The primary goal of this research is to demonstrate a method for the design of robust systems using computer simulation experiments. The research starts by studying the main concepts and strategies in the development of robust production systems. An attempt is then made to assess the appropriateness of the use of Taguchi method along with simulation. This research used simulation for the purpose of system design. The research is not restricted to any specific system at the outset. The concepts developed are demonstrated on example problems from selected application domain.

1.2 DESIGN FOR ROBUSTNESS AND QUALITY

In statistics, robustness is an important criterion for evaluating statistical inference. According to Huber (1981), "robustness signifies insensitivity to small deviations from the assumptions." From an engineering product design viewpoint, robustness refers to the relative insensitivity of the functional performance of a product, when its operating conditions deviate from their specific values (Kacker *et al.*, 1983). These deviations from the nominal conditions usually occur with certain factors of design, such as noise factors. A robust product is relatively insensitive to noise variations. The focus of this research is on the design of robust production systems.

Quality may be understood differently by different people. It is also different for different products, processes, or services under discussion. Even in strictly technical terms, quality can be performance, durability, reliability, delivery, shape or size. Here we intend to relate the concept of robustness with quality. We use the definition that quality is conformance to requirements or specifications. This definition was used by Crosby (1979). According to Juran, "Quality is fitness for use", this is a more general definition of Quality (Juran, 1988).

After the industrial revolution there have been tremendous improvements in the quality of the products being manufactured. Quality has been improved in design as well as in performance. The ideal quality is the target performance of the product each time the product is used by the customer, under all the specified operating conditions throughout its intended life (Wadsworth, 2002).

Quality can affect vital elements of a company such as productivity, cost, and delivery schedules. It also has a great impact on the workplace environment. When a product or a service has been designed to meet the expectations of the customer, the associated process may not always produce every unit conforming to the design. The defects in materials, parts, assemblies and the final products occur. In order to minimize or remove these defects, the product or the production process may be redesigned as per the requirements.

Quality control methods such as control charts, cause and effect diagrams, process capability studies and Statistical Process Control (SPC) are known as on-line quality control methods, since they concentrate on the manufacturing (on-line) stage in order to reduce manufacturing imperfections in the product and to keep the process in control. Among these, SPC is a powerful cost saving and quality enhancing approach to reducing variability within the production phase. However, SPC cannot compensate for poor quality in design. If there is large variability due to uncontrollable factors during manufacture, prohibitively expensive process control schemes may be required to improve the process capability, and they cannot guarantee a product robust to deterioration and variability due to uncontrollable environmental factors. Additional expense might be incurred due to service costs under warranty and, more importantly, due to the loss of market share because of customer dissatisfaction.

However, if the quality concept is moved further upstream to the design process and product development stage, these costly eventualities can be avoided. The need for costly process control, mass inspection, and service costs is minimized if one optimizes product and process design to ensure product robustness.

1.3 PRODUCT AND PROCESS DESIGN

Design involves making a system or product, when it does not come from an existing product. Quality has been concerned with two types of design problems: Product design and Process Design. Product design normally involves (Smith, 1998):

1. System Design

System design refers to activities needed to formulate an initial prototype design. This involves decisions about choosing the independent and dependent variables of the design, the ranges of values for the chosen parameters.

2. Parameter Design

Parameter design is concerned with the target values, or any other attributes involved, whereas the allowance design sets the range of variations for the target values. In other words, the parameter design refers to the investigation process carried to choose the best settings of the product and process parameters to achieve the performance goals of reaching the target performance while keeping sensitivity to noise minimal.

3. Allowance or Tolerance Design

Allowance or Tolerance design is used, if the variation in the product or process is beyond tolerable limits. The systematic changes are made on a tolerance magnitude to determine which of the factors contribute most to the variation in the end product.

Process design involves making a set of actions to convert inputs into desired outputs. Process design problem exists when a new process is created or an existing process is re-designed or revised substantially. Process design depends mainly on how much the existing process is being changed or whether a completely new process is being designed. In general, the former is process improvement and the latter is process innovation. The quality of a process depends on its capability to meet the specification limits, to produce the units that confirm to the specifications as required.

1.4 PRODUCTION SYSTEM DESIGN AND ROBUSTNESS

A robust production system is a stable system which can handle planned as well as unplanned changes. To move systems without modifications between production sites is quite common in today's global market and production place. Such as Taguchi methods and robust design methodology, product as well as process design. However a majority of the examples shown in the literature concerns product design only, not process design. This together with the awareness of that it is during the design of production system that the production system capability to a large extent is determined, motivates further research into how the design and evaluation process can support production system robustness (Chen and Chen, 1996).

There has been limited research for maintaining robustness, and for continuous improvement of quality through production system design in the literature. The conventional knowledge in studying quality related problems is largely concentrated on improving the quality of product design (Jackson, 2000).

In today's market, customers demand the best products at the best price with immediate availability. Manufacturing companies are increasingly competing against each other for market share, and they need to maintain a low cost of quality, trim their production lines, reduce waste and speed up manufacturing. This brings new possibilities but also new challenges to researchers and practitioners.

Figure 1.1 displays various tools to design and manufacture products of higher quality. The boxes on the left of the figure show the various requirements for high quality product design and production. The boxes on the right show various quality techniques interacting with the product or production process decisions. Also, the shading of the boxes represents the quality efforts, denoting the density of research in that area. The research areas represented by the three darkly shaded boxes have had substantial research attentions (Inman *et al.*, 2003). It is apparent that more research work is required in the area of robustness of production system design for better product quality.

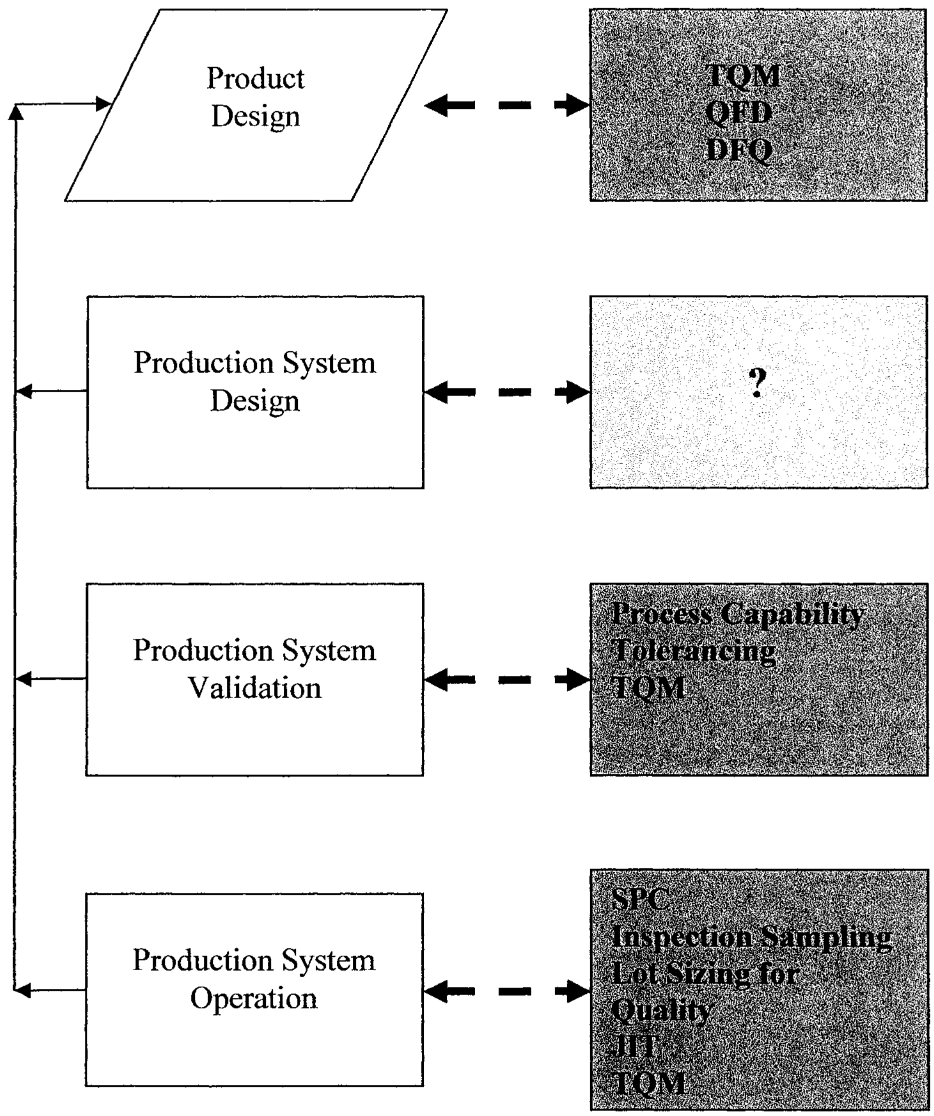

Figure 1.1: Quality Efforts Supporting the Process of Bringing a Product through Production (Inman *et al.*, 2003).

1.5 OBJECTIVES AND CONTRIBUTION OF THIS RESEARCH

In this thesis, the efforts done in the past for robust and quality production system design are studied. As there has been less work done on this topic, this thesis first reviews the limited literature related to robustness and quality in production system design and then suggests the use of robust engineering approach as a tool for production system design. This research focuses on the interaction of production system design for system performance improvement from the robustness point of view.

The main contributions of the research are as follows:

- Design a system that is robust to the uncontrollable factors, and reducing the number of experimental trials.
- Develop a quality design approach focusing on factors for evaluating the production system design.
- To optimize a production process through simulation and use Taguchi's design method to make the system robust to noise factors.

1.6 ORGANIZATION OF THE THESIS

Chapter 2 lists the previous studies in designing production systems for quality and also significant advances made in the field of design of experiments (DoE) / robust engineering for designing production systems. Various research studies in robust production system design using simulation and other important issues will be discussed.

Chapter 3 discusses various approaches for production system design. It can be understood that the main possibility to influence the system is during the design-stage.

Chapter 4 explains the Design of Experiments (DoE) approach, the robust design methodology (Taguchi Method), and the techniques used in this research. The detailed reasons for choosing the robust design methodology that satisfies the objectives of this research will be discussed. Also, the methodology by using simulation for production system design and optimizing the design through Robust Design method is discussed.

Chapter 5 presents the numerical examples and discusses features of the system used for the approach to the solution and its analysis. The process under consideration was simulated using ARENA® software and optimized using Taguchi Method through Qualitek-4® software, by Nutek Inc. and the results are analyzed.

Chapter 6 presents summary and conclusions of this research, and future research directions in this area.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

In this chapter, the literature is reviewed in two main groups: (1) studies in production system design, and (2) studies using the design of experiments (DoE) / Robust Engineering approach, and studies using simulation along with Taguchi methods. The first five sections address the first group. The last two sections review the studies done in the second group.

2.2 THE EVOLUTION OF PRODUCTION SYSTEMS

Industrial Revolution in England in the seventeenth and the eighteenth century can be considered as the beginning of a new industrial and manufacturing era. The industrial revolution led to mass production of relative simple products. The interchangeability of parts was an important landmark in the history of production systems, as it formed a pre-condition for flow-line assembly of products. The principle of interchangeable part manufacturing can be described as the art of producing complete machines or mechanisms that any part may be fitted into any of the given mechanisms (Wild, 1972; Roe, 1916).

By the mid 1800s the interchangeable parts concept had been used in making different products such as guns, clocks, sewing machines and farm machinery. By the late 1920s, a general trend had emerged that waste was wrong and efficiency should be increased; Taylor's methods represented the best way to achieve this (Wild, 1972). Taylor's Scientific Management focused on the division of labor and management, job design and setting standards in production. The next landmark was mass production, consisted of innovations in product-process technology made by Henry Ford. Also, at the time of Ford the ideas of Taylor were widely known and used in automobile manufacturing, and Ford used many of Taylor's ideas. Ford Motor Company's great contribution to automotive manufacturing was the moving assembly line. This new technique allowed individual workers to stay in one place and perform the same task repeatedly on multiple vehicles that passed by them. This type of production lines made the vehicles more affordable (Kanigel, 1997).

By the end of World War II, the American industry was doing well, as compared to the industries in Europe and Japan, as shown in Table 2.1.

Table 2.1: The Superior Market Share of the USA (Bolwijin et al., 1986)

Share in World Production 1965			
Industry	USA	Europe	Rest
Machining	70%	13%	17%
Cars	76%	13%	11%
Oil	73%	14%	13%
Electronics	68%	15%	17%
Chemistry	62%	21%	17%

By the end of 1980s the Japanese share of the world markets grew significantly as can be seen in Table 2.2., particularly in electronics.

Table 2.2: Japanese Share of the World Markets (Bolwijin et al., 1986)

Product	Percentage Share
35mm cameras	84
Video Recorders	84
Watches	82
Calculators	77
Microwave Ovens	71
Motorcycles	55
Color Televisions	53

Japan started from a different position than Europe as they lacked space, energy and other natural resources. The emphasis on the reduction of waste became the basis of Japan's Toyota production system. This system is based on two pillars: 1.) Just in Time (JIT) and 2.) Autonomation, the concept of jidoka (Ohno, 1988)

By the use of JIT management philosophy the set-up time are reduced which can be done through better planning and process redesign. The reducing set-up time allows economical production of smaller lots, which can be achieved by cooperation with the suppliers, since it will require more frequent deliveries. Preventive maintenance is followed strictly, by using machine and worker idle time to maintain equipment and prevent breakdowns. The workers are trained to work on several machines, perform maintenance tasks and quality inspections, facilitating into a flexible work force. JIT requires supplier quality assurance and implement a zero defects quality program.

The concept of jidoka is applied, which is also called as autonomation. It is through autonomation is a mechanism to prevent mass-production of defective work in machines and product lines. The mass-production of defects can be prevented and the machine break-downs are automatically checked. Toyota recognizes that in an assembly environment the highest quality control can be achieved by applying human judgment as conditions vary.

2.3 PRODUCTION SYSTEM DEFINATIONS

A production system is the part of an organization encompassing the production process, including manufacturing and assembly, maintenance process and regulatory process planning, quality control and production planning; the people carrying out these processes, the production resources used to make the processes feasible; and the organizational arrangements used to divide and ordinate the processes distinguished (Ruffini, 1993).

A production system is a facility which manufactures physical goods from raw materials using machinery and labor. Each production system is the result of a unique and context dependent development process. Its comprising design and evaluation activities are most vital for the system performance. The design of a production system is important as to how the systems can adapt to expected and unexpected production situations. The evaluation is equally important which checks how good the system is and also it helps to compare the alternative approaches (Bennett and Forrester, 1993).

There are two main approaches to the development of a suitable production system. The first is planning and control of the existing production system, and the second, is designing a new system. The planning and control of a production system are concerned with operating the resources on daily basis, and the physical design provides the fixed resources that are capable of satisfying the customers' demands (Slack, *et al.*, 1998).

The production system inputs include financial capital, consumable materials and supplies, skill and knowledge of the work force and services from outside contractors. Most of the production system analyses suggest that there are three key tangible resources, namely labor, physical facilities and materials. The outputs are generally goods and services. In manufacturing companies, physical goods as well as advice and service may be produced. For example, in the case of computer manufacturers customer service may assume greater importance than primary physical products.

Various elements of a production system are illustrated in Figure 2.1, below. The quality and maintenance sub-systems are important components which determine the performance of the overall production system. It is the quality of the manufactured product, and the robustness of the production system which is the end-result of the overall production system, and maintenance supports it to run effectively. The quality sub-system checks any non-conformance, and helps to take any effective action, if required (Bennett, 1986; Wild, 1972).

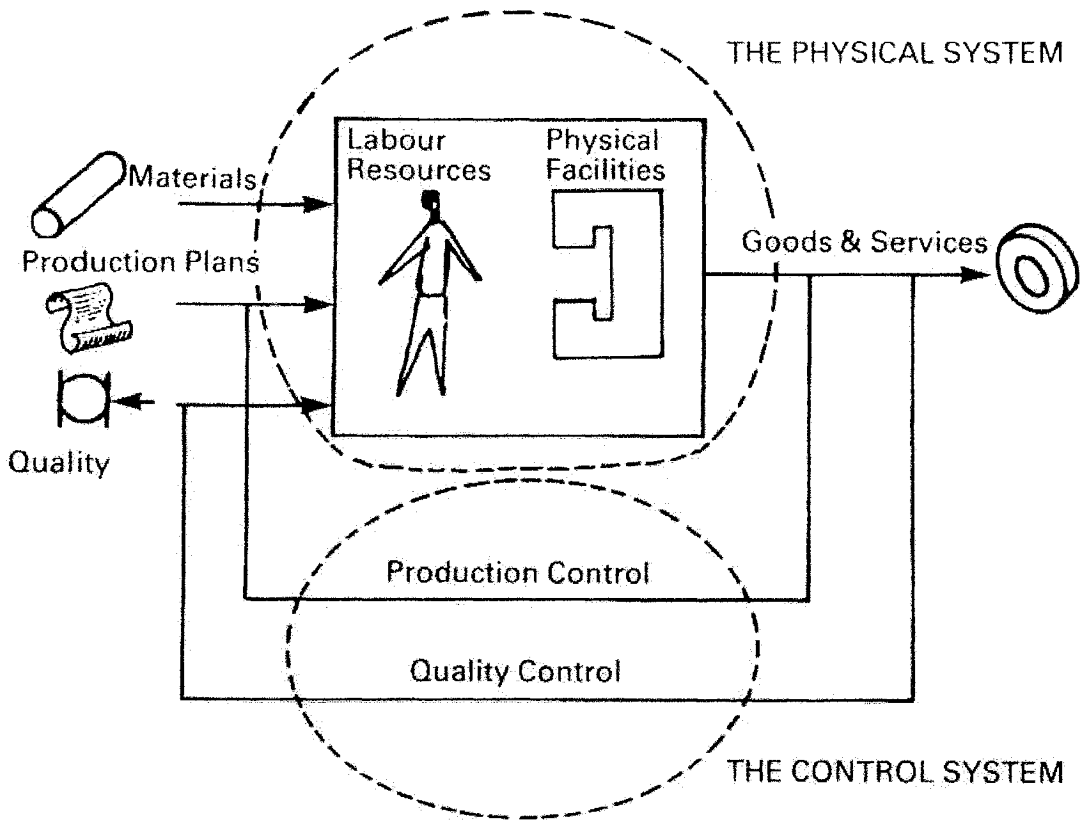

Figure 2.1: The Elements of a Production System (Bennett, 1986)

2.4 THE MANUFACTURING SYSTEM

The manufacturing system is the most important part of a production system. The manufacturing system plays a key role in carrying out the transformation processes in a manufacturing company (Wild, 1972).

The structuring of the primary process in a manufacturing system is important as it forms the basis of the physical goods flow (Hill, 1995). A description of the process choice concept is illustrated in Figure 2.2, and it clearly shows the comparisons between them. By overlapping, it is implied that going from one type to another is not difficult. For example, high volume and low variety would require a continuous process, and as the volume decreases a little, and the variety goes high, the transition from continuous to mass is required and so on.

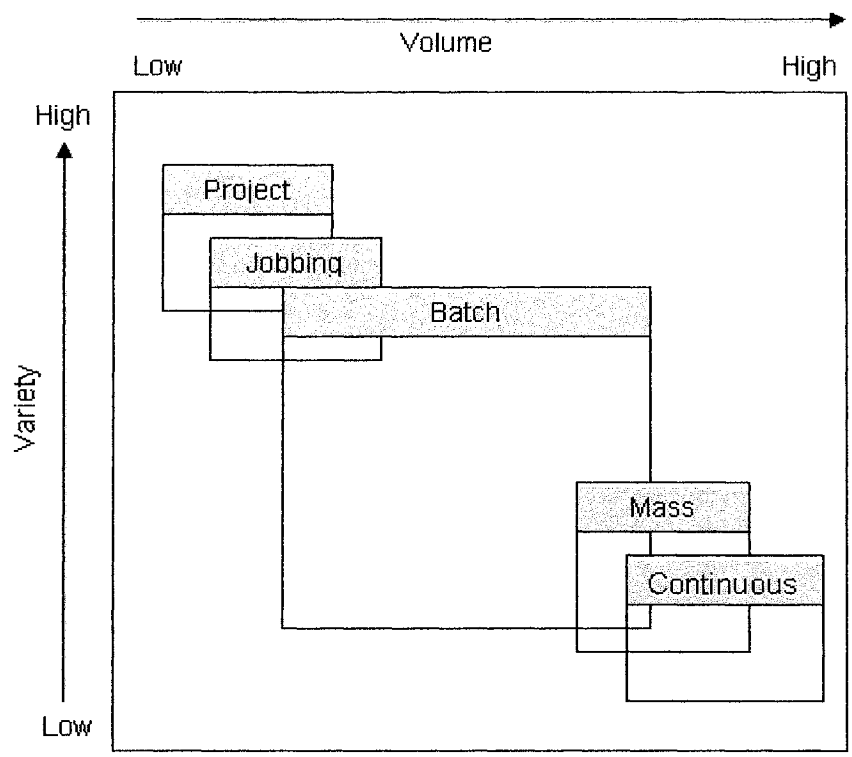

Figure 2.2 Generic Type of Process in Manufacturing

A manufacturing system designed from the outset will lead to fewer problems, and will minimize, although not eliminate, the need for changes at a stage when the system is built. This is due to the fact that re-design of an existing system cannot be as easy as and better than a system designed with the results in focus. On the other hand a manufacturing system that is imperfectly designed concerning, for example, performance quality, material flow and product flow, can bring about immense costs through high tied-up capital, rejected products, low deliverability, low reliability, etc. Deficiencies and faults in the work of preceding phases such as engineering or design manifest themselves in the start-up of a manufacturing system.

2.5 PERFORMANCE MEASURES FOR PRODUCTION SYSTEMS

The performance of a company can be expressed in terms of profit, return on investment and other financial terms. In the case of production, performance is often about efficiency and effectiveness in actions. In addition, incorporating quality, reliable delivery, short lead times, flexible capacity and efficient capital deployment, is the primary source of competitiveness (Skinner, 1996).

The performance measures for the production system can be shown by the means of a link with the number of different performance measures. Performance measures provide a series of indicators, expressed in qualitative, quantitative or other tangible terms that indicate whether current performance is reasonable and cost effective. The various performance objectives discussed in the Table 2.3, are cost, quality, speed, flexibility and dependability. The second column explains the performance objective. In the third column the various performance measures are given, categorized according to its performance objectives.

Table 2.3: Performance Objectives, Explanations and Performance Measures

(Duda, 2000; Safsten, 2002)

Performance Objectives	Explanation	Performance Measure
Cost	The cost of material, labor, and other resources to produce a product	Unit production cost Cost relative to competitors Manufacturing cost Total factor productivity Direct labor Inventory
Quality	The manufacturing of products with high performance and conformance	Number of complaints Warranty returns Percentage scrap Rework cost Incoming supplier quality Mean time between failure
Speed	Speed of Delivery	Cycle time Vendor delivery time Response time System throughput time
Flexibility	The ability to react to changes in volume, changes in product mix, modifications to design etc	Set-up time Time needed to develop new products Range of Products Time to change schedules Minimum order size Number of options Percentage of workforce cross trained
Dependability	The reliability of delivery	Percentage on time delivery Average lateness Proportion of products in stock Mean deviation from promised arrival

2.6 ROBUST PRODUCTION SYSTEMS

Companies may measure product/process performance using metrics such as warranty costs, scrap or rework costs, or the number of customer complaints. One of the main problems is that the engineers who developed the product may not be able to measure the loss that has occurred. The post-design and post production loss can only be measured after the product is designed and manufactured. By involving the Taguchi's Robust Design, the engineers may be able to identify a function for a particular design to enable a paradigm shift in the way products are being measured towards a higher quality at lower costs (Wilkins, 2002).

Various control charts developed from statistical quality methodology can be used to detect whether a process is in or out of control. If the process is out of control there must be certain mechanism for taking necessary actions to rectify the situation. For this purpose a feedback system has to be incorporated in which the output from the process is being monitored using a control chart and significant changes are reported to control function (Bennett, 1986). A better approach is to make the system robust at the initial design.

Figure 2.3 displays three important production system design objectives: productivity, flexibility and quality.

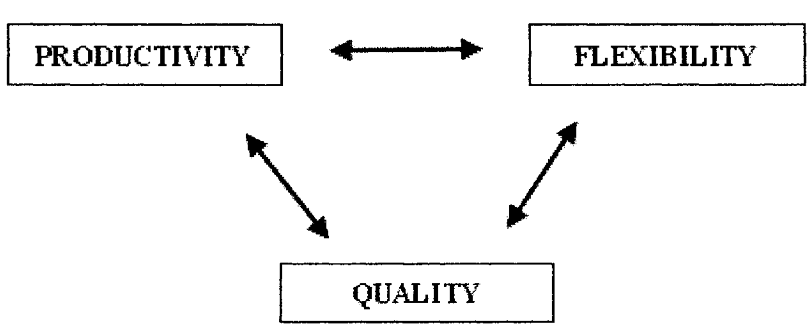

Figure 2.3: Objectives in Production System Design (Inman, *et al.*, 2003)

The well designed production system of Toyota contributes significantly to its high quality of products, as Toyota has made different production system design choices to improve quality, despite of the additional investment and reduced production throughput. Toyota made such production system design choices to achieve higher product quality (Ohno, 1988).

As an example, Andon is the Japanese term for a signaling device that an assembly line worker can trigger to call for assistance or stop the line. Most North American auto manufacturers have no Andon, whereas at Toyota, "every worker is not only empowered, but roundly encouraged, to slow or even stop the line if problems arise" (Mayne *et al.*, 2001, Inman, *et al.*, 2003).

Toyota also manages quality by designing inspection into its production system. It first introduced its Lexus model into a plant, and added five extra quality-control inspections, and allowed 40 to 50 percent more labor-force in the plant. Toyota may bring the car to a halt during the setting and bolting process. Bringing the vehicle to halt will provide lower throughput than letting the vehicle continue moving, and the main purpose of which is to ensure quality.

The system design procedures vary depending on the company's specific requirements. The most common design procedure was to develop a few alternatives and then rather quickly choose one alternative which was developed further. Most companies use layout and paper models to test them (Bellgran, 1998).

It is well known that product design plays a very important role for the product quality, but production system design also has a significant impact. Taguchi method is mostly applied to product development, and there have been efforts of using Taguchi method for robust production system design. A procedure for designing a job shop manufacturing system using computer simulation is described in Chen and Chen (1995). The job shop manufacturing system is designed for high-variety production and small quantity, so the need for a robust system to reduce variation in system performance caused by uncontrollable production factors is significant. Various production factors such as number of machines at each workstation, average flow time, etc. are taken into consideration for the robust design of the job shop.

A simulation model was proposed by Cabrera-Rios *et al.*, (2001) for designing a manufacturing cell aiming at profit maximization over a certain period of time. The proposed model was run for selected control factors, noise factors and their experimental regions. This simulation model was then used to generate required data for the analysis. Regression analysis was performed to find 15 best results. Using Robust Design approach, the best combination of the controllable factors that has the lowest variation was determined for system robustness.

When production systems are not designed in an efficient way, this may cause disadvantages, such as:

- The time for designing the production system is not utilized.
- The design costs are high.
- The outcome, i.e., the production system is negatively affected.

The outcome of the production system can be measured in terms of the performance measures as discussed in Table 2.3, which makes it possible to know the conditions which are a priority in a particular production system and indicating the performance.

Delays from original timetables, high costs compared to investments and budgets, and poor production system performance are typical problems when designing and implementing new production systems (Duda, 2000).

A better designed production system will lead to fewer problems, and will tend to minimize the need for changes. A poorly designed production system can be associated with high capital, rejected products, low deliverability, low reliability, etc. Therefore, how the system design is performed is important for the success of the production system and long-term profitability and it offers a large potential for improvements (Wiendahl *et al.*, 1996).

2.7 STUDIES ON DESIGN OF EXPERIMENTS (DoE) APPROACH

Design of Experiments (DoE) is a statistical method used in designing for better value (for example, lower cost and higher quality, etc). It was first introduced by R.A. Fitcher in England in the early 1920s (Moen *et al.*, 1999). Fitcher used DoE technique to determine the optimum water, sunshine, fertilizer and soil conditions needed to produce best crop. Trial conditions of the factors included in the experimental study were created using a matrix. After Fisher introduced the technique for agricultural experiments much more research and development were carried out in other areas (Moen *et al.*, 1999).

DoE is a well planned set of experiments, in which all parameters of interest are varied over specified ranges to obtain systematic data. Usually the number of experiments and resources required are large. In many cases, particularly those in which some optimization is required, the method does not point to the best values of the parameters. Taguchi (1987) developed a method based on orthogonal array experiments which gives much reduced variance for the experiment with optimum settings of control parameters. The combination of DoE with optimization of control parameters to obtain best results is achieved in the Taguchi Method. Also, the orthogonal arrays provide a set of well balanced experiments used in robust engineering method.

Vining and Schaub (1991) proposed a methodology to estimate process mean and variance in a DoE application. They used a one-step approach which assumes that the process variance is constant over the region of interest. They also used a semi-Bayesian approach which attempts to develop an experimental plan with prior information on the nature of the variance. They then compared these two approaches in a simulation study. Some of the key issues of using DoE for quality improvement were discussed in Blake *et al.* (1994). The earliest application of DoE, in the area of assembly systems was developed by Law (1988). He used a 2^3 full factorial design to study the effects of system configuration, relative stage position, and buffer capacity allocation in automatic transfer lines (Blake *et al.*, 1994).

DoE approach was also applied to stereo lithography (SL) for process design of turbine engine airfoils by Schaub and Montgomery (1992). The variables were studied that allow holding tighter tolerances. They stated that the use of statistically designed experiments resulted in increased process knowledge not only for the particular test situation, but also for the overall operation of a SL process. A factorial experimental design based on discrete event simulation was proposed by Leung and Sanders (1986). They discussed the effects of different design factors on the performance of automatic assembly systems with tunnel-gated stations.

2.8 STUDIES ON ROBUST DESIGN METHOD AND ITS APPLICATIONS

Robust design was first introduced by Taguchi (Phadke, 1989). Robust design method has been used in many areas of engineering. In 1960s a small ceramic tile company in Japan was facing a serious problem. Many of the ceramic floor tiles produced were failing final inspection and had to be scrapped. The main reason was misshaped tiles, not within specific dimensions. Analysis was done and the reason found out was the kiln. Tiles fired at the centre of the kiln were fine, and those at the edges were out of specified dimensions. At first the solution seemed to replace the kiln, which was very expensive to do. Later, the solution was found, using the Robust Design method. By changing the mixture of lime and clay, a tile formation that was robust to temperature variations in the oven could be produced. This concept of changing some variables in a process to make the process unaffected to variation in other variables has become known as robust design. Taguchi and Phadke designed experiments that pointed to a way to reduce variation in microprocessor window openings by a factor of 4. These changes in the process design reduced defects by 67% and the processing time by 50%. Robust design was also used in the design and manufacture of new microprocessors at AT&T Bell Laboratories and Western Electric (Godfrey *et al.*, 1986; Phadke, 1989).

Taguchi method was applied to aircraft engine development by Ryoichi (2003). He found that the Taguchi method is the only design method where variations can be studied by a single metric known as Signal-to-Noise (S/N) ratio. It is a scale of stability with respect to noise. Also, it was pointed out that variations are a cause of failure and noise is a cause of variations.

At AT&T, experiments were carried out to optimize the process of forming contact windows in 3.5 μ m complementary metal-oxide semiconductor (CMOS) circuits as described in Kacker *et al.* (1983). As a large scale integrated circuit chip has many such windows, it is important to produce windows with target dimensions. Using Robust Design, it shows the variance of the window size being reduced four-times with a substantial reduction in processing time.

Taguchi method leads the designer into determining optimum parameters, having fully investigated the variability, or more specifically, the sensitivity of the system specification to the casual factors of variability. Then it leads to the specification of optimum parameters for the constituent parts of the system (Bendell *et al.* 1989; Taguchi *et al.*, 2000).

In the present time, robust design methodology has received widespread use in USA, Canada, and many European countries. There are many industries which employ Robust Design, ranging from service industries to high tech industries (Appendix VI). When there is sufficient information on the fundamental mechanisms governing the process and the interactions between the input, Taguchi method would perform at its best, and optimize the underlying process as shown in Cesarone (2001). Table 2.4 shows the application of Taguchi method in plastics, automotive, process, metal fabrication, food and electronics and semiconductor industries (Rowlands *et al.*, 2000).

Table 2.4: Benefits by Application of Taguchi Method (Rowlands *et al.*, 2000)

Process/ Product	Nature of Problem	Experiment Size	Benefits
Injection molding process	High Scrap rate due to excessive process variability	8 trials	Annual savings were estimated to be over £40,000
Diesel injector	High rework rate	16 trials	Annual savings were estimated to be over £10,000
Welding process	Low weld strength	16 trials	Annual savings were estimated to be over £16,000
Chemical process	Low process yield	8 trials	Process yield was improved by over 10 per cent
Biscuit	Excessive variability in biscuit length	16 trials	Biscuit length variability was reduced by over 25 percent
Wire-bonding process	Low wire pull strength	16 trials	Annual savings were over £30,000

The use of Taguchi method for the above processes resulted not only in savings of large amount of money, but also improved quality. Further information and discussion on Taguchi method and robust design can be found in (Bendell et al., 1989 & 1990; Roy, 2000, Phadke, 1989; Montgomery, 1991; Taguchi *et al.*, 2000).

2.9 SUMMARY

In this chapter various performance measures for designing production systems have been discussed for improved product and process quality. It has been emphasized that there is a need for robust production systems. The basic difference between DoE and

Robust Design methodology is described, and the latter is suitable for designing a production system taking effective factors into consideration.

CHAPTER 3

APPROACHES TO PRODUCTION SYSTEM DESIGN

3.1 INTRODUCTION

This chapter presents different theoretical and practical approaches to design in general and in particular for production systems.

It has been established that production systems must be consistent with the business strategy, which can be accomplished by defining a manufacturing strategy. System design can be defined as the conception and planning of the overall set of elements and events constituting a system, together with the rules for their relationships in time and space (CIRP – International Institution for Production Research, 1990).

3.2 THE DESIGN PROCESS

The design process is a form of problem-solving, where the means to achieve a goal are sought intentionally. When problem solving is specifically concerned with design, the basic cycle can be employed, see Fig. 3.1. The activities described in the different phases are not necessarily carried out in the given order. A design process ideally is a decision on appropriate design in accordance with stated objectives. Decisions during design are often made more or less intuitively. The design process would stagnate without the intuitive decisions. A difference from the problem solving cycle is that the implementation is not considered in the basic design cycle. Also, the issue of selecting the best system is divided into evaluation and decision, where evaluation is concerned with determining the value of a provisional design and deciding whether the design is good enough (Roozenburg and Eekels, 1995).

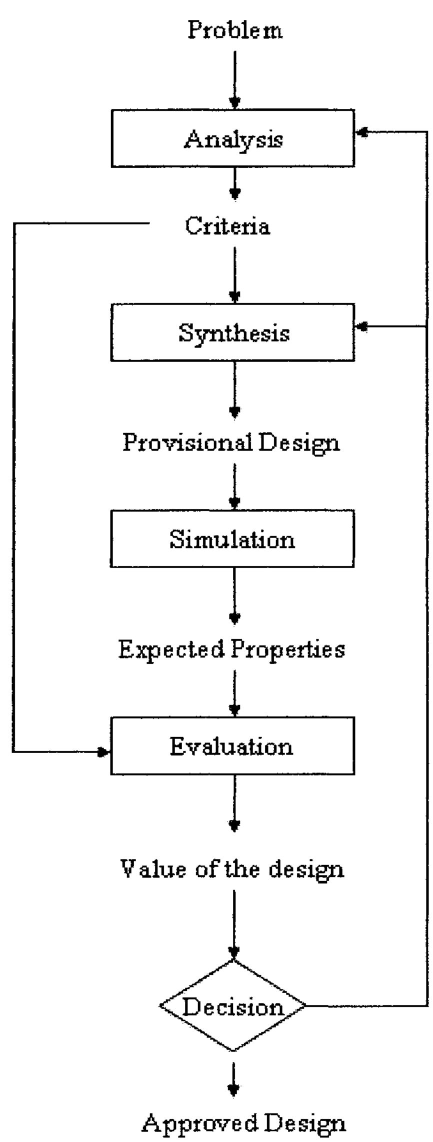

Figure 3.1 The Basic Design Cycle (Roozberg and Eekels, 1995)

If the design is as per the requirements, it is approved or else again the analysis and synthesis should be done. The criterion for which the analysis is done is evaluated and further evaluated again as shown through a loop. The activities which are described in the boxes are carried out in a detailed manner and consume more time as compared to the ones which are not.

The production system is the result of implementing the ideas that are created and specified in the system design process. The design process could also be further divided into preparatory design and design specification. In the preparatory design phase, the preconditions are analyzed and the requirements are specified to create a conceptual production system. In the design specification phase, the detailed design with the actual creation is done and the evaluation of the proposal is made. A production system design task model developed for assembly system design contains three parts as shown in Figure 3.2 (Bellgran, 1998).

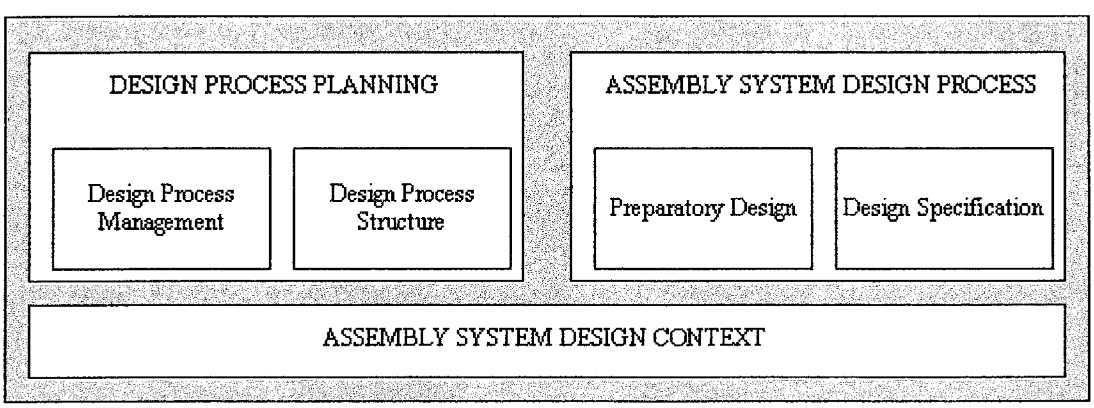

Figure 3.2: A Model showing the Design Process Planning, the System Design Process for Analysis of Assembly System Design (Bellgran, 1998)

For the production system design process, the goal is to design the best possible production system. During the system design process, the selection of the options is made on the conceptual and detailed levels. The conceptual level is to select the production principle, automation degree, principle of material flow, type of work organization, etc. The detailed level can be classified as selecting the suppliers, equipment, job design, etc. The determination of physical features during the system design process controls the qualities of the production system (Safsten, 2002).

3.3 MODIFIED VERSUS EXISTING DESIGN

A change in the production system design can imply that something within the existing system has been altered to meet the new requirements. System improvement is a transformation or a change that brings system closer to normal operating conditions. System design is a creative process (Van Gigch, 1991).

The design process can result in highly or less modified production systems. The extent of the changes varies from being incremental, to major changes, which might lead to a new system design. Depending on the extent of the change, different terminology for the altered production system may be used (Almgren, 1999) as given in Table 3.1.

Table 3.1: Existing, Modified and New Production System Characteristics (Almgren, 1999)

PRODUCTION SYSTEM CHARACTERISTICS	
Existing	• No Changes made
Modified	• A system that has undergone some technical redesign • A minor change in comparison with a new system
New	• Major technical redesign (new machinery and equipment, new layouts and flows • The organizational dimensions are related to the changes in the technical system • A new industrial facility without previous experience of manufacturing

According to the result of a process, a distinction between original design and improvement of the existing design can be made. There is a difference between the way in which goals are determined in the original design and the improvement of the existing design. When the issue is a new system, goals are determined in a solution-neutral environment unbiased by preconceived solutions, whereas when the issue is improvement of an existing design, goals reflect the existing design (Suh, 1990).

Either designing a new production system or an existing one, the goal should be to create a robust system able to cope with changing conditions. Therefore, acting in anticipation of future problems is necessary to eliminate or to prevent possible disturbances during different product lifecycle phases.

3.4 SYSTEM DESIGN MODELS

A general design framework for design and development of production systems was suggested by Wu (1994) as shown in Fig 3.3. The framework is based on the general problem solving cycle. According to Wu (1994), there are two main approaches to design a system. The first approach starts with a set of objectives and creates a model that fits the objectives without considering the previous systems. The second approach is to consider the existing system, and trying to modify in order to fulfill the future requirements. When the concept-generating approach is applied, the design process will follow the phases prescribed in the general design process given in Figure 3.3.

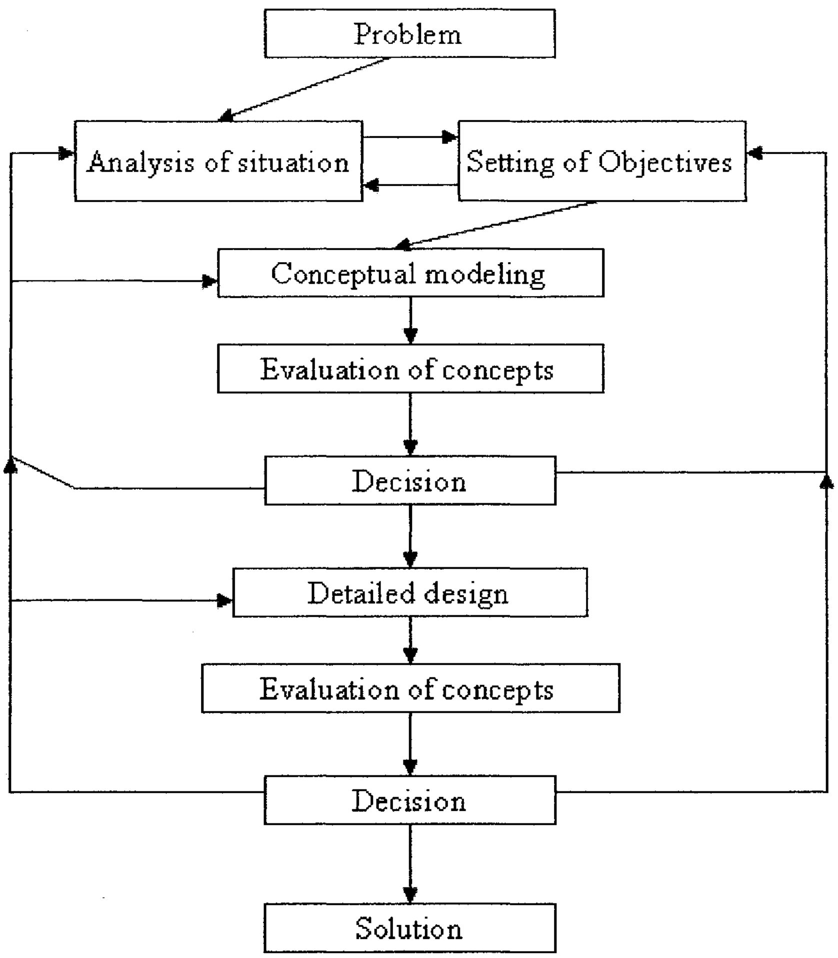

Figure 3.3: Structure of the Design Approach: The Concept-Generating Approach (Wu, 1994; Bellgran and Safsten, 2004)

When the design process is mainly driven by external considerations, such as an existing design, the process is concept-driven (Engstrom, 1998), as shown in Figure 3.4.

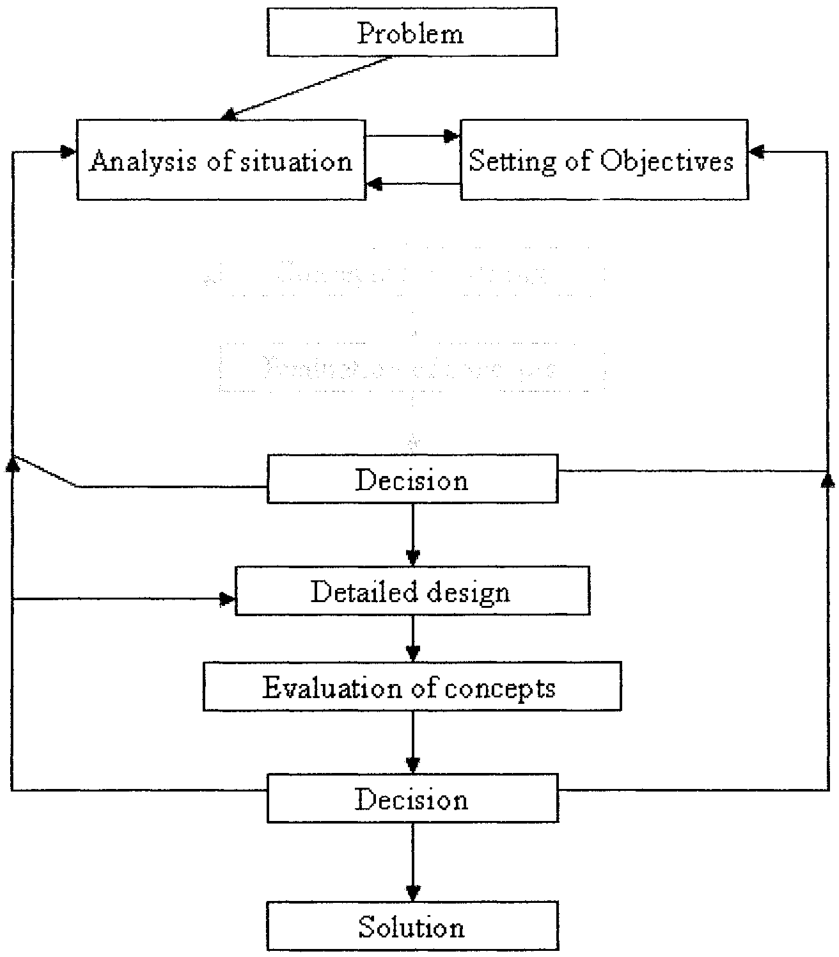

Figure 3.4: The Concept-Driven Approach (Bellgran and Safsten, 2004)

When the concept-driven approach is applied, a preferred production system concept was given from the beginning of the design process and the conceptual design phase was excluded, as shown in Figure 3.4. Also, the described consequences for the design process from the concept-generating and the concept-driven approaches presupposed that production system design would be carried out at the manufacturing company (Bellgran et al., 2002; Bellgran and Safsten, 2004).

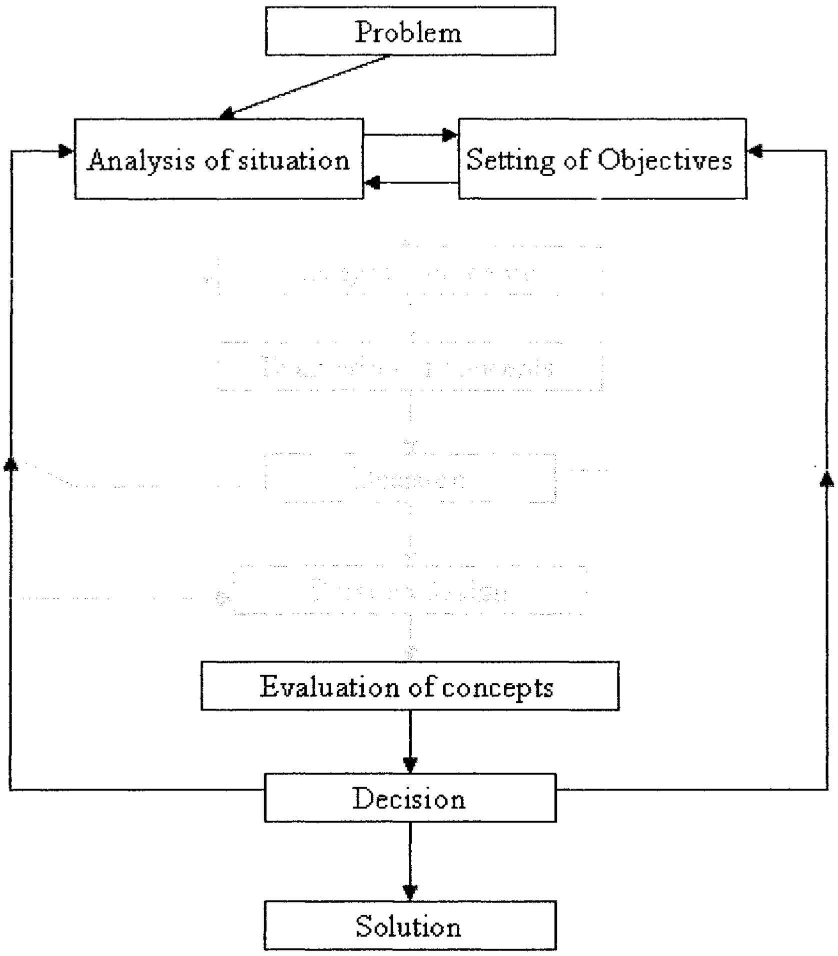

Figure 3.5: The Supplier-Driven Approach (Bellgran and Safsten, 2004)

The supplier-driven approach is more often followed by the manufacturing companies, as shown in Figure 3.5. From the perspective of the system, the supplier-driven design process can be either of concept-generating or concept-driven. The system suppliers often use standard solutions which are modified according to the specific situations. If needed, the concept-driven approach can be applied.

3.4.1 EVALUATING THE DESIGN APPROACHES

The purpose of evaluation is to assess whether a system conforms to some specified goals. The evaluation is the result of an activity that is investigated in order to improve an ongoing activity.

Evaluation is the process of investigating and judging a production system in accordance to certain criteria or the result of that process. The evaluation process normally involves (Scriven, 1991):

- Identification of relevant standards of the evaluation criteria
- Investigation of the performance of the evaluation object
- Integration or synthesis of the results to achieve an overall evaluation

When the concept-generating approach is applied, various extensive evaluation efforts are made during the design process. The production system can be evaluated during the design process as various informal evaluations preceded the different decisions made during the process. The concept-driven approach can be compared to improvement, while the concept-generating approach can be compared to design, when the design aims at producing new solutions. The difference between improvement and design has implications for the evaluation. In improvement, the solution needs to be evaluated against the standard or the normal operating conditions. In design, the goal might be unclear, and therefore the focus might be on comparing different solutions during design process (Chen, 1996).

When the supplier-driven approach is applied, the system design process is more or less a black box from the perspective of the manufacturing company. The difficulty here lies in finding the appropriate relations between the objective and the result. The supplier-driven approach for the design typically results in several production system solutions, in comparison with the concept-generating approach and the concept-driven approach, which normally results in one solution.

3.5 SUMMARY

This chapter discusses various approaches that can be used for designing production systems. The focus of this thesis is to design robust production systems. Understanding related to basic design concepts is important.

CHAPTER 4

METHODOLOGY FOR PRODUCTION SYSTEM DESIGN USING ROBUST ENGINEERING AND SIMULATION

4.1 INTRODUCTION

A designed experiment is a test or series of tests in which purposeful changes are made to the input variables of a process so that we may observe and identify the reasons for the changes. An experimental design dictates the number of runs, the levels at which the factors must be set on each run, and the sequence in which these runs are performed. In summary, the experimental design dictates how to run an experiment (Moen *et al.*, 1999, Phadke, 1986).

The use of design of experiments (DoE) approach allows one to study the factors in different levels, their interactions, and to identify the important effects. The DoE methodology suits best for determining a set of variables to design a manufacturing system. Taguchi's method and robust design methodology use a different experimental pattern when compared to basic DoE approach, while the underlying concept is same. The Taguchi method makes use of orthogonal arrays to set up multiple experiments and signal-to-noise (S/N) ratio for analysis of result (Roy, 2001). It assures a design that is robust to the influence of uncontrollable or noise factors described in the next sections in detail. In this research, we have used Taguchi's method for the analysis combined with the implementation steps of as robust engineering design methodology. The robust design enables the system response to be robust to uncontrollable factors. It is a unique method to determine the most suitable combination of the controllable factors so as to minimize the effects of uncontrollable factors for the designed system.

4.2 DESIGN OF EXPERIMENT METHODOLOGY

An experiment consists of a series of tests on a system by changing the levels of factors and background variables and observations of the effects on one or more response variables. The basic reason to carry out an experiment is to provide a basis for action on the system. DoE approach enables one to study the factors and their interactions and to recognize how they affect the results. It is a set of experiments in which various purposeful changes are made to the input variables of a process or a system so that one may observe and identify the reasons for changes in the output of the response (Montgomery, 1991). Therefore, the DoE approach gives substantial information on the system in addition to suggesting solutions to the problem.

4.3 BASIC PHASES FOR APPLYING DESIGN OF EXPERIMENTS

It is important to follow the steps in applying Design of Experiments approach. Figure 4.1 shows different phases of DoE applications.

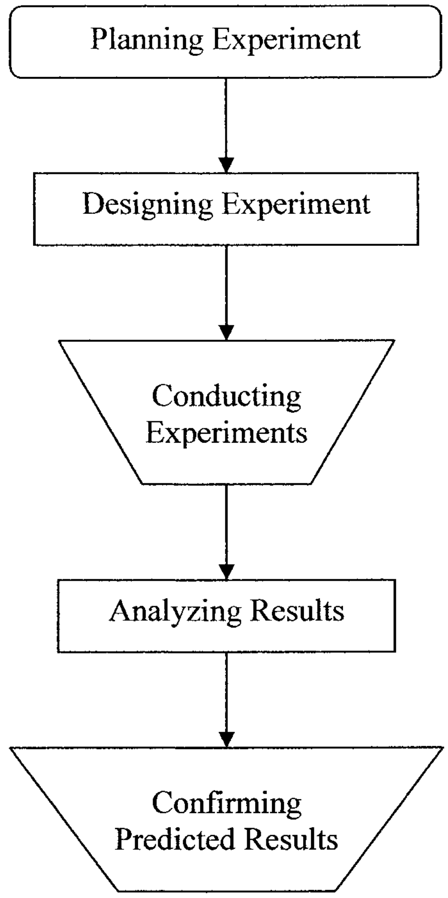

Figure 4.1: DoE Application Phases.

I. **Planning:** This is also called Brainstorming phase. According to Roy (2001), "Taguchi regards brainstorming to cross organizational barriers. By including representatives of all the departments, from design through marketing, the quality demanded by the customer can be considered and those production factors which may contribute towards quality can be identified and incorporated into the design of experiments". Decisions on the project objectives, its measurement method, and the factors that may influence the results, are made by the participating members. In this brainstorming session, information pertinent to the design and execution of the experiment is gathered together.

II. **Designing:** At this phase, the factors and their levels are identified, and an experiment is designed, which specifies the number of experiments and the pattern in which the experiment will be carried out.

III. **Conducting Experiments:** After the experiments are designed, they are conducted by following the design combination for the statistical validity. The symbol used for conducting the experiments in Fig. 4.1, indicates a sequence of commands that will continue to repeat until stopped manually.

IV. **Analyzing:** The results collected by conducting the experiments are analyzed in this phase. Analysis of Variance (ANOVA) may be used to determine statistical significance of the factors and, of their interactions, for direct responses and for Signal to Noise ratios (Taguchi, et al., 2000).

V. **Confirming:** To determine whether the improvement is really achievable or to determine how close the estimate matches actual performance, the new product / process as per new specifications is tested. The objective of DoE approach is to improve the system by selecting the appropriate level of factors. If a 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 effects (Roy, 2001).

4.4 FACTORS AND VARIABLES

Factors are used to describe the input variables within the system. They may be system parameters or operation conditions. Levels are the different settings over the operating range for each factor.

Taguchi divides factors into control factors and noise factors. Control factors can be varied as desired, whereas noise factors cannot. Although both control and noise factors affect the process, optimum levels can be specified only for control factors as noise factors cannot be adjusted. Control factors are often referred to as inner array factors and noise factors are called outer array factors. The levels for the control factors should be specified after they have been identified (Phadke, 1989; Roy 2001). The output of a process is influenced by the input and also by different number of variables associated with the process. The variables which can be changed are called the control variables. In a typical manufacturing process the control variables are temperature, electrical charge, flow rate, type of process, etc. The noise variables are known to have an influence on the output but are either unidentifiable, difficult to control due to technical difficulties, or are not economically controlled. Machine operator skill, operating environment, time of the day, etc. are some examples of the noise variables. The noise variables are the main cause for quality loss.

The main aim of the robust engineering methodology is to determine the optimum combinations for the control variables so that the effect of the noise variables is nullified. Robustness is the insensitivity of the system to the noise variables.

4.5 THE 2^n FACTORIAL

For applying the DoE approach there are three main strategies: full factorial design, fractional factorial design, and orthogonal design. The full factorial design consists of all possible combinations of the factors and levels. When the interaction effects are considered potentially important and economically feasible, the full factorial design is recommended. In such experiments the design is expressed by a^b where,

a: number of levels of each factor

b: number of factors

In this section we are emphasizing on 2^n because they are easy to use for studying and have been found to meet the majority of the experimental needs for the improvement of the processes. Table 4.1 is a sample listing of the combinations of factors in a design matrix. It has 4 factors with 2 levels each. "+" indicates the factor is set at the first level and "-" indicates it is set at the second level. The experiments provide information on the four main factors and all their interactions.

Table 4.1: 2^4 Design Matrix

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

The fractional factorial design is used to reduce the size of an experimental design for experimenters to study most of the factors and their interactions. Some of the information on the effects of the main factors and their interactions may be lost due to confounding.

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

a: number of levels of each factor

b: number of factors

c: the fraction level (it indicates the number of experiments which will not be conducted compared to the full factorial design)

Table 4.2: Design Matrix for 2^4 Full Factorial Pattern

Test	**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	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+

If the experimenter would like to reduce the size of the 2^4 pattern in Table 4.2 to eight tests, it is important to choose the eight tests so that as much information as possible about the effects is preserved. The 2^4 pattern indicates a full factorial pattern using four factors in 16 runs, 2^{4-1} indicates a ½ fraction of a 2^4 pattern, using four factors in eight runs. The columns corresponding to the various interactions are obtained by multiplying the signs for the factors contained in the interactions. Hence, it is desirable that the eight tests be chosen so that each of the columns in the design matrix has four minuses and four pluses. This selection would provide a balance to the design. Also, the least important estimate is obtained from a full 2^4 design is the four-factor interaction. This estimate would usually be readily given up to reduce the size of the experiment. The eight tests are chosen by selecting only rows in the design matrix in which the sign of the column headed 1234 is plus (or, alternatively, minus). This results in the design matrix in Table 4.3. It is seen that columns 14 and 23 are identical, which means that the estimates of the two effects will be identical. The estimate provided by either column is actually an estimate of the sum of the 14 and 23 interactions. These two interactions are said to be confounded with each other. If any one of the factors has a negligible effect on the response, then the other three can be analyzed as a full 2^3 factorial design. Such type of analysis is performed under the assumption that the factor having a negligible average effect does not interact with any of the other factors. From this design matrix, it is seen that the desired balance has been obtained. A justification for using this type of pattern is that any three of the four factors form a full factorial design. If any one of these factors has a negligible effect on the response, then the other three can be analyzed as a 2^3 factorial design. Also, this analysis is performed under the assumption that the factor having a negligible average effect also does not interact with any of the other factors.

Table 4.3: Design matrix for a ½ Fraction of 2^4 Pattern

Test	1	2	3	4	12	13	14	23	24	34	123	124	134	234	1234
1	-	-	-	-	+	+	+	+	+	+	-	-	-	-	+
4	+	+	-	-	+	-	-	-	-	+	-	-	+	+	+
6	+	-	+	-	-	+	-	-	+	-	-	+	-	+	+
7	-	+	+	-	-	-	+	+	-	-	-	+	+	-	+
10	+	-	-	+	-	-	+	+	-	-	+	-	-	+	+
11	-	+	-	+	-	+	-	-	+	-	+	-	+	-	+
13	-	-	+	+	+	-	-	-	-	+	+	+	-	-	+
16	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+

4.6 ORTHOGONAL ARRAYS

The third design strategy is using the orthogonal arrays, used in Taguchi's method as show in the tables in Appendix I. They are fractional factorial designs based on using symmetrical subsets of all the combinations of factor levels in the corresponding full factorials. The orthogonal arrays allow the factors to have the pair wise balancing property so that every level of a factor occurs with every level of all other factors for the same number of times. Orthogonal arrays are fractional factorial designs which minimize the number of trials but keep the pair wise balancing property. For example, L_{16} orthogonal array is used to design an experiment with 15 factors all at two levels, which requires only 16 experiments, instead of the 32,768 combinations. Therefore, experiments designed using orthogonal arrays reduce the number of experiments to a much more practical and affordable size. Table 4.4, illustrates the common experimental situations and the corresponding experimental configurations.

Orthogonal arrays emphasize the investigation of the main factors with a small design, while ignoring most of the interactions (Bendell *et al.*, 1990).

Table 4.4: Various Experimental Situations and Corresponding Experiment Size

Experimental Situation	Maximum Possible Combinations	Combinations Using Orthogonal Arrays
3 two-level factors	8	4
7 two-level factors	128	8
11 two-level factors	2,048	12
15 two-level factors	32,768	16
4 three-level factors	81	9
7 three-level factors	2,187	18

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

a: number of experimental runs

b: number of levels of each factor

c: number of columns in the array

The most commonly used orthogonal arrays for experimental design are illustrated in Table 4.5.

Table 4.5: Orthogonal Arrays Most Commonly Used for Experiment Design

ARRAY	INTENDED USE	
$L_4(2^3)$	3 two-level factors	**Two-level arrays**
$L_8(2^7)$	7 two-level factors	
$L_{12}(2^{11})$	11 two-level factors	
$L_{16}(2^{15})$	15 two-level factors	
$L_{32}(2^{31})$	31 two-level factors	
$L_9(2^4)$	4 three-level factors	**Three-level arrays**
$L_{18}(2^1, 3^7)$	1 two-level and 7 three-level factors	
$L_{27}(3^{13})$	13 three-level factors	
$L_{16}(4^5)$ modified	5 four level factors	**Four-level arrays**
$L_{32}(2^1, 4^9)$ modified	1 two-level and 9 four-level factors	

The arrays can have factors with many levels, although two and three levels are most common. An $L_{12}(2^{11})$ array is illustrated in Table 4.6. It can handle up to 11 factors at 2 levels each, under 12 experimental conditions.

Table 4.6: L_{12} (2^{11}) Orthogonal Array

Expt. No.	Experimental Combination Column										
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	2	2	2	2	2	2
3	1	1	2	2	2	1	1	1	2	2	2
4	1	2	1	2	2	1	2	2	1	1	2
5	1	2	2	1	2	2	1	2	1	2	1
6	1	2	2	2	1	2	2	1	2	1	1
7	2	1	2	2	1	1	2	2	1	2	1
8	2	1	2	1	2	2	2	1	1	1	2
9	2	1	1	2	2	2	1	2	2	1	1
10	2	2	2	1	1	1	1	2	2	1	2
11	2	2	1	1	2	1	2	1	2	2	1
12	2	2	1	1	2	1	2	1	2	2	1

L_{15}, L_{18}, L_{36} and L_{54} arrays are among a group of specifically designed arrays that enable the designers to focus on the main effects. Such an approach helps to increase the efficiency and reproducibility of small scale experimentation. Among them, L_{18} is the most widely used array for DoE applications (Phadke, 1989). The L_{18} array is used to design experiments with 1 two level factor and 4, 5, 6, or 7 three level factors.

The process of selecting the proper array consists of first calculating the degree of freedom (DOF) of each factor and their interactions. Interactions are also treated as factors for calculating DOF. The total DOF required for the design is equal the sum of all the DOF of the individual factors and interactions. Therefore, the available DOF within an array can be calculated by adding the DOF for all the columns of the array. A list of various standard arrays can be seen in Appendix I. The proper array can be selected by comparing the DOF required by the design with the available DOF of each standard array.

4.7 ANALYSIS TOOLS

Analytical methods designed for making the design robust, improving the quality and statistical methods should be used for data analysis. Some of them are introduced below.

The quality characteristic specifies whether the performance attribute quantified by the evaluation criteria needs to be maximized, minimized or optimized.

The three quality characteristics are:

1) Bigger is better
2) Smaller is better
3) Nominal is best

For the bigger is better type of measurement, the large magnitude of evaluation will be preferred over smaller ones. Theoretically, there is no upper limit. In practice, some upper limit in required for numerical correctness. In the case of smaller is better type of measurement the smaller magnitude is preferred. The theoretical target is zero.

The practical value of the lowest achievable value can be set to some appropriate number. In the third category of measurement, nominal is best a fixed value is always desired. The fixed level of achievement desired is called the target or nominal value.

4.7.1 QUALITY LOSS FUNCTION

The quality loss function, proposed by Taguchi, is given in Equation (4.1).

$$L(y) = k(y - m)^2 \qquad (4.1)$$

In this equation,

$L(y)$ is the quality loss

k is the constant called quality loss coefficient

y is the quality characteristic of a product or a process

m is the target value for y

The general form of such function is plotted in Fig. 4.2. The loss due to performance variation is proportional to the square of the deviation of the performance characteristic from its nominal value. This standard representation of the loss function demonstrates several key attributes of loss. For example, the target value and the bottom of the parabolic function intersect, implying that as parts are produced at the nominal value, little or no loss occurs. Also, the curve flattens as it approaches the target value.

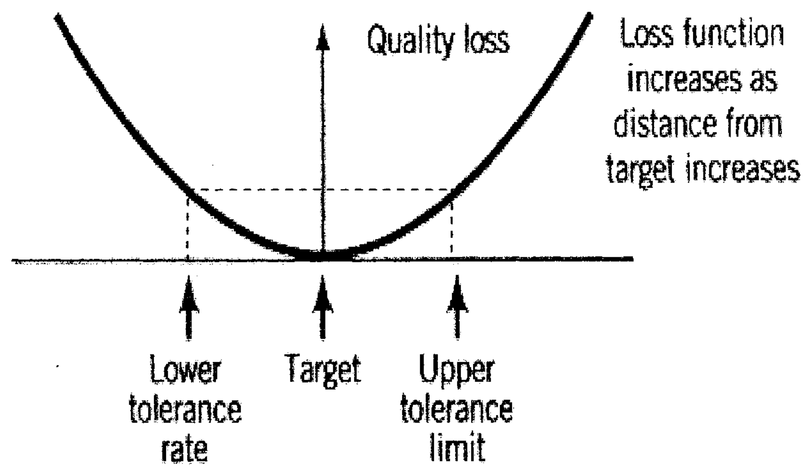

Figure 4.2: Quality Loss Function

At $y = m$, the loss is zero as shown in Fig. 4.2. If $m \pm \Delta_0$ are the functional limits and the loss at $y \pm \Delta_0$ is A_0, the value of the quality loss coefficient can be calculated by

$$k = A_0 / \Delta_0^2 \tag{4.2}$$

Equation (4.1) does not imply that every customer who receives a product with y as the value of the quality characteristic will incur a precise quality loss equal to $L(y)$. Instead, it implies that the average quality loss incurred by those customers is $L(y)$.

4.7.2 QUALITY CHARACTERISTIC

Data generated from the experimental trials can be analyzed in two different ways, namely, standard analysis and signal to noise ratio analysis. Either of these analyses produces an operating characteristic curve plotting the levels of each factor versus the criterion for evaluation. The standard analysis is used when there is just one column of results and it is relatively simple which uses the average values in the data set from each trial. The standard analysis should be performed if there is only one observation per trial.

The signal to noise ratio analysis can be used if the number of observations is large. Another situation where standard analysis is recommended is when the spread within the sample, containing multiple observations, is small. In the case of a sample with multiple observations, the average of all the observations for a trial should be computed.

The Signal to Noise ratio (S/N ratio) is a variability index and it measures relative quality characteristics, to be used for comparative purposes. The S/N ratio analysis should be performed when there are multiple observations per trial. There are two classes of S/N ratio, static and dynamic. The static S/N ratio applies in cases where the quality characteristic target has a fixed value. The dynamic S/N ratio is an extension of the static S/N ratio. The dynamic S/N ratio applies where output function vary with input function. Equation (4.3) is used to calculate the static S/N ratio (Bendell *et al.*, 1989; Roy, 1990).

$$S/N = -10 \log_{10} (MSD) \tag{4.3}$$

Where, MSD is the mean squared deviation from the target value, of the quality characteristic. The MSD is calculated for each quality characteristic (Roy, 1990).

For smaller is better,

$$MSD = (y_1^2 + y_2^2 + y_3^2 + \ldots + y_n^2) / n \tag{4.4}$$

For nominal is best,

$$MSD = [(y_1 - y_0)^2 + (y_2 - y_0)^2 + (y_3 - y_0)^2 + \ldots + (y_n - y_0)^2] / n \tag{4.5}$$

For bigger is better,

$$MSD = (1/y_1^2 + 1/y_2^2 + 1/y_3^2 + \ldots + y_n^2) / n \tag{4.6}$$

where, $y_1, y_2, \ldots y_n$, are the different observations for each trial and y_0 is the desired nominal value

n is the number of observations for each trial

4.7.3 INTERACTIONS OF FACTORS

Most factors have certain interactions with other factors. A factor behaves differently in the presence of other factors and its trend changes when the levels of other factors change. It is important to consider the interactions in planning an experiment.

The interactions between more than two factors are possible, but it is often neglected in an experiment design (Roy 1990; Moen et al., 1999).

The DOF value of an interaction can be calculated simply by multiplying the factors DOFs:

$$DOFs\ of\ interaction\ A \times B = (DOF\ of\ A) \times (DOF\ of\ B) \tag{4.7}$$

Factor interaction can be obtained by using one column of the orthogonal array (OA), as shown in Table 4.7, where A, B, C and D are factors; A × B, A × C and A × D are the interactions between the factors. The best way to relate to interaction is to view it as an factor effect. In Table 4.7, the interaction A × B gives information which relates to the interdependence of factors A and B. It also gives an idea to the experimenter to check the influence of the factor interaction on the results. It can be seen that the levels are taken such that it is a combination of the two factors to be considered in the experimental trail.

Table 4.7, $L_8(2^7)$ layout, factors and their interactions

Expt. No.	1	2	3	4	5	6	7
	A	**B**	**A x B**	**C**	**A x C**	**D**	**A x D**
1	1	1	1	1	1	1	1
2	1	1	1	2	2	2	2
3	1	2	2	1	1	2	2
4	1	2	2	2	2	1	1
5	2	1	2	1	2	1	2
6	2	1	2	2	1	2	1
7	2	2	1	1	2	2	1
8	2	2	1	2	1	1	2

4.7.4 ANALYSIS OF VARIANCE (ANOVA)

Analysis of variance (ANOVA) is a statistical technique to calculate the contributions of individual factors towards the variability of the evaluation criterion. In the context of Taguchi Method, ANOVA is also needed for estimating the error variance for the factor effects and variance of the prediction error (Phadke 1989, Roy 2001).

In this research, we have used Qualitek-4® software for such analysis. The software is able to perform the analysis for L_4 to L_{64} arrays. Up to 63 factors can be selected with 2, 3 and 4 levels for each factor. It also provides options of standard or signal to noise data analysis with choices of bigger, smaller or nominal categories for quality characteristics. The standard analysis identifies which factors affect the average response, whereas the signal to noise analysis consolidates several data points into one value to reflect the level of variation.

4.8 ROBUST ENGINEERING OVERVIEW

Robust engineering is an application of DoE approach to reduce the variability of the system against uncontrollable factors. Robust engineering methodology is an optimization tool widely used for the development of new technologies in the area of product and process design.

The main features of robust engineering can be summarized as (Taguchi *et al.*, 2000; Roy 2001):

- It is the application of Taguchi methods for product/process development activities to optimize the performance.
- It identifies noise factors that are controllable in the laboratory but may not be controllable in a real production system.
- It combines the noise factors using an orthogonal array to produce extreme noise conditions (see Appendix II).
- It identifies the "ideal functions" for a specific technology or product/process design.
- It emphasizes on selectively choosing the best nominal values of design to optimize performance reliability at the lowest cost and to produce least variation in the results.

4.8.1 IMPLEMENTATION OF ROBUST DESIGN

For successfully implementing robust design, proper implementation methodology has to be followed. The various steps for the implementation of the robust design can be described as below (Taguchi et al. 2000; Chowdhury, 2003):

1.) Management Commitment

With a supportive and encouraging top management, the rest of organization will follow the guidelines for the implementation strategy.

2.) The Corporate Leader and the Corporate Team

The organization should be certain that they have chosen the right individual for the job. Defining the overall goals and the vision for the project will be the responsibility of a strategic planning team and the corporate leader should maintain active involvement with the strategic planning implementation process.

3.) Effective Communication

Robust Engineering methodology requires that the proper flow of information is clear, concise and timely. Each should be able to enhance the others' work by using a communication system that is not only accurate but also timely.

4.) Education and Training

It is essential that each employee has an understanding of how his or her part in the process can contribute. Everyone needs to commit to the needs and the position of the organization.

5.) The Integration Strategy

The Robust Engineering methodology enhances other quality programs. Various quality programs such as quality function deployment (QFD), failure modes and effects analysis (FMEA), test planning and reliability analysis are much more effective, less time intensive, and give higher performance when used simultaneously with Robust Engineering methodology.

6.) Bottom Line Performance

While measuring the results in the production system design, it is desired to achieve new improved method as compared to the old ones. It is desired for the system in focus to produce high quality products according to the customer demand. The system has to combine with robustness and profitable production costs.

4.9 ANALYZING A PRODUCTION SYSTEM

There various ways to study a production system, such as experimenting with the actual system or with the model of the system. Mostly, the experiments are done using the models for production systems, using simulation. For some cases even experiments with real system could also be feasible (Law and Kelton, 1991).

The production system is analyzed in accordance to the problem depending on the type of case. The various system design approaches are discussed in Chapter 3. As we can see that in the case of a production system the actual experimentation can be done with the actual system or experiment by making a model of the system. The financial resources would be much higher, if the experimentation is done with the actual system. The model of the system is further categorized into a physical model or a mathematical model. In this research, we have simulated the system using simulation software. Experimentation with real world systems would either be impossible or not cost effective.

Table 4.8, describes simulation benefits instead of other analysis. The main reason for the use of simulation is its ability to deal with complicated systems and reduced cost, which makes it a powerful and versatile tool. In our research, a real time production system problem has been studied by using simulation which had another advantage of repeating various experimental combinations in less time.

Table 4.8 Comparative benefits of simulation

Benefits over real life experimentation	Benefits over mathematical modeling	Managerial benefits includes
Cost, repeatability, control over the time base, legality and safety	Dynamic and transient effects, non-standard distributions, interaction of random events	Fosters creative attitudes, promotes total solutions, makes people think, communicating good ideas

4.9.1 SIMULATION

A simulation is to create and conduct experiments with a model that mimics reality. Simulation can be defined as the imitation of the operation of the real-world process or system over time. Simulation involves the generation of an artificial history of the system and the observation of that artificial history is to draw inferences concerning the operating characteristics of the real system (Banks *et al.*, 1996). Simulation by definition, allows for experimenting with a model of the system to better understand processes, with a goal of improving performance. Simulation modeling incorporates various inputs to a system and provides a means to evaluate, redesign, and measure or quantify customer satisfaction, resource utilization, process streamlining, and time spent (Kelton *et al.*, 1998).

Process performance analysis approach was developed to collect performance data related to each activity in the process and then to use this data to calculate and improve the performance of the total process, and the quality. Typical information to collect related to each activity is:

- Cycle time
- Processing time
- Wait time
- Yield
- Quantity processed per time period

There are various factors that cause variations in the process, for which process variation analysis is done. Variation may occur simultaneously in each activity in random. The various factors causing variations are workload buildup, utilization of machines, equipment downtime, etc.

4.9.2 PROCESS SIMULATION

In this research, discrete-event simulation was used for robust system design. A simulation model for a hypothetical but typical manufacturing system was constructed. Experiments were conducted following the robust design approach aiming at improved product and system quality.

Discrete event simulation involves the modeling of a system as it progresses through time. It is a system in which the state variables change only at a discrete set of points in time. These models produce output that is only an estimate of the true behavior of the model. It is widely used for simulating manufacturing systems. Discrete event simulation is one way of building up models to observe the time based behavior of a system. During the experimental phase the models are executed in order to generate results. The results can then be used to provide insight into a system and a basis to make decisions.

4.10 SIMULATING THE PRODUCTION SYSTEM

Simulation models can be used to determine optimal system parameters when the models are run following certain optimization methods such as response surface methods, gradient search method, heuristic search methods, etc. These methods may provide certain strategies searching for a robust design system. Taguchi method also supports modeling and experimentation and provides guidance to improving the effectiveness of the optimization procedure.

The flow of parts, conditions about processes, layout facilities, etc. which are not desired to control or have been designed can be viewed as the characteristics of the system, and are modeled. The operational parameters and their variables are the system inputs. The performances are the system outputs. The typical goal of simulation study is to predict results from operational parameters.

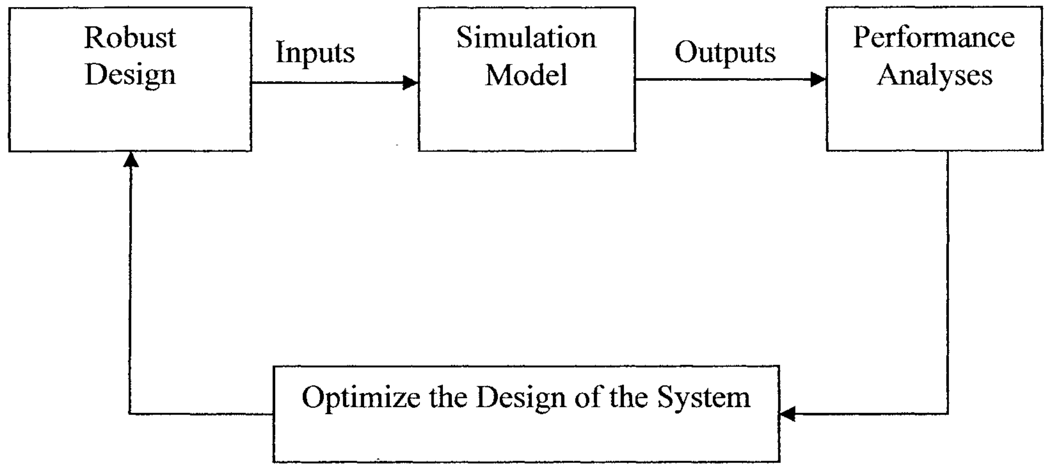

Figure 4.5: Combined Simulation and Optimization Process

To optimize the performance the robust design method is used which enables to experiment systematically, and also with which the data can be analyzed in the presence of noise. Figure 4.5, shows how simulation can be used for robust system design. The simulation model of the real production system, under study, is built and initialized to the exact current state of the production process.

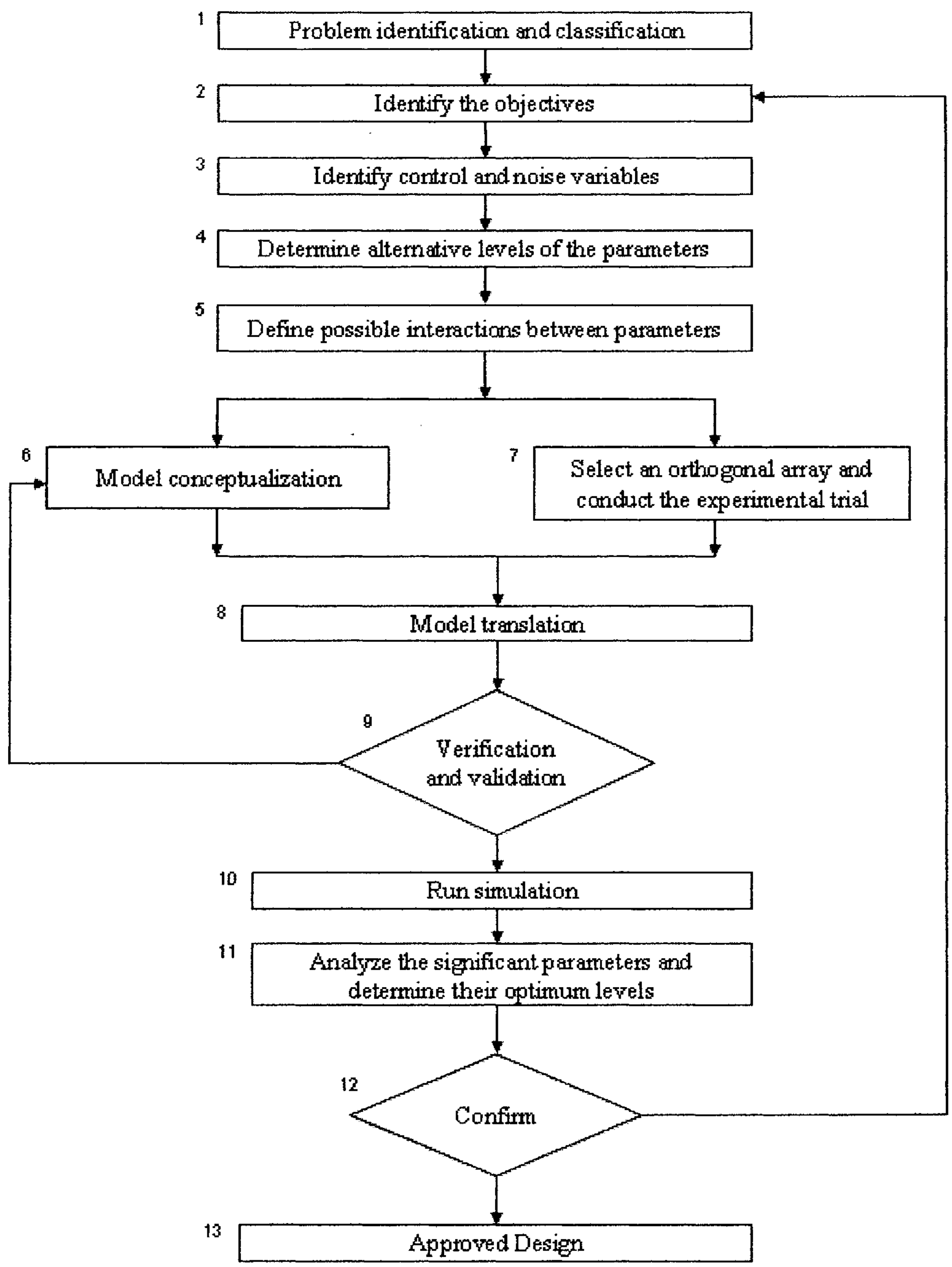

Figure 4.6: The Steps in the Activities of Simulation Using Robust Design

As seen in Fig. 4.6, the steps for simulation comprise three stages: system modeling, experimental design and analysis. The first four steps are used for problem definition. The steps five to seven are the robust design which is used for planning and conducting the experiments. Then, the simulation model is executed with verification and validation. After running the simulation, in the tenth step experimental results are analyzed and the optimum settings of the parameters are determined. Finally, a confirmation experiment is carried out to validate the results. The first loop originates from the decision box (step 9), which makes sure that the model is translated perfectly. The second loop originated from the decision box (step 12) which confirms whether the design is approved of not. In case the design is not approved, then the process is repeated from step 2, which again identifies the objectives and the alternative parameters for the ones taken into consideration till we get an approved design, and the experiment is complete.

The algorithm described above is generic approach and also the activities of simulation may follow a different pattern other than the steps shown.

4.11 USING TAGUCHI METHOD FOR SIMULATION BASED SYSTEM DESIGN

The method of using simulation with Taguchi's method for robust system design consists of the following steps (Wisner *et al.*, 1991; Azadivar 1992; Mayer and Benjamin, 1992):

1. Identify factors and specify targets: Identify the relevant performance measure, design factors and noise factors, for the system under study. The set of

independent variables of the model is divided into two disjoint subsets; the design (control) factors and the noise factors. The system under study should be modeled using appropriate simulation software, which should be verified and validated. The detailed description of the design and noise factors is given in section 4.4. At this stage, the target value for the performance measure is set and the ranges of permissible values of the design and noise variables are specified.

2. Formulation of the experiment: The matrix of the experimental design is made up of two components. The design matrix is a matrix of design (control) factors. Various level combinations are stored in the design matrix. The other matrix is known as the noise matrix, and it is a combination of the noise factors. The choice of how many levels to use for each factor is determined from prior knowledge of the anticipated behavior of the performance characteristic. If a design matrix has m rows and there are n rows in the noise matrix. For each of the experimental conditions specified by a row i of the design matrix, the experiment is replicated n times to yield measurements for the performance characteristic. This procedure is repeated for each of the m rows of the design matrix, making a total of $m \times n$ experimental conditions.

3. Conducting the experiments and analyzing the data: A total of $m \times n$ experiments are conducted and the results are compiled. The performance statistics of interest, the signal-to-noise ratios (S/N), are computed for each of the m rows of the design matrix.

4. Parameter setting: ANOVA is performed using the signal-to-noise ratio as the response. At this stage, factors which have a significant effect on S/N are

identified. These factors are now adjusted and set at the optimum levels. The levels of those factors are now treated as fixed, and hence will not be considered for further adjustments to improve performance.

5. Tuning the performance to target: The set of design factors which significantly influence the model performance are identified by performing ANOVA with the model performance as the response. Among the factors which have a negligible effect on S/N, those which have a significant effect on the model performance measure are identified. The model performance is tuned, to bring the value of its performance measure closer to target by properly setting the adjustment factors.
6. Performing conformation experiments: For the confirmation that the chosen settings of the model indeed yield the desired behavior, confirmation experiments are run at the new parameter settings. If the model performs as predicted, the chosen design is considered as adequate, and the analysis is complete. If not, then a new cycle is again initiated and gives an indication that some of the assumptions made during the analysis are not valid.

In this research, we followed these steps in the sequence they are explained, and some of them are followed more closely.

4.12 SUMMARY

This chapter discusses DoE and Robust Engineering in more detail. Various terms and formulae are explained. Implementation issues of the Robust Design have been discussed. The use of simulation along with Taguchi's method provides a solution for improved performance characteristics in a production system. The concerned problem under study in a production system can be simulated before an actual model is formed, which would enable and ensure that the investment made on the modification or construction would be justified. Whether the process would actually be robust, is carried out by performing a confirmation experiment using simulation.

CHAPTER 5

NUMERICAL EXAMPLE AND ANALYSIS

5.1 INTRODUCTION

This chapter presents an example to illustrate the methodology described in Chapter 4 and its solution method. An experiment was designed to study the effect of several factors of a simulated manufacturing job shop. The approach used in studying this problem is a concept-driven approach, which results from concept-generating approach discussed in Chapter 3. We have chosen to follow the approach described in Section 4.10, because there was a need for a decision-making tool along with the activities of simulation. The reason for the selection of robust design method was to obtain optimum performance along with its ability to design a better and robust system.

The problem represents a standard design problem. It is one of the contentions of this research that robust performance is more critical in the design of the production systems of the future.

5.2 PROBLEM STATEMENT

The quality and supply schedule of the input castings is highly unreliable, and consequently the enterprise cannot adhere to its customers delivery requirements. Various efforts to improve the reliability of supply have not been successful. At this stage it is decided to simulate the process, studying the system and find out ways of improving the system design so that the production commitments are most consistently met. The specific objective of the experiment is to minimize the average system time. The manager's primary goal is to seek a design of the job shop which would reduce the average system time and stabilize the system in the presence of the noise factors.

5.3 A MANUFACTURING JOB SHOP

In order to present how a production system can be designed using the robust engineering method, a simulation model of a manufacturing job shop is constructed using ARENA®. We considered a metal cutting job shop, processing different types of gear housings. Figure 5.1 shows the main elements of the job shop along with the possible process flow routes. The job shop has two groups of milling machines (M1, M2), a set of boring machines (B1, B2), two groups of drilling machines (D1, D2), and three inspection stations (I1, I2, I3). The three inspection workstations are placed by the processing machines. Each processed part is inspected before it is sent to the next set of machines. After inspection, the parts found defective can be rectified by re-work, while some are scrapped. The operation times (in minutes) of the part are given in Table 5.1. The average inspection time is 14 minutes.

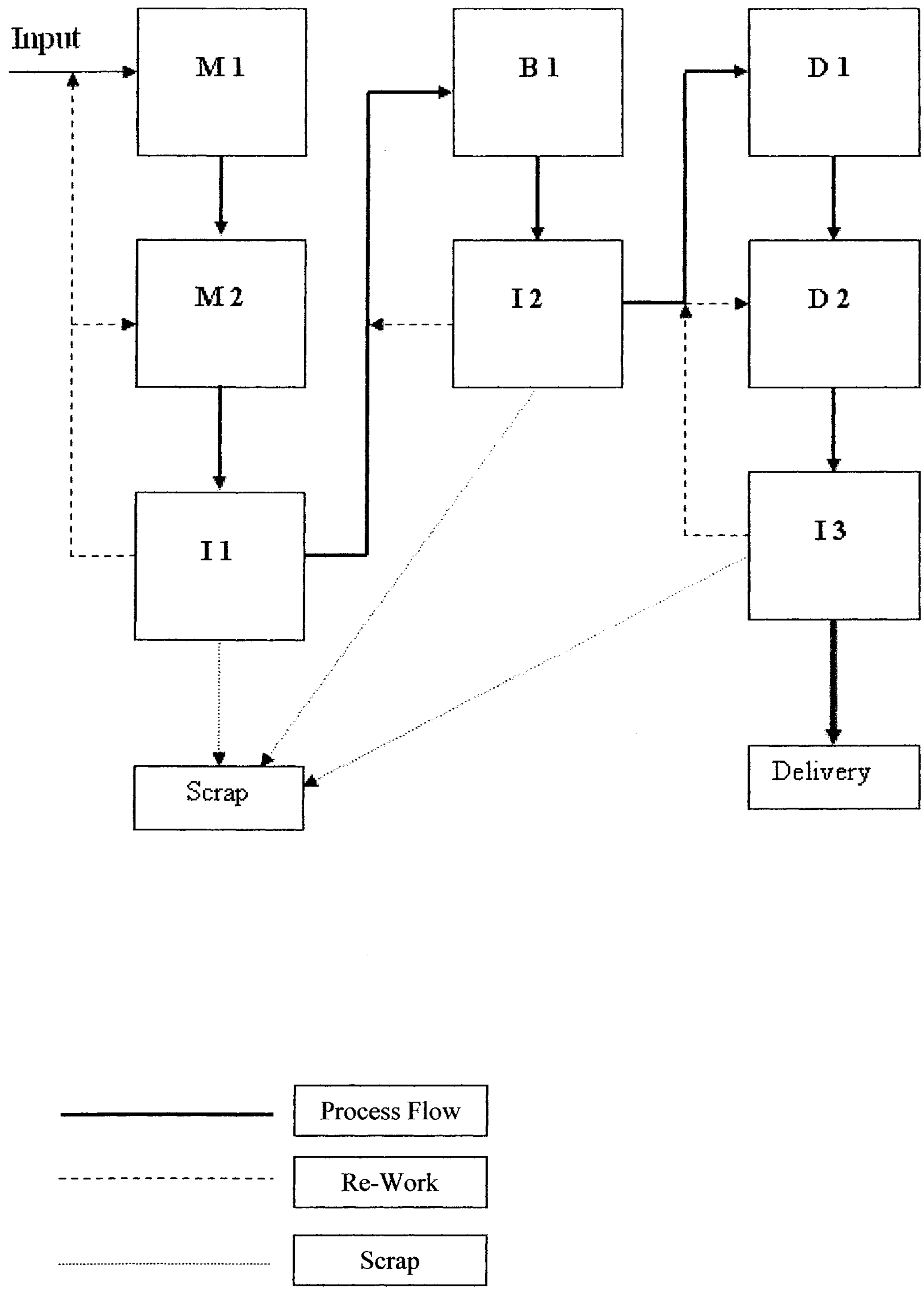

Fig. 5.1: A Manufacturing Job Shop

5.4 PLANNING THE EXPERIMENT

The job shop is capable of producing various types of jobs, which have different process flow routes and operation times. Assume that the timely supply of the Job Type 1, is most critical. The elements of the job shop which can be possibly adjusted are the number of type 1 and 2 milling machines, the number of boring machines, number of type 1 drilling machines, and the inspection time, in terms of better inspection machines. There is a maximum limit to which the number of machines can be afforded by the factory management. The scheduling rule used to simulate the system is FIFO (first-in-first-out).

Table 5.1 Process Flow Details of the Job Shop

Job Type 1	
Operation	**(mean, σ)**
Milling 1 (M1)	(14, 1)
Milling 2 (M2)	(29, 2.5)
Boring (B1)	(22, 2)
Drilling 1 (D1)	(17, 1.5)
Drilling 2 (D2)	(12, 1)

5.4.1 CONTROL AND NOISE FACTORS

It is decided to design an experiment to study the effects of increasing the number of machines, and a limit is set for the purpose. The factors in Table 5.2 are those variables that can be changed by the manager, at some cost.

Table 5.2 Controllable Factors and Levels

CONTROLLABLE FACTORS	LEVELS
F1 = Number of Type 1 Milling Machines	(1)1 machine (initial configuration)
	(2) 2 machines
F2 = Number of Type 2 Milling Machines	(1) 3 machines (initial configuration)
	(2) 4 machines
	(3) 5 machines
	(4) 6 machines
F3 = Number of Type 1 Drilling Machines	(1) 1 machines (initial configuration)
	(2) 2 machine
	(3) 3 machines
F4 = Number of Boring Machines	(1) 2 machines (initial configuration)
	(2) 3 machines
	(3) 4 machines
F5 = Inspection Time (Average)	(1) 14 minutes (initial configuration)
	(2) 11 minutes
	(3) 7 minutes

The factors in Table 5.3 are the noise factors. The rework rate is influenced by the input quality of the job which meets the tolerances limits or the ones which meet the target. It is assumed, as the raw material's specifications deviate from the target, the quality becomes progressively worse.

Table 5.3 Noise Factors and Levels

NOISE FACTORS	LEVELS
Inter- Arrival time of Input castings	(1) 11 minutes
	(2) 23 minutes
Rework rate after inspection	(1) 5 percent
	(2) 15 percent

5.5 PERFORMING THE EXPERIMENT

The model was developed using ARENA® Simulation which is a flexible and powerful software tool from Rockwell Software Corp. (see Appendix III, IV). The simulation model was developed and used to determine the average system time. The goal was to analyze the model with the initial configuration, and the various trials using the robust engineering methodology through Qualitek-4® software.

This study was treated as a terminating simulation since we are interested in measuring the performance for a limited time: 2880 minutes of operation, considering two days of continuous job shop processes. Ten replications of the simulation were done for each of the experimental trial conditions. Thus a total of 640 simulation runs are performed for the initial stage of the analysis. Currently, the average system time (for the initial configuration) is 734.594 minutes, but highly variable, taking noise factors into consideration. All the values are calculated up to three decimal places, for uniformity and consistency.

We have selected a L_{16} Orthogonal array (inner array) which is in its modified form. There are 3 factors which have 3 levels, and 1 factor with 2 levels and 1 factor with 4 levels. The L_{16} modified orthogonal array has 5 four-level columns. The design of the modified array was selected by using Qualitek-4® software, and for the noise factors, an outer array, L_4 was selected, since there are 2 factors with 2 levels each. The various trial conditions are described in Table 5.4, along with the trial average and S/N ratio. Each trial was experimented with four combinations of noise conditions.

Table 5.4: Description of Trial Conditions and S/N Ratio

	Factors and Levels								
Trial Conditions	F1	F2	F3	F4	F5	Random Order of Running the Trial	Average	Mean Squared Deviation (MSD)	S/N ratio
1	1	1	1	1	1	11	743.232	570295.650	-57.561
2	1	2	1	2	2	9	786.727	645802.900	-58.101
3	2	3	1	3	3	4	872.600	766655.182	-58.846
4	2	4	1	1	1	5	730.677	556288.413	-57.453
5	1	3	2	1	1	13	643.120	430130.340	-56.336
6	1	4	2	2	3	12	816.525	675927.332	-58.299
7	2	1	2	3	2	7	929.852	872331.600	-59.407
8	2	2	2	1	1	14	784.002	639145.934	-58.056
9	2	4	3	1	2	6	738.872	558856.100	-57.473
10	2	3	3	2	1	16	693.050	498081.000	-56.973
11	1	2	3	3	1	8	808.922	677953.628	-58.312
12	1	1	3	1	3	10	758.827	589114.990	-57.702
13	2	2	1	1	3	15	781.275	638263.575	-58.050
14	2	1	1	2	1	3	798.197	641357.264	-58.071
15	1	4	1	3	1	1	727.400	553477.550	-57.431
16	1	3	1	1	2	2	700.642	512271.300	-57.095
								Average (S/N Ratio)	-57.823

5.6 DATA ANALYSIS

Fig 5.2 shows the graph of each trial, and the shaded portion of the graph shows the range of variation for the results within the same trial condition. The variation is highest in the trial no. 4, 13 and 16 and the least in trial no. 3 and 14.

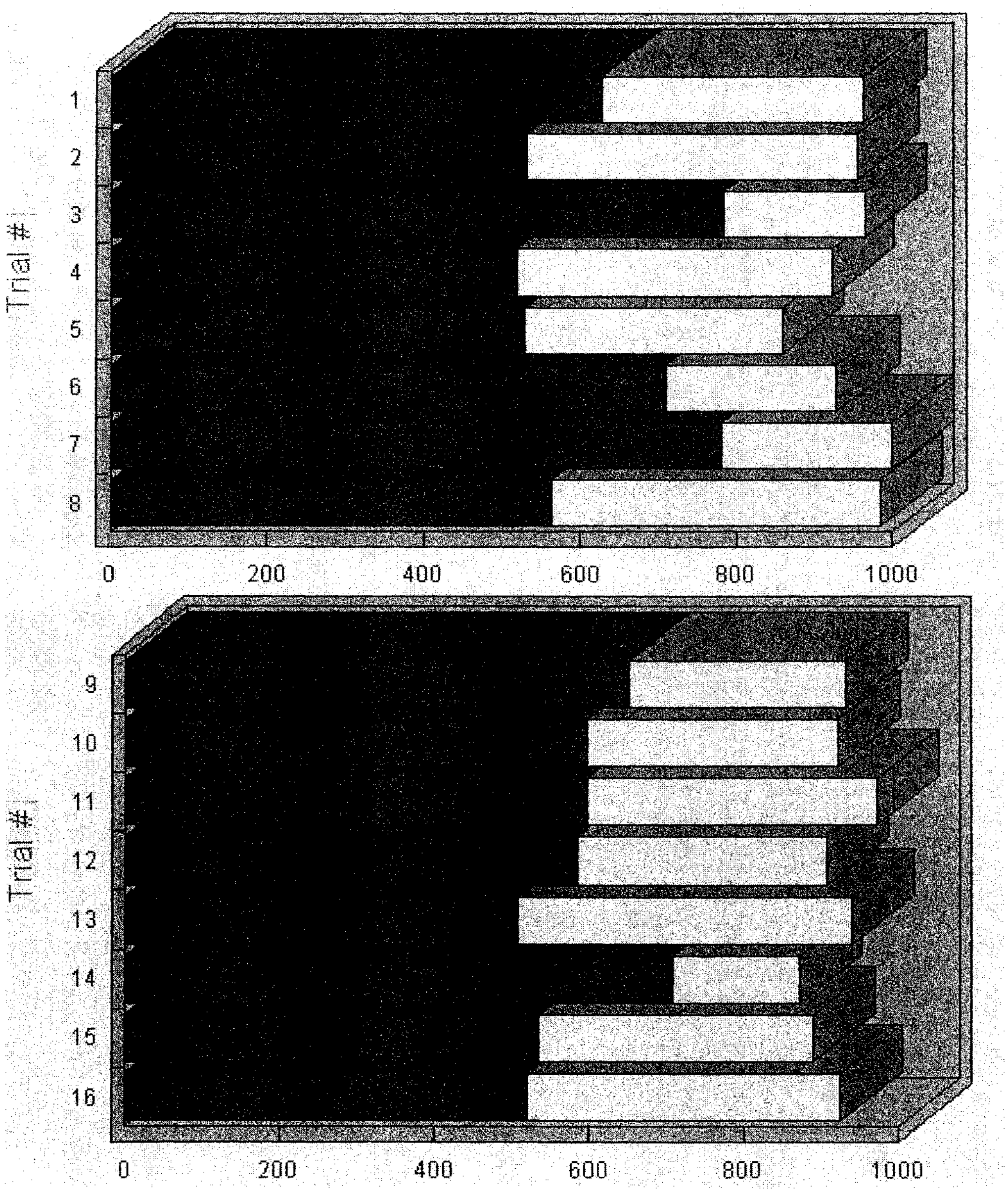

Fig 5.2 Experimental Trial Results

The graphs in Fig 5.2, give indication about the set of factors and levels which cause less variation for a particular set of factors and levels in the different trials.

5.6.1 S/N RATIO CALCULATION

Example of S/N ratio calculation for trial # 7:

Calculating the average system time from the four experiments for each trial,

Average system time, (998.321 + 952.832 + 987.630 + 780.630) / 4 = 929.850 minutes

The MSD, using equation 4.3, we have,

MSD, $[(998.321)^2 + (952.832)^2 + (987.630)^2 + (780.630)^2] / 4 = 872331.600$

From equation 4.2, calculating S/N ratio,

S/N ratio = $-10 \log_{10} (872331.600)$

S/N ratio = -59.407

5.6.2 MAIN EFFECTS BASED ON THE QUALITY CHARACTERISTIC

The main effects represent the trend of influence of a factor assigned to the column for which the column may be reserved. The numbers in the table represents average effects of the factors, shown in Table 5.5.

Table 5.5 Main Effects (Average Effects of Factors)

Factors	Level 1	Level 2	Level 3	Level 4
F1	-57.605	-58.041		
F2	-58.185	-58.130	-57.313	-57.480
F3	-58.025	-57.926	-57.655	
F4	-57.706	-57.351	-58.399	
F5	-58.224	-58.019	-57.524	

As we can see the average effects of various factors, in the Fig. 5.3-5.7, it shows the S/N ratio of the respective factor at its different level. In the case of factor F2, the S/N ratio is maximum when it is at level 1, and minimum at level 3, so in our optimum results we choose level 3, for the purpose of our robust design for the manufacturing job shop.

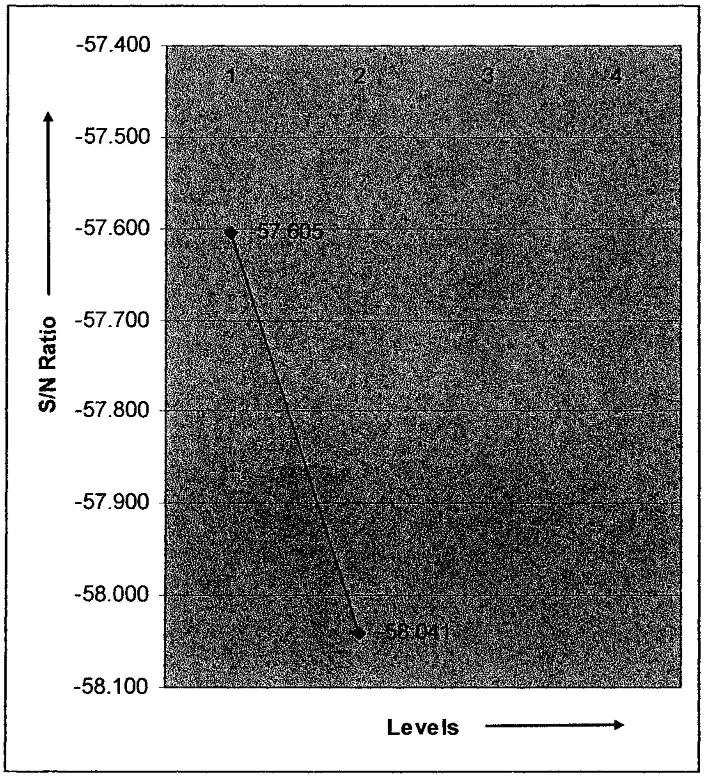

Fig.5.3: Average Effects of Factor F1

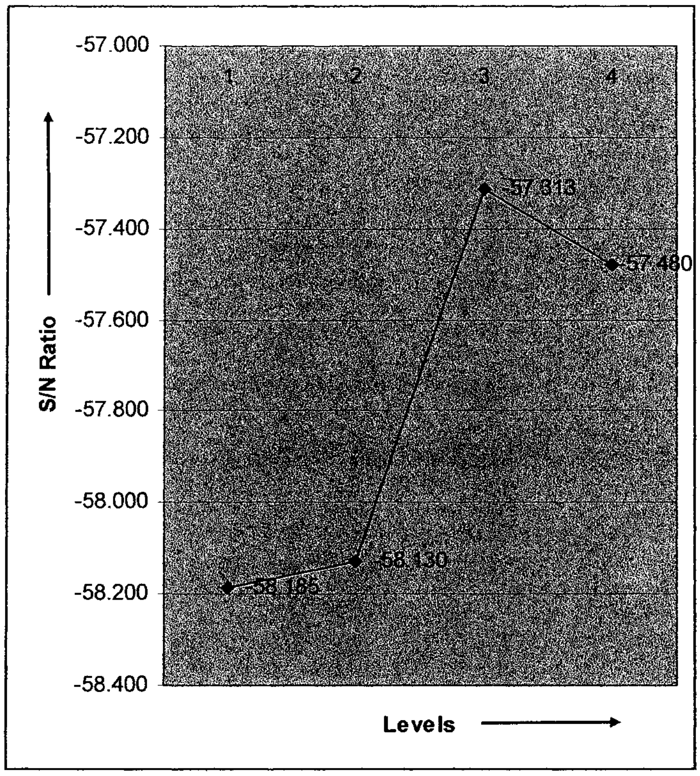

Fig.5.4: Average Effects of Factor F2

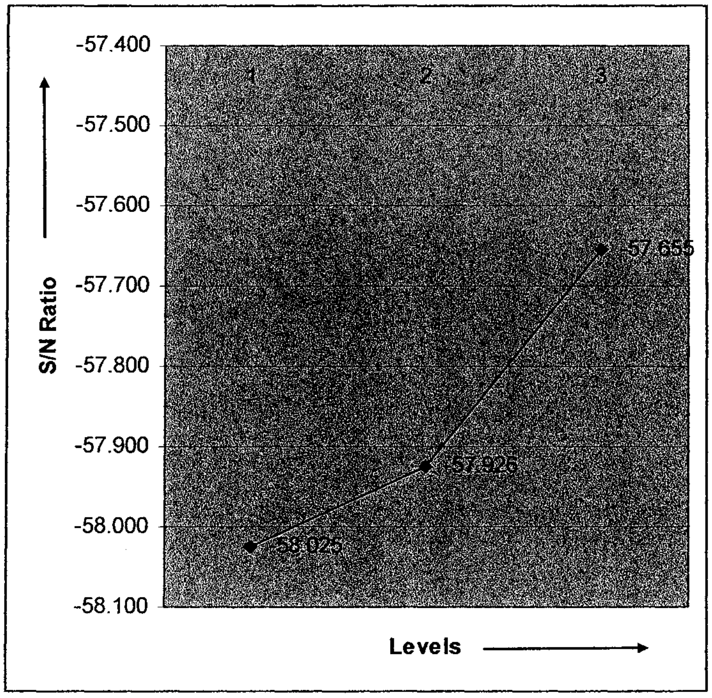

Fig. 5.5: Average Effects of Factor F3

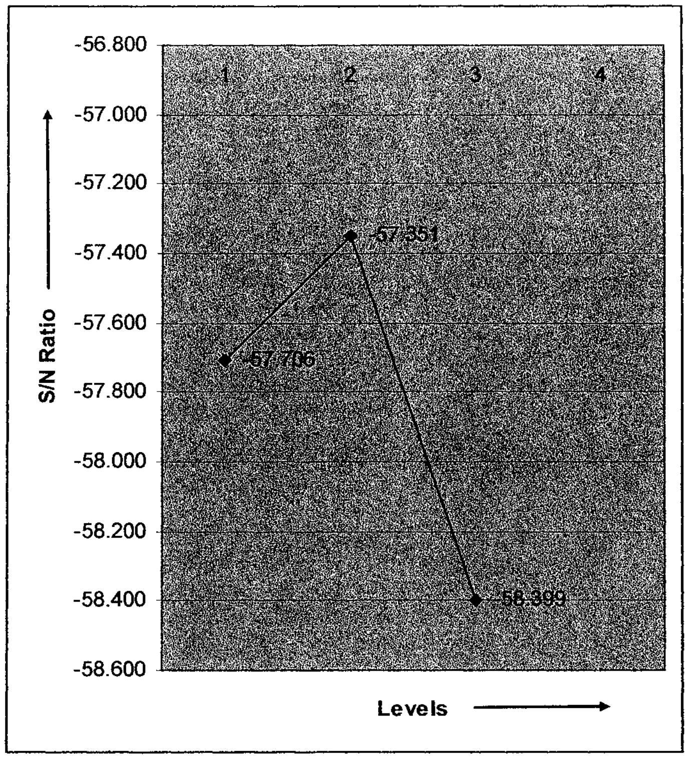

Fig. 5.6: Average Effects of Factor F4

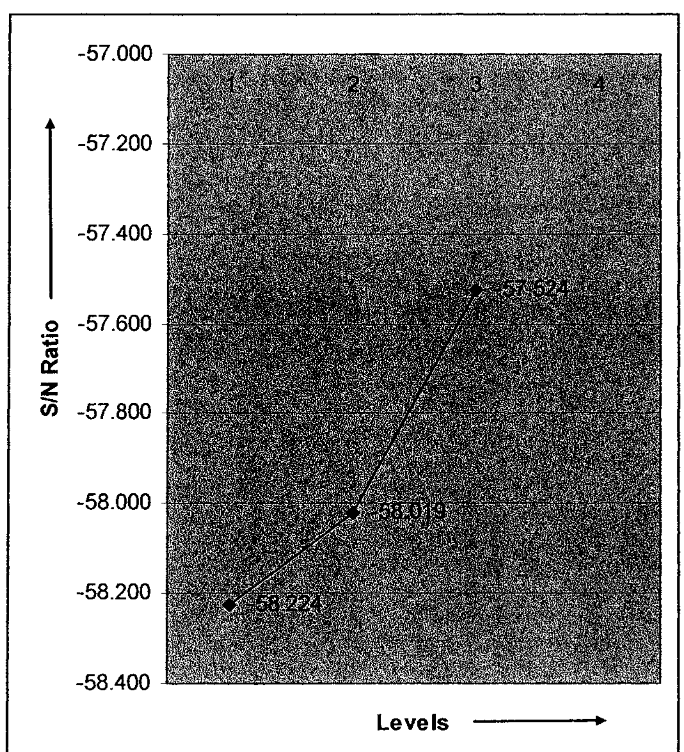

Fig.5.7: Average Effects of Factor F5

5.6.3 ANALYSIS OF VARIANCE – ANOVA

The main objective of ANOVA is to know how much variation each factor causes relative to the total variation observed in the result. By using ANOVA we can determine those factors, which have strong effects on the responses of the experiment, clearly shown in Table 5.5 and Figure 5.8. In Table 5.5, f is the number of degrees of freedom, S is the factor sum of squares, V is the sum of squares per DOF and is the variance, F is the ratio of factor variance and the variance of the error term, S' is the net variation and it is also known as pure sum of squares, and P is the percent influence of each factor.

Table 5.6: Analysis of Variance

ANOVA TABLE						
Factor	**f**	**S**	**V**	**F**	**S'**	**P**
F1	1	0.765	0.765	5.365	0.623	7.574
F2	3	2.048	0.682	4.783	1.620	19.695
F3	2	0.653	0.326	2.295	0.369	4.487
F4	2	2.856	1.428	10.005	2.570	32.252
F5	2	1.509	0.754	5.288	1.224	14.879
Other / Error	5	0.712	0.142			21.113

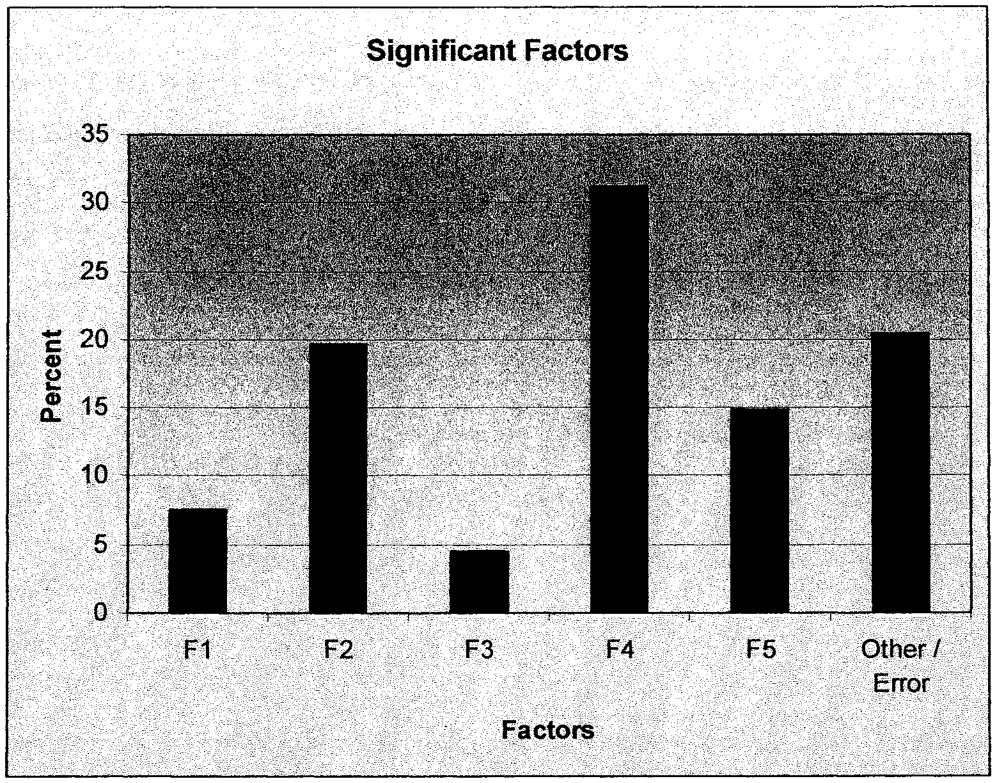

Fig 5.8: Percent influence of all factors including the error term

The error term or error factor in Table 5.5 is calculated by the software Qualitek-4®, which analyses the experiment and the chances of error. In reality this term is more than just experimental error. It is a representation of the collective influence of all factors not included in the study. The error term combines the effects of three sources:

1. Factors excluded from the experiment
2. Uncontrollable Factors (noise factors)
3. Experimental error

The total percent influence in the ANOVA table is set to 100%. The percent influence of the error term is calculated by the sum of all factor influences subtracted from the total.

It is calculated as the relative percent influence,

$$P_e = 100 - (P_{F1} + P_{F2} + P_{F3} + P_{F4} + P_{F5}) \tag{5.1}$$

Where, P_e is the percent error term and P_{F1}, P_{F2}, P_{F3}, P_{F4} and P_{F5} are the percent influence of each factor.

5.7 OPTIMUM CONDITIONS AND PERFORMANCE

The optimum condition gives the description of the optimum levels and the expected performance. The significant factors are included in the description, as given in Table 5.6. The numbers on the right hand side in the table indicate the contribution that a factor or interaction makes to the improvement of the expected performance. The expected performance at optimum represents what the population mean of results is obtained from tests.

Table 5.7 Optimum Conditions

Factor	Level	Contribution
F1	1	0.218
F2	3	0.510
F3	3	0.207
F4	2	0.357
F5	3	0.298
Total contribution from all factors = 1.590 Current Grand Average of Performance = -57.823 Expected Result at Optimum Condition = -56.233		

5.8 PERFORMING CONFIRMATION EXPERIMENTS

The last step of applying robust engineering method is to perform the confirmation experiment using the optimum conditions. The transformation of the predicted signal-to-noise ratio gives an average system time of 648.112 min. We have to perform additional experiments with the factors set at their optimum levels in order to confirm that the new design actually performs better, as predicted. The level for each of the significant factors, are given in Table 5.5, and 10 more replications of the simulation were conducted. The average system time obtained with the final design is 649.890 min. At the initial configuration of the design, as shown in Table 5.2, the average system time obtained by simulation is 734.594 min. Therefore, a reduction of 11.53 % is achieved in the time in system of the model as an outcome of the analysis.

The main goal of this study was to generate a system which is robust in the presence of noise factors. As the signal-to-noise ratio was used as a metric to guide the search for better designs in our numerical example, the resulting design is likely to be robust which is also validated by the confirmation run.

5.9 SUMMARY

A set of experiments were designed to study the effect of several factors in a manufacturing job shop. The specific objective of the experiment was to reduce the average system time, and to keep the variation from noise factors to a minimum.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

6.1 CONCLUSIONS

The robustness of production system is important for a manufacturing company's capability to produce consistent high-quality products on customer demand with costs that creates profitability. It is well understood that the robustness can be achieved during the design process more easily and to lower costs, than during operation phase when most system parameters are already set. There is a need to develop optional strategies for production system design for robustness and quality. By explicitly considering robustness as an objective in the problem formulation, it helps the designer to build a system which not only performs well, but are also robust. This research is an attempt to apply robust engineering approach for production system design for better system efficiency and product quality. The product quality can be ensured in the long term, by the efficiency of better performing production system.

The application of Robust Engineering Methodology is a straightforward process that verifies control factors for the variation in a given process through experimental design. The information obtained in the experiments provides the basis for reducing the impact of noise factors on system performance. The proposed method uses orthogonal arrays to reduce the use of resources for the experiment. This research also integrates computer simulation and robust design methodology for the purpose of production system design. The numerical example presented in this thesis demonstrates the potential for applying the method in robust production system design in real-world application.

By the use of simulation, the cost of extensive experiment can be offset which enables the industry practitioners to analyze without the need to consider the high expenditure. A good simulation study depends to a large extent, on the knowledge and views of the analyst in the domain of study and skills in the efficient use of a simulation tools.

6.2 LIMITATIONS

The proposed method is not the best optimization method, although it targets the noise, making the production system robust. Robust design methodology might not be optimum in the cases where profit maximization is a priority. It involves improved designs only in the regions where the responses are measured.

The use of Signal to Noise Ratios without studying the nature of the underlying model would not give a comprehensive detail. Also, there would be cases where the system would not give control and noise factors for study.

The method considers the problem with only a single performance measure. However, considering the robustness in the system can be extended to design situations where there are two or more performance metrics. This aspect is important, since most of the design problems would consider more than one performance metrics.

6.3 FUTURE RESEARCH

Various methods, models and other types of supportive tools are means to create and maintain knowledge between and within people being involved in the process of designing robust production systems. Currently, there are no standard yardsticks for the design analysts to access the practice of production system design using robustness as a factor in the computer simulation. The creation of sustainable knowledge should be considered a relevant factor when improving conditions for robust production. The knowledge and experience by those individuals designing and evaluating production systems are central for a possibility top create robust production systems. Thus, this is an area with potential for more research. One of the proposed extensions to this research would be to add more features to handle noise, and give more numerical examples, which may lead to building more robust systems.

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APPENDIX I

TABLE A1: Standard $L_8 2^7$ Array

Experimental No.	**Columns**						
	1	**2**	**3**	**4**	**5**	**6**	**7**
1	1	1	1	1	1	1	1
2	1	1	1	2	2	2	2
3	1	2	2	1	1	2	2
4	1	2	2	2	2	1	1
5	2	1	2	1	2	1	2
6	2	1	2	2	1	2	1
7	2	2	1	1	2	2	1
8	2	2	1	2	1	1	2

TABLE A3: Standard $L_9 3^4$ Array

Experimental No.	Columns			
	1	**2**	**3**	**4**
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

Table A3: Standard $L_{27}3^{13}$ Orthogonal Array

Expt.No.	Column												
	1	2	3	4	5	6	7	8	9	10	11	12	13
1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2	2	2	2	2	2	2
3	1	1	1	1	3	3	3	3	3	3	3	3	3
4	1	2	2	2	1	1	1	2	2	2	3	3	3
5	1	2	2	2	2	2	2	3	3	3	1	1	1
6	1	2	2	2	3	3	3	1	1	1	2	2	2
7	1	3	3	3	1	1	1	3	3	3	2	2	2
8	1	3	3	3	2	2	2	1	1	1	3	3	3
9	1	3	3	3	3	3	3	2	2	2	1	1	1
10	2	1	2	3	1	2	3	1	2	3	1	2	3
11	2	1	2	3	2	3	1	2	3	1	2	3	1
12	2	1	2	3	3	1	2	3	1	2	3	1	2
13	2	2	3	1	1	2	3	2	3	1	3	1	2
14	2	2	3	1	2	3	1	3	1	2	1	2	3
15	2	2	3	1	3	1	2	1	2	3	2	3	1
16	2	3	1	2	1	2	3	3	1	2	2	3	1
17	2	3	1	2	2	3	1	1	2	3	3	1	2
18	2	3	1	2	3	1	2	2	3	1	1	2	3
19	3	1	3	2	1	3	2	1	3	2	1	2	3
20	3	1	3	2	1	3	2	1	3	2	1	3	2
21	3	1	3	2	3	2	1	3	2	1	3	2	1
22	3	2	1	3	1	3	2	2	1	3	3	2	1
23	3	2	1	3	2	1	3	3	2	1	1	3	2
24	3	2	1	3	3	2	1	1	3	2	2	1	3
25	3	3	2	1	1	3	2	3	2	1	2	1	3
26	3	3	2	1	2	1	3	1	3	2	3	2	1
27	3	3	2	1	3	2	1	2	1	3	2	3	2

APPENDIX II

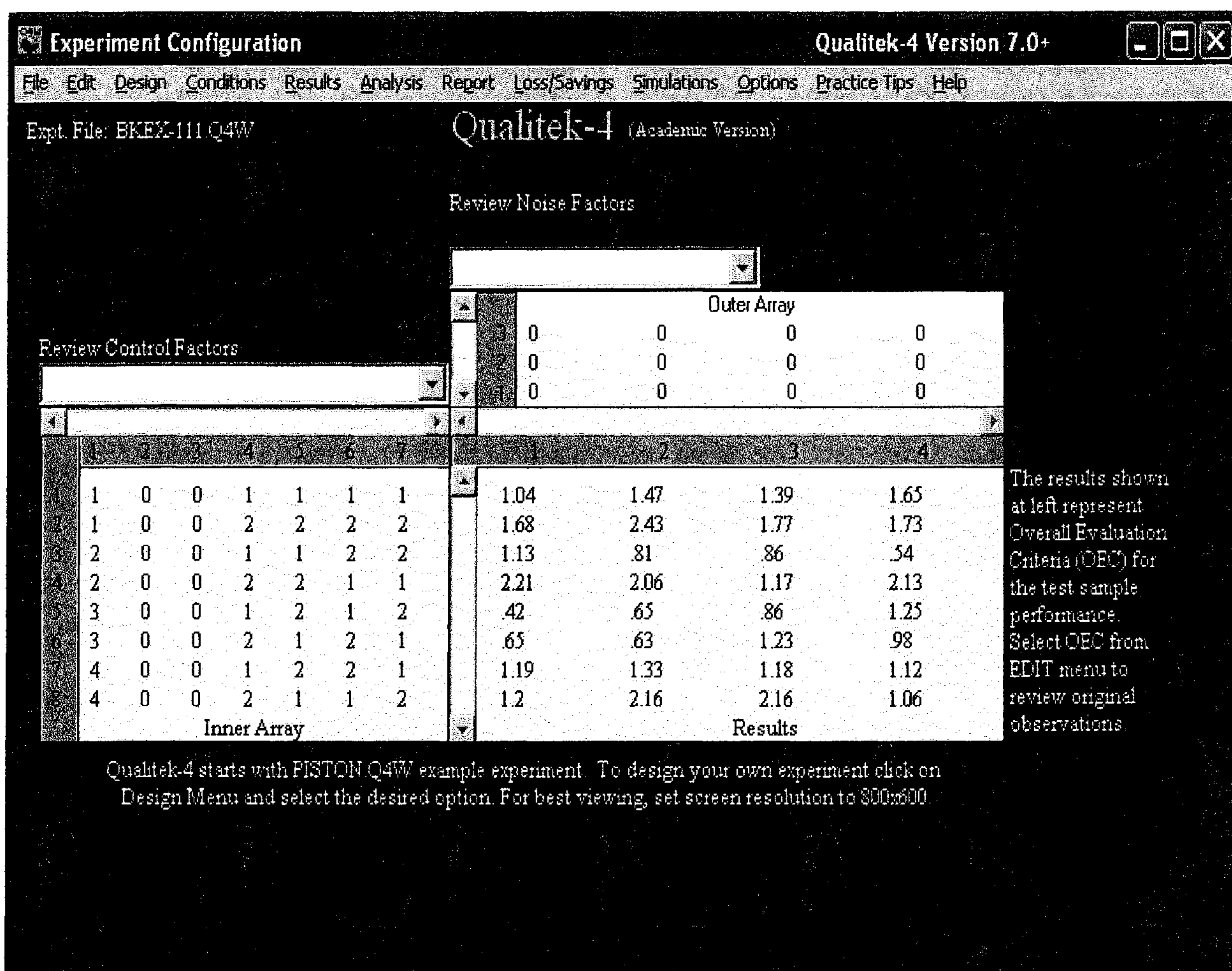
Table A4: Experiment Design with Noise Factors Using an Outer Array [50]

								Outer Array (L_4)			
							Z	1	2	2	1
							Y	1	2	1	2
							X	1	1	2	2
Control factors								**Results**			
Trial	**A**	**B**	**C**	**D**	**E**	**F**	**G**	1	2	3	4
1	1	1	1	1	1	1	1	R11	R12	R13	…
2	1	1	1	2	2	2	2	R21	…	…	…
3	1	2	2	1	1	2	2	…	…	…	…
4	1	2	2	2	2	1	1	…	…	…	R44
5	2	1	2	1	2	1	2	R51	…	…	…
6	2	1	2	2	1	2	1	…	R62	…	…
7	2	2	1	1	2	2	1	…	…	R73	…
8	2	2	1	2	1	1	2	R81	…	…	R84
Inner Array (L_8)											

The size of the outer array, which dictates the number of samples, required to complete an experiment, is independent of the inner array and depends strictly on the number of noise factors and their levels. It is also independent of the size of inner array and the control factors included in the study. The purpose of an outer array in the experiment is to combine the noise factors and run multiple samples in the same trial condition exposed to the conditions.

A snapshot of Qualitek-4®:

Robust Design Experiment using Inner and Outer array



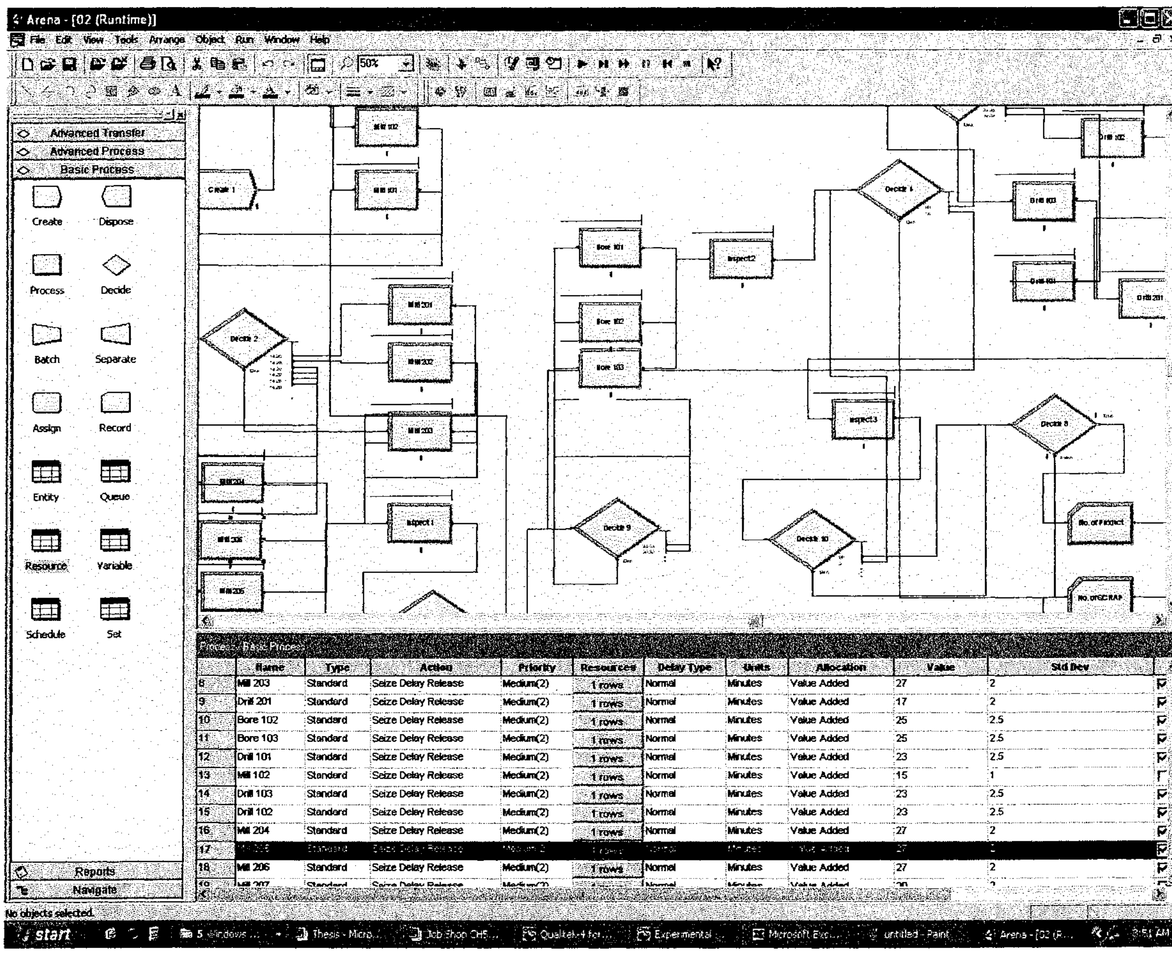
APPENDIX III

Various simulators found on the Web.

Automod / Autosched	http://www.autosim.com
Promodel	http://www.promodel.com
MODSIM III	http://www.modsim.com
Rockwell	http://www.arenasimulation.com
Factor/AIM	http://www.pritsker.com
Witness	http://www.lanner.com
Taylor II	http://www.taylorii.com
Micro Saint	http://www.madboulder.com
Taylor ED	http://www.taylor-ed.com
Quest	http://www.deneb.com, http://www.tdm.fi
Simple ++	http://www.aesop.de, http://technomatix.com
Extend	http://www.imaginethatinc.com
MAPICS	http://www.symix.com
Dassualt	http://www.3ds.com
Visual8	http://www.visual8.com
CACI	http://www.caci products.com
CMS	http://www.powernetonline.com/~cms
Deneb Robotics	http://www.deneb.com
Factory Flow	http://www.eai.com
Geer Mountain	http://www.gensym.com
Ithink Analyst	http://wwwhps-inc.com
Extend	http://wwwimaginethatinc.com
SimEngine	http://wwwsimengine.com
Adept Work cell	http://www.adept.com
Ben Graham	http://www.worksimp.com
CFM	http://www.teamflow.com
Epix	http://www.epixinc.com
ProcessModel	http://www.processmodel.com
Scitor	http://www.scitor.com
Silma	http://www.silma.com
Skymark	http://www.skymark.com

APPENDIX IV

A snapshot of simulation using Rockwell software ARENA®



APPENDIX V

Taguchi Methods Trademark

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Mark Drawing Code	(1) TYPED DRAWING
Serial Number	73758696
Filing Date	October 20, 1988
Current Filing Basis	1A
Original Filing Basis	1A
Published for	May 29, 1990

Opposition	
Registration Number	1610798
Registration Date	August 21, 1990
Owner	(REGISTRANT) AMERICAN SUPPLIER INSTITUTE, INC. CORPORATION MICHIGAN 38701 SEVEN MILE ROAD, SUITE 355 LIVONIA MICHIGAN 48152
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Prior Registrations	1435003
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Type of Mark	SERVICE MARK
Register	PRINCIPAL-2(F)-IN PART
Affidavit Text	SECT 15. SECT 8 (6-YR). SECTION 8(10-YR) 20010925.
Renewal	1ST RENEWAL 20010925
Live/Dead Indicator	LIVE

APPENDIX VI

Name of some Robust Design Methodology Implementing Companies or Organizations:

Abbott Laboratories; Agilent Technologies, CA; Allied Signal; Aluminum Federation of South Africa, Isando; Amoco Ploymers, Inc. Tulsa, OK; Arvind Replacement Products, Pulaski, TN; ASAT Ltd., New Territories, Hong Kong; ASMO North Carolina; AT&T; Ashland Chemicals; Aspen Technologies; Auto Alliance International; A. T. Cross, Atlantic Steel Co.; Avon Automotive - Cadillac Plastics; Black & Decker; Boeing, Seattle, WA; Borg Warner Automotive; Boston Scientific, Wayne, NJ; Brechteen Co.; Briggs & Stratton, Milwakee, WI; BTU International, Billerica, MA; Burton Rubber Processing Co.; Budd Co. Plastics Division, Troy, MI; Cadillac Rubber & Plastic; Carbonic Tech Center; Carborundum Universal, Chennai, India; Cardiac Control System; Caterpillar, Joliet, IL; CeraMed, Lakewood, CO; Certainteed Corp. Jackson, MI; Chrysler Corporation; CommScope Inc.; Contech-Auburn, IN; Copeland Corp.; Cordis Corporation; Cryovac; CutlerHammer/Eaton, Watertown, WI; U.S Army, Dept. of Defence, PA; DaimlerChrysler, Auburn Hills, MI; DJ Orthopedics, Vista, CA; Donnelly Corp.; Dolphinc, Inc. Phoenix, AZ; Eagle Ottawa Leather Company; Ford Motor Company, Dearborn, MI; Ford Motor Company, Batavia, OH; Eastmen Kodak; Ford Motor Company, Sharonville, OH; Ford Motor Company, Lima, OH; Ford Motor Company, Livonia, MI; Ford Motor Company, Sterling Heights, MI; Ford Motor Company, Chihuahua, Mexico; Ford Motor Company, FTDC, Dearborn, MI; G. M. Powertrain, Toledo, OH; G. M. Powertrain, Ypsilanti, OH; Gates Rubber CO.; Giddings & Lewis; GKN Industries; Glit/Gemtex, Etobicoke, Ont. Canada; Goshen Rubber Co, Goshen, IN; Grimes Aerospace, Ocala, FL; Honda Motor Co.; HT Troplast AG, Troisdorf, Germany; Huchinson Technology; Hughes Aircraft of Canada; Johnson Controls, Plymouth, MI ; Kautex Corp.Ont. Canada; Kay Automotive Graphics; Kyocera; Leer Corp., Div of Ford; Livantech Corp, Largo, FL; Locheed Martin, Owege, NY; Nortel Networks, Wilmington, MA; Offermatica, San Francisco, CA; Olin Corp.; Ovonic Battery Co.; Orthovita, Malvern, PA.; Pall Europe Corporate Services, Portsmouth, UK; Parker Amchem; Pacific Coast Technologies, Wenatachee, WA; Perry Chemicals; Peterson Springs; Precision Coatings, MI; PT. South Pacific Viscose; Qualcomm, Inc. Sandiego, CA; Rapistan Damage Corp.; Reckit & Coleman; Reynolds Metal Co.; Robotron Corp.; Siemens Automotive; Siemens Energy and Automation; Smith & Nephew Richards; Snap on Tools; Sony Display Device, Kanagawa, Japan; Sponsera, NJ; Square 'D' Company; St. Clair Die Casting, LLC. MO.; Stackpole Corp.; Steelcase, Grand Rapids, MI; Stryker Howmedica Osteonics, Allendale, NJ; Summit Polymers; Vermont American; Visteon, Dearborn, MI; Visteon, Connersville, Indiana; Volvo GM Heavy Truck; Walbro Corp.; Waterford Stanley, Ireland; Wegu Canada; Wellman Friction, Solon, OH; Westinghouse Electric Corporation; Winfield Industries; Wishbro Company, apple Valley, MN; Wisconsin Centrifugal, Waukesha, MN; Wolverine Plastics Tech.; Yazaki EDS Engineering Inc.;