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Quality prediction in manufacturing system design.

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QUALITY PREDICTION IN MANUFACTURING SYSTEM DESIGN

by

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ABSTRACT

Manufacturing system design can significantly affect the resulting product quality level. Therefore, the early prediction of product quality, as affected by manufacturing system configuration decisions, can enhance the manufacturer's competitiveness through achieving higher quality levels at lower costs in a responsive manner.

In this research, a conceptual framework is proposed for the proactive assessment of product quality in terms of the manufacturing system configuration parameters. A new comprehensive model that can be used in comparing different system configurations based on quality is developed using Analytic Hierarchy Process. In addition, a hierarchical fuzzy inference system is developed to model the ill-defined relation between manufacturing system design parameters and the resulting product quality. This model is capable of mapping the considered manufacturing system configuration parameters into a Configuration Capability Indicator (CCI), expressed in terms of sigma capability level, which can be compared to the benchmark Six Sigma capability.

The developed models have been applied to several case studies (Test Parts ANC-90 and ANC-101, Cylinder Head Part Family, Gearbox Housing, Rack Bar Machining, and Siemens Jeep Intake Manifold) with different configuration scenarios for illustration and verification. The results demonstrate the capabilities of the CCI in comparing different system configurations from quality point of view and in supporting the decision-making during the early stages of manufacturing system development.

The included application of the developed models emphasized that high quality levels can be achieved by investigating all the improvement opportunities and it is recommended that efforts should be directed in the first place to design the system with high defect prevention capability. This can be achieved by using highly capable processes, implementation of mistake proofing techniques, as well as minimizing variability due to parallel processing and variation stack up. Considering the relationship between quality and complexity, it has been concluded that the CCI represents the time-independent real complexity of a system configuration. Furthermore, it has been

demonstrated that the product complexity adversely affects the resulting product quality. Therefore, it is recommended that high product quality levels can be achieved not only by using highly capable system configurations, but also by minimizing the product complexity during the design stage.

To my lovely twin sons,

Sherif and Shady

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LIST OF ABBREVIATIONS

AHP	Analytic Hierarchy Process
BS	Buffer Size
CCI	Configuration Capability Indicator
CI	Coefficient of Inconsistency
CIE	Capability of Inspection Equipment
CRI	Coefficient of Random Inconsistency
DDC	Defect Detection Capability
DDP	Defect Prevention Capability
DFSS	Design For Six Sigma
DIS	Distribution of Inspection Stations
ECN	Engineering as Collaborative Negotiation
EDR	Error Detection Responsiveness
FIS	Fuzzy Inference System
JI	Jidoka Implementation
HEP	Human Error Probability
IR	Inconsistency Ratio
MPI	Mistake Proofing Implementation
NFP	Number of Flow Paths
NSS	Number of Serial Stations
OCP	Overall Capability of Processes
QCMS	Quality of Configuration Morphological Structure
QFD	Quality Function Deployment
VRM	Variation Risk Management

NOMENCLATURE

$AIEP$: Average Inspection Error Probability

AIS : A measure for assessing the allocation of inspection station

AP : Average number of processes performed before inspection

D_{cj} : Inherent difficulty of cognitive task element j

D_{pk} : Inherent difficulty of physical task element k

I_i : Inspection station number i, $i = 1, 2, \ldots, n_I$

M_C : Number of cognitive task elements

M_P : Number of physical task elements

M : Total number of task elements, $M = M_C + M_P$

M_D : Number of unique task elements

m_{cj} : Cognitive task element j, $j = 1, 2, \ldots, M_C$

m_{pk} : Physical task element k, $k = 1, 2, \ldots, M_P$

n_I : The number of inspection stations

P_T : Total number of processes

P_{I_i} : The number of processes performed before inspection station I_i

Y_{RT} : Rolled throughput yield of a product and it represents the fraction of product units that pass through all the stations without rework or scrap

Y_i : Yield of an individual process i, $i = 1, 2, \cdots, P_T$

P_T : Total number of processes

$p(HE)_i$: Probability of human error in performing inspection task i, $i = 1, 2, \cdots, n_I$

$p(EE)_i$: Probability of equipment error in performing inspection task i, $i = 1, 2, \cdots, n_I$

$p(E)_i$: Probability of error in performing inspection task i, $i = 1, 2, \cdots, n_I$

$T_{coupling}$: Coupling between task elements

T_D : Diversity of task elements

T_{tp} : Task time pressure

X : Set of attributes representing the task error proneness, $X = \{x_1, x_2, x_3, x_4, x_5\}$

x_1 : An attribute representing the average inherent difficulty of cognitive task elements

x_2 : An attribute representing the average inherent difficulty of physical task elements

x_3 : An attribute representing the diversity between task elements

x_4 : An attribute representing the coupling between task elements

x_5 : An attribute representing the level of job aids and mistake proofing implementation

$u_x(x_i)$: Task error proneness utility for the attribute x_i, $i = 1, 2, ..., 5$

$u_y(y_i)$: Operators characteristics utility for the attribute y_i, $i = 1, 2$

$u_z(z_i)$: Work environment utility for the attribute z_i, $i = 1, 2, ..., 4$

$u(X, Y, Z)$: Overall utility function for the sets of attributes X, Y, Z

Y : Set of attributes representing the operator's characteristics, $Y = \{y_1, y_2\}$

y_1 : An attribute representing the operator's personal capabilities

y_2 : An attribute representing the operator's professional capabilities

Z : Set of attributes representing the work environment as well as system's operational characteristics, $Z = \{z_1, z_2, z_3, z_4\}$

z_1 : An attribute representing the physical work environment

z_2 : An attribute representing the psychological work environment

z_3 : An attribute representing the time pressure

z_4 : An attribute representing the frequency of reconfiguration

1. INTRODUCTION

1.1. MOTIVATION AND PROBLEM STATEMENT

Quality is one of the most critical performance measures that can significantly affect the manufacturer's competitiveness. Introducing high quality products to the customers involves two important aspects as shown in Figure 1.1. One aspect is related to the quality of the product design; which necessitates designing the product with all the quality features that satisfy and delight the customer. These features include the "must-have" quality characteristics as well as the "attractive" quality characteristics [Kano, et al., (1996)]. The other aspect that should be considered to achieve high quality products is the conformance quality, which ensures that the manufactured product conforms to the design specifications. The later involves the development of a manufacturing system that is capable of producing products with minimal deviation from the design targets. Assessing the capability of a system configuration is a challenging task, especially, at the early stages of manufacturing system design and this represents the main focus of this research.

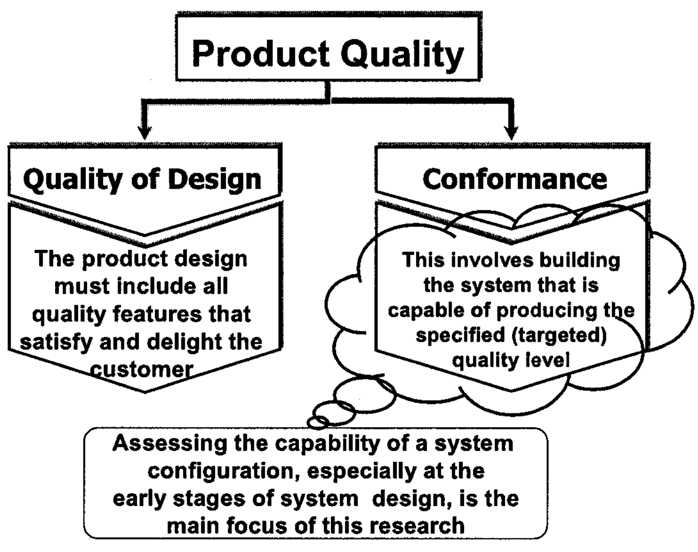


Figure 1.1. Product Quality Pre-requisites

Several scenarios from the automotive industry have been provided by Inman et al. [2003], which demonstrate that the manufacturing system design does significantly affect the product quality. Assessing the impact of manufacturing system design on quality at the early stages of system development can help in achieving high quality products at lower costs. This is because modifications in the system design are always less expensive at the early stages compared with those made during the production. In addition, the current and future manufacturing environment that is associated with frequent changes in customer requirements will force the manufacturing organizations to utilize manufacturing systems that can be reconfigured during its life cycle [Koren 1999]. This trend will make the manufacturing system configuration and reconfiguration an ongoing activity within the manufacturing organizations. These systems also are not expected to achieve their potential effectiveness unless the ramp up time is kept to a minimum. In such an environment, at the early stages of system configuration or reconfiguration, the designer is faced with many configuration alternatives. In order to cost effectively achieve high quality products in a responsive manner, it is critical to have the tools that can assess and compare different system design options from a product quality point of view. In addition, it has been reported by Ceglarek and Jin [2004] that there still is a tremendous resistance toward the implementation of advanced technology or innovations in new manufacturing system development. This resistance is a result of the lack of confidence in predicting the performance of these systems. This emphasizes the importance and the significance of research work related to the proactive assessment of these systems in the early design stages.

In spite of the various approaches proposed in the literature for quality assessment and prediction, little research investigates the impact of system design on product quality. Tools that can help the system designer compare different system design options based on the resulting product quality are still lacking. Therefore, this research is directed to the assessment and prediction of product quality in the early stages of manufacturing system design. This involves identifying the system configuration parameters that significantly affect the resulting product quality. Furthermore, investigating how those effects can be assessed or quantified and how the product quality can be predicted in terms of the configuration parameters in the system's design stage. The developed model can also be used for comparing different system configuration alternatives from the quality point of view and to predict the resulting product quality in terms of the manufacturing system parameters.

1.2. RESEARCH OBJECTIVES

The main objective of this research, as shown in Figure 1.2, is to develop a Configuration Capability Indicator (CCI) that is capable of mapping manufacturing system configuration parameters into an expected product quality level at the early stages of manufacturing system development. This objective is achieved through the following:

- Identifying the different system configuration parameters that could affect the resulting product quality level and developing a conceptual framework that links these parameters to quality.
- Analytic Hierarchy Process (AHP) to develop a relative Configuration Capability Indicator (CCI).
- A Configuration Capability Indicator (CCI) in terms of sigma capability levels using a hierarchical fuzzy inference system.
- The errors due to human involvement in manufacturing tasks assessed using multi-attribute utility analysis.

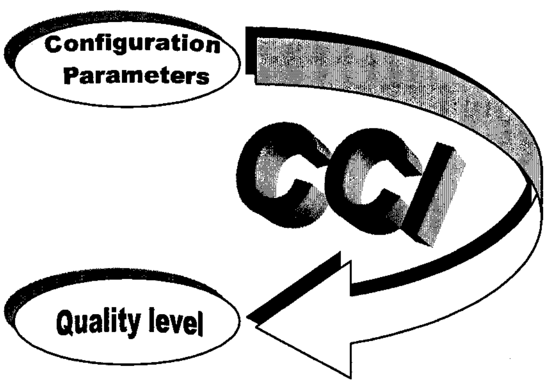


Figure 1.2 Configuration Capability Indicator (CCI) for Mapping Configuration Parameters into an Expected Product Quality Level

1.3. DISSERTATION OUTLINE

The remainder of this dissertation is organized as follows:

Chapter 2: In this chapter, an extensive literature review is conducted, which includes research work related to various quality approaches, impact of manufacturing system design on quality, and different approaches for quality prediction. This chapter highlights the lack of research work that investigate the impact of manufacturing system design on the resulting product quality as well as the need for models for assessing the expected product quality level as affected by manufacturing system design decisions.

Chapter 3: In this chapter, a conceptual overall framework is proposed for the proactive assessment of quality. The framework proposed two approaches for quality assessment. One is using the direct links between configuration parameters and the resulting quality. The other is an indirect one, in which complexity is proposed be used as an intermediate link between configuration parameters and quality. This chapter also highlights and details the approach to be considered in this research for quality assessment.

Chapter 4: In this chapter, the Analytic Hierarchy Process (AHP) is used to develop a model that can be used in comparing different system configuration alternatives based on quality. This model can provide the system designer with a relative measure that can be used as a Configuration Capability Indicator (CCI), which is assessed based on the configuration defect prevention capability as well as defect detection capability. The configuration defect prevention capability is assessed based on the overall capabilities of processes, implementation of mistake proofing, variability due to mixing or stack-up of variation as affected by the number of parallel and serial stations. The configuration defect detection capability is assessed in terms of distribution and capabilities of inspection stations, the implementation of Jidoka, as well as the buffer size. The results of the model application to case study are presented and the limitations of the model are discussed.

Chapter 5: In this chapter, a hierarchical fuzzy inference system is developed to model the ill-defined relation between manufacturing system design parameters and the resulting product quality. This model is capable of mapping the considered configuration parameters into a Configuration Capability Indicator (CCI) expressed in terms of sigma capability level, which can be compared to the benchmark Six Sigma capability level. The proposed CCI predicts the system's output quality based on the manufacturing system's defect prevention capability as well as defect detection capability. The defect prevention capability is assessed based on the overall capability of processes, the quality of the system configuration morphological structure, as well as the level of mistake proofing implementation. The defect detection capability is assessed based on the accuracy of error detection as well as the system responsiveness in error detection; which is assessed based on the allocation of inspection stations, the implementation of Jidoka, as well as the buffer size. For a system configuration that produces more than one product, a configuration capability zone is proposed to graphically represent the manufacturing system configuration capability and compare it to the benchmark Six Sigma capability zone. The developed model is applied to several case studies with different scenarios for illustration and verification. Results and discussions for different scenarios are presented.

Chapter 6: In this chapter, a model is developed using multi-attribute utility analysis in order to estimate the probability of errors due to human involvement in manufacturing tasks. This model provide an assessment of human errors based on the task error proneness, the operator capabilities, the work environment as well as the system's operating characteristics.

Chapter 7: Conclusions and recommendations for future research are presented.

2. RESEARCH BACKGROUND AND LITERATURE REVIEW

2.1. QUALITY IN MANUFACTURING

Quality is a complex, multidimensional concept for which a global and unidimensional definition does not exist. Table 2.1 summarizes some of the Quality definitions provided by different authors in the literature [Kolarik, 1999], and [Haasan, 2000].

Table 2.1 Definitions of Quality [Hassan *et al.*, 2000]

Juran	Fitness for use (1964), conformance to specifications (Juran, 1988)
Crosby	Conformance to requirements (Crosby, 1979)
Deming	Aims at the needs of the customer, present and future (Deming, 1986)
Taguchi	Loss to society (Taguchi, 1986)
ISO 9000	Totality of features and characteristics of a product or service . . . To satisfy stated or implied need (IS0 9000, 1992)

For a better understanding of what is the meaning of quality, the different quality dimensions and perspectives should be considered [Zhang, 2001] and [Sebastianelli and Tamimi, 2002]. Zhang [2001] introduced a framework capturing the relationship among production cycle, quality perspectives and quality dimensions as shown in Figure 2.1. It is clear from that figure that the quality at the strategic and customer levels is mainly assessed by subjective measures, however when it reaches the manufacturing level it is assessed by objective measures.

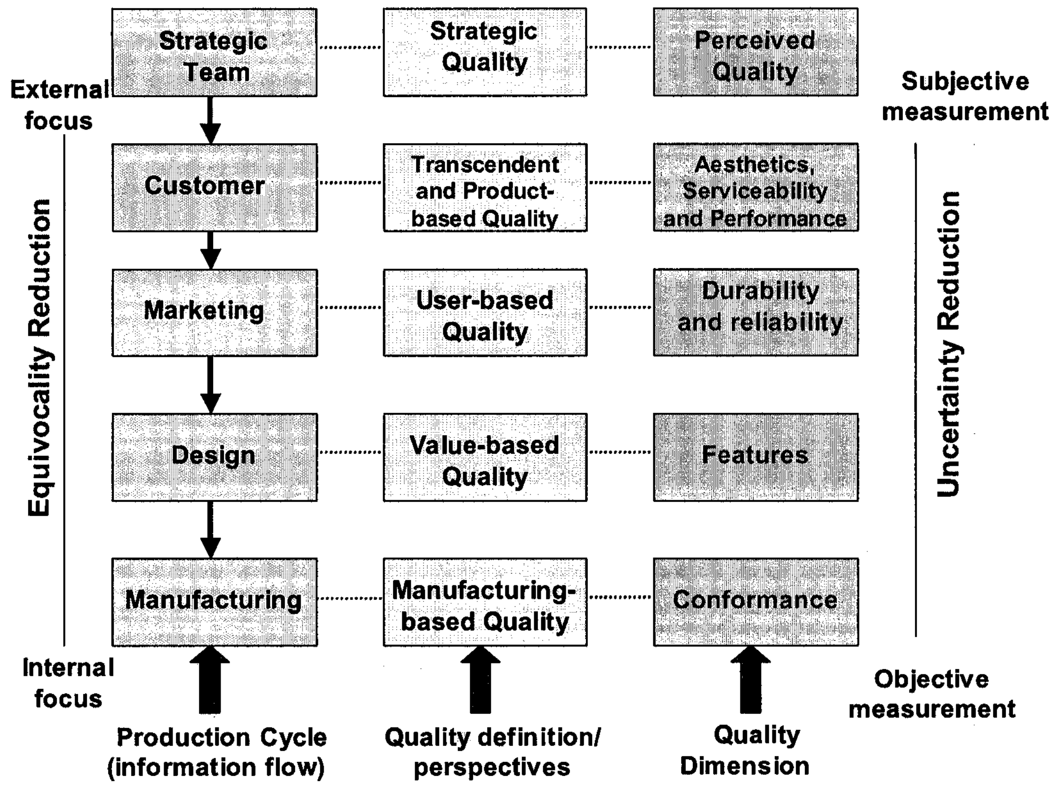


Figure 2.1 The Relationship between Quality Perspectives, Dimensions and Production Cycle [Zhang, 2001]

2.2. QUALITY APPROACHES

Quality approaches can be classified as either reactive approaches or proactive approaches as illustrated in Figure 2.2. The reactive approaches rely on setting an acceptable quality level and inspecting in order to detect the non-conforming items. On the other hand the proactive approaches rely on designing quality into products and processes from the early beginning.

2.3. MEASURES OF QUALITY

Quality measurement is the act of assessing whether a product possesses a certain quality characteristic (usually subjective), or quantifying the level of a quality characteristic. Quality measurement at the manufacturing level is a critical activity as it allows the assessment of the degree of conformance to specifications. This can give the people involved in the manufacturing process an indication of how close they are to their targets and this, in turn, helps them to set the appropriate improvement priorities. Reviewing the literature for identifying the different measures of quality reveals that variability, process capability [Kane ,1986], [Chan *et al.*, 1988], [El-baba ,1997], [Fen and Ravi, 1999], [Wu *et al.* ,1999 and 2001], [Majeske and Andrews ,2002], [Chen *et al.*, 2001 and 2003], [Pearn and Shu, 2003], [Van den Heuvel and Ion, 2003], [Vermani, 2003], quality costs and quality loss [Nandakumar et al.,1993], [Yacout and Boudreau, 1998], [Campanella, 1999], [Clark and Tannock, 1999], [Fen and Ravi, 1999], [Jeang, 2001], [Li and Chou, 2001], [Chen and Weng, 2002], [Oppermann, 2003] are the most widely used measures of manufacturing quality.

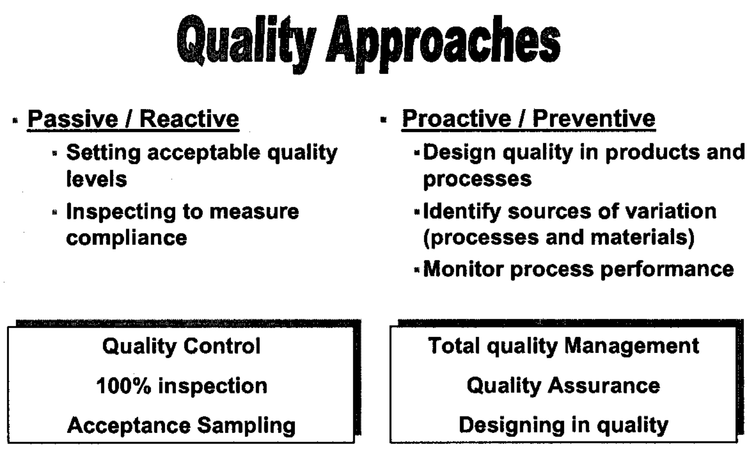


Figure 2.2 Quality Approaches: Passive and Proactive

2.4. VARIABILITY AND PROCESS CAPABILITY

Quality is inversely proportional to variability; hence, quality can be improved through two approaches as indicated in Figure 2.3 . One relies on reducing the manufacturing variation, whereas the other relies on reducing the design sensitivity to variations. The first approach involves the use of tools such as statistical process control and Six Sigma in order to control manufacturing and process variations. However, the second approach involves the use of robust design methodology to modify the design so that it is less sensitive to variations [Thornton, 2001].

Figure 2.3 Ways for Achieving Product Quality [Thornton, 2001]

Process capability is a critical measure for establishing the relationship between the actual process performance and the manufacturing specifications. Several capability indices, such as C_p, C_{pk}, and C_{pm}, have been widely used in industry to quantitatively assess the process potential and performance.

The C_p index measures potential or inherent capability of the production process (assuming a stable process), and it is defined as in Ledolter and Burrill [1999]:

$$C_p = \frac{USL - LSL}{6\sigma}, \tag{2.1}$$

where USL and LSL represent the upper and lower specification limits, respectively and σ is the process standard deviation. In case of $C_p = 1$, it can be declared that the process is potentially capable (in a marginal sense; as shown in Figure 2.4). The greater the value of the C_p, the greater is the process capability. However, if the $C_p \leq 1$, this represents the case of an incapable process. The main limitation associated with the C_p index is its ability to assess only the process variation without considering the process location with respect to the target value.

The C_{pk} index, Kane [1986], was proposed to offset some of the limitations of the C_p. The C_{pk} is defined as:

$$C_{pk} = \min\left\{\frac{\mu - LSL}{3\sigma}, \frac{USL - \mu}{3\sigma}\right\}. \tag{2.2}$$

From that expression, it is obvious that the C_{pk} index takes into account process variability, as well as the process mean μ. However, it still only measures the degree to which the process output is within specification. In contrast, the C_{pm} process capability index, developed by Chan [1988], measures the deviation of the mean of the process from its target T. This measure is defined as:

$$C_{pm} = \frac{USL - LSL}{6\sqrt{(\mu - T)^2 + \sigma^2}}. \tag{2.3}$$

Pearn et al. [1992] proposed a capability index called C_{pmk}, which has been shown to be a useful capability index for processes with two-sided specification limits. This index is defined as:

$$C_{pmk} = \min\left\{\frac{USL - \mu}{3\sqrt{(\mu - T)^2 + \sigma^2}}, \frac{\mu - LSL}{3\sqrt{(\mu - T)^2 + \sigma^2}}\right\}. \tag{2.4}$$

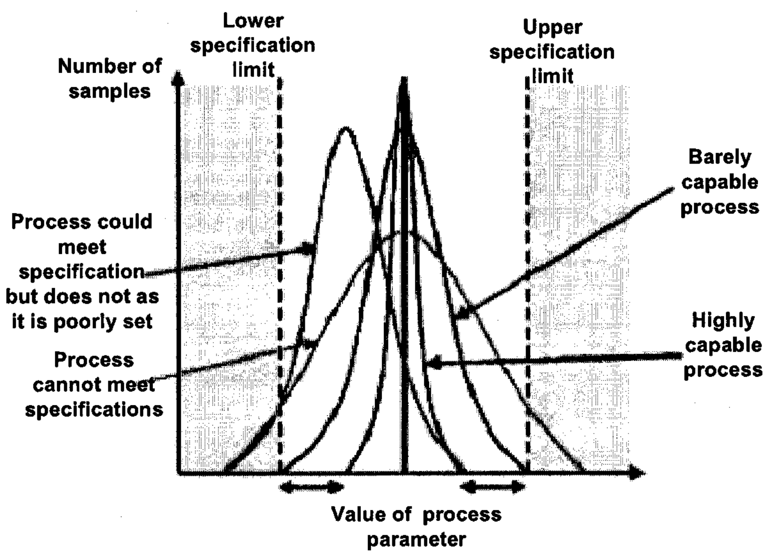


Figure 2.4 Different Levels of Process Capability, [Kolarik, 1999]

The above mentioned process capability indices are mainly used to assess the process capability level. Therefore, the availability of the historical process capability data is critical when introducing new designs.

2.5. THE CONCEPT OF SIX SIGMA QUALITY

In announcing the achievement of total customer satisfaction as the corporation's fundamental objective, Motorola introduced the concept of Six Sigma as a statistical way of measuring quality [George, 2003]. Motorola views its failure rates in terms of defective parts per million. Motorola's objective is 3.4 defects per million. Obviously, achieving such a goal requires very capable processes. Actually, this requires the specification limits to be at least "six sigma" away from the target as shown in Figure 2.5.

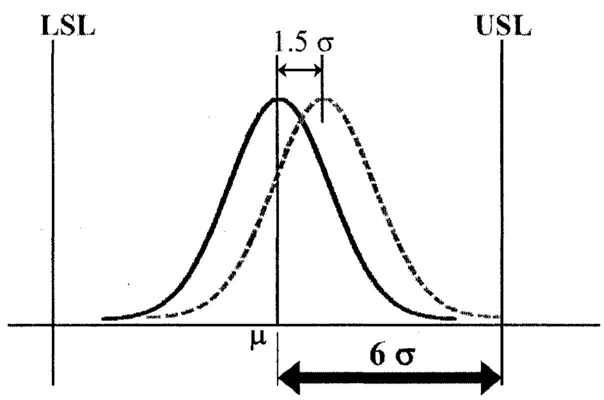


Figure 2.5 Process Variability and Specification Limits for a Six Sigma Process

Mapping such a requirement onto the process capability domain means that the process capability index C_p should be at least equal to 2.0 as shown in Table 2.2. For more details about calculating the number of defective items per million associated with each sigma level, one can refer to Ledolter and Burrill [1999].

Table 2.2 Defective parts per million associated with each X –Sigma Quality Level [Ledolter and Burrill, 1999]

X-Sigma Quality	C_p	Defect level (parts per million)	
		Without shift in mean	With mean shifted by 1.5 sigma
3	1	2,700	66,803
4	1.33	63	6,200
5	1.67	0.57	233
6	**2**	**0.002**	**3.4**

To continuously improve the process and achieve Six Sigma quality level, Harrold [1999] indicates that combining statistical process analysis techniques with the understanding of process capability is the only way to achieve that improvement. This can be done, as shown in Figure 2.6, through the application of so-called "Six Sigma improvement projects" which, in turn, follow the "Six Sigma DMAIC" sequence of steps (Define, Measure, Analyze, Improve, and Control) as follows:

Define: the *Define* phase is concerned with the definition of project goals and boundaries, and the identification of issues that need to be addressed to achieve the higher (better) sigma level.

Measure: the goal of the *Measure* phase of the Six Sigma strategy is to gather information about the current situation, to obtain baseline data on current process performance, and to identify problem areas.

Analyze: the goal of the *Analyze* phase of the Six Sigma quality effort is to identify the root cause(s) of quality problems, and to confirm those causes using the appropriate data analysis tools.

Improve: the goal of the *Improve* phase is to implement solutions that address the problems (root causes) identified during the previous (*Analyze*) phase.

Control: the goal of the *Control* phase is to evaluate and monitor the results of the previous phase (*Improve*).

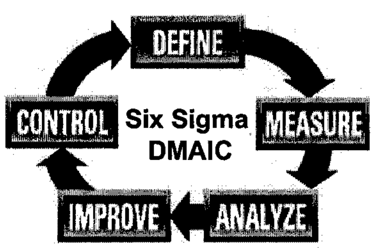


Figure 2.6 Six Sigma DMAIC [Harrold, 1999]

The main difficulty with this approach is the evaluation of the system and the prediction of the quality level after improvement, as these depend on the existence of perfect information about the process capability. However, the estimation of the process capability during these stages of product development is always associated with many of uncertainties.

2.6. PROCESS CAPABILITY UNCERTAINTY

Tata [1999] pointed out that perfect information about process capability is rarely, if ever, available. The uncertainties associated with the estimation of process capability is a critical research issue, as the designers still have to make decisions regarding configurations, components, and dimensions under these uncertainties.

Generally, there are two methods used to predict process capability data; these are: process capability databases and manufacturing knowledge [Thornton, 2001]. Process capability databases provide surrogate data for similar parts. It is obvious that surrogate data is not always an accurate indicator especially for new designs. The inaccuracy associated with these databases arises from differences in material, geometry and process parameters. Moreover, most of the time, the process capability measures are mainly based on short-term evaluations. Hence, it does not account for process degradation. In case of unavailability of capability databases, educated guesses about the variation, based on experience, have to be made.

In case of process capability uncertainty, designers have two alternatives as indicated by Thornton [2001]. The first one assumes the worst case for the process capability "pessimistic approach"; this approach requires the use of expensive components and processes, as well as controls to detect quality failures. Following this approach can significantly increase the unit cost. The other approach assumes the best case for process capability "optimistic approach"; in which designers can use lower cost parts and processes. But this approach increases the risk of quality-failure and its associated costs.

2.7. VARIATION RISK MANAGEMENT

Variation risk management (VRM) is a systematic method to identify, assess, and mitigate variation throughout the product development process [Thornton *et al.*, 2000]. VRM can be applied either proactively, during product development, or to an existing product being manufactured. Variation risk management integrates all functional groups impacting product quality including design engineering, manufacturing, quality engineering, system engineering, customers, procurement, and suppliers. The variation risk framework developed by Jay [1998] and Thornton [1999] is described in a three-step process as follows:

Risk Identification (I)

- Identify variation sensitive system requirements & latitudes
- Identify system, sub-system, feature and process characteristics contribute to the system variation

Risk Assessment (A)

- Quantify the probability of variation
- Quantify the cost of variation

Risk Mitigation (M)

- Select mitigation strategy based on costs, schedule and strategic impact
- Execute the strategy

Figure 2.7 indicates how this framework can be replicated in the product development stages. Thornton *et al.* [2000] concluded that industry typically applies VRM practices late in the design process when the product is about to be transitioned into manufacturing. The problems associated with the industry implementation are due to a lack of qualitative models that enable designers to make quick and accurate decisions regarding the considered design.

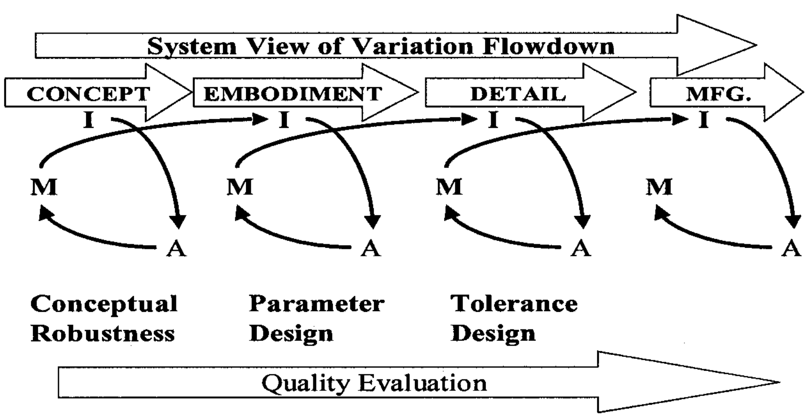


Figure 2.7 The Implementation of VRM Framework throughout the Product Development Thornton [1999]

2.8. DESIGN OF MANUFACTURING SYSTEMS FOR QUALITY

Generally, producing a product with a high quality level involves two main activities. The first one is concerned with designing the product so that it has all the features and the quality characteristics that satisfy the customer requirements. The second activity is mainly concerned with the quality of conformance; meaning how the product is manufactured to exactly meet the design specifications. This stage necessitates the design or redesign of the manufacturing system so that it is capable of satisfying the design requirements. There are many different quality tools that are used either for product design or for on-line quality control as shown in Figure 2.8.

The question is for manufacturing system configuration or reconfiguration, which of these tools can be applied?

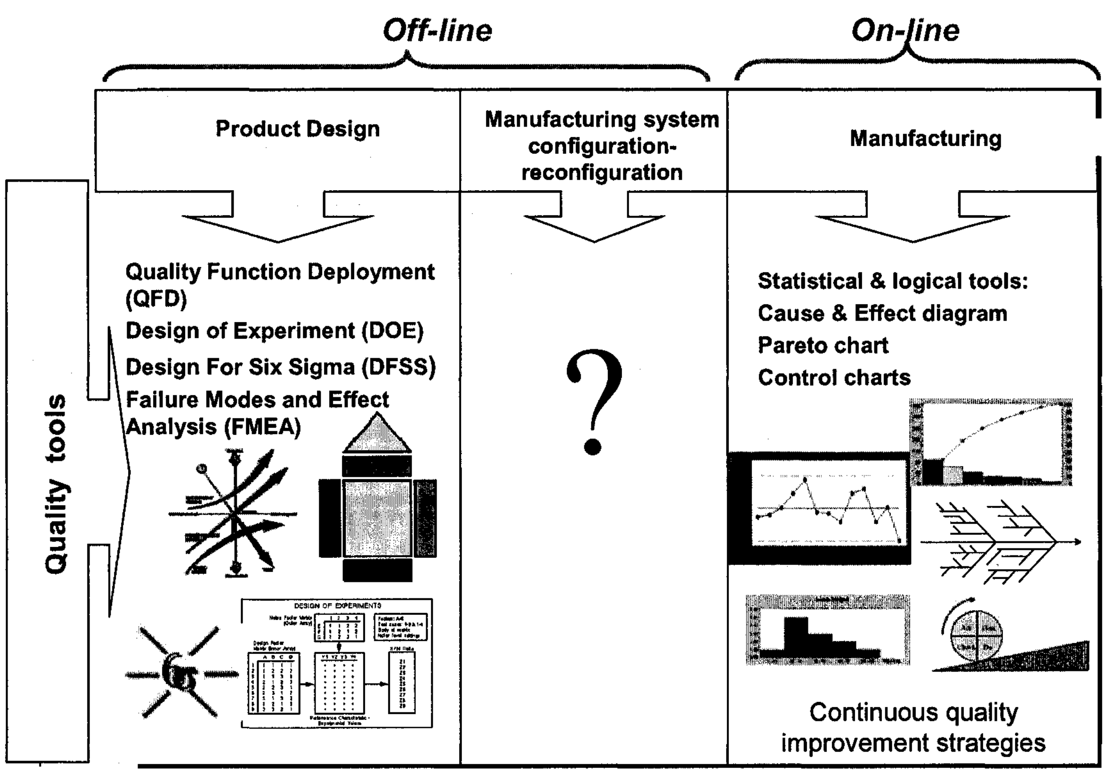


Figure 2.8 Different Quality Tools and Product Development Stages

The application of the customer-driven approaches and the design for quality (DFQ) methodologies is of vital importance at the product design stage. Booker [2003] reviewed the main DFQ supporting techniques, including quality function deployment (QFD), failure mode and effect analysis (FMEA), and robust design. He also provides a framework for the application and integration of quality tools to support the concurrent product development.

It has been pointed out, by Mezgár *et al.* [1997], that high-quality products can be manufactured only by similar high-quality manufacturing systems. These systems themselves can be treated with some restrictions as products. Therefore the design methodologies applied in product design can be used in the manufacturing system design as well.

QFD as a methodology for translating the 'voice of customer' into product features is widely adopted in the product development activities [Sivaloganathan, and Evbuomwan, 1997], [Prasad, 1998], [Shen, 2001], [Franceschini and Rossetto, 2002], [Fung *et al.*, 2002], [Kwong and Bai, 2002], [Lin, 2003]. Moreover, some researchers have used the QFD methodology in other applications. For instance, Muhamed [1996 and 1997] used the QFD planning matrices to deploy the strategic requirements in manufacturing system design. The author developed a framework for the hierarchical decomposition of the requirements for manufacturing system design. His approach has the advantage of identifying the complex relationships that exist among the requirements at various deployment levels. Also, it enhances the utilization of the strategic requirements as a basis for decision making through different levels. However, the author did not indicate the effect of the existence of conflict or overlap, which arises when the same element at one level can contribute to more than one requirement in the level immediately above it, on the developed design.

Taguchi methods have been also applied to design robust production systems. Chen and Chen [1995] presented a procedure for designing a job shop manufacturing system based on the Taguchi approach and response surface methodology. Mezgár *et al.* [1997] proposed a methodology for the design and real-time reconfiguration of robust manufacturing systems. The methodology combines the design of experiments, Taguchi method and Knowledge-based simulation techniques. The authors focused on the reconfiguration of the manufacturing systems and included the use of artificial neural networks for mapping between design factors and system performance. It is obvious that their approach is important as it is real-time applicable. However, one of its limitations is that the real-time, robust reconfiguration can be applied only in the modification of the factors that have already been included in the simulation trials. Moeeni *et al.* [1997] proposed a method, also based on the Taguchi concepts, to implement Kanban systems in uncertain environments. Cabrera-Rios et al. [2002] proposed a method for designing a manufacturing cell using Taguchi methods.

Moreover, Design For Six Sigma (DFSS) is a powerful approach, addressed by several authors [Antony and Coronado, 2002], and [Olexa, 2003], for the design of products and processes. The power of this methodology relies on its "empirical" data-driven approach, and its focus on using quantitative measures for systems' performance.

2.9. RESEARCH WORK FOR PREDICTING MANUFACTURING QUALITY

Despite the importance and the wide applicability of the above reviewed quality measures, these measures cannot predict the quality level of the manufactured product in terms of the manufacturing system parameters at the design stage. To illustrate, El-baba [1997] introduced a regression method that is based on search methods to quantify the manufacturing quality in terms of the mean and the standard deviation. The author indicated that the developed method is able to provide a visual image of the trends of the mean and the standard deviation as well as the normal distribution curve regardless of the considered sample size. Although the developed method is simple and can significantly improve the assessment of quality, it is clear that its application is limited only to the on-line quality control activities.

One of the approaches concerned with assessing the defect level in assembly is based on assembly complexity and is called "Assembly Quality Methodology" [Shibata, 2002], and [Shibata et al., 2003]. In the Assembly Quality Methodology, assembly complexity is assessed using two engineering measures; these are: assembly time estimates and a rating for ease-of-assembly. Despite the effectiveness of this methodology in assembly defect prediction, it can only predict the defect rate for a new product to be manufactured by a system that already exists and has been tested for previous products to empirically obtain the effect of the system. Similarly, the Assembly Reliability Evaluation Method (AREM) that has been developed by Suzuki et al. [2001] estimates defect rates of new products. The assembly fault occurrence model formulates a correlation between the estimated assembly defect rates, and part characteristics and assembly operations.

The use of neural networks for quality prediction at the process level has been widely addressed in the literature [Hanna 1994 and 1999], [Moller and Rowe, 1998], [Ivezic et al.,1999], and [Cho and Rhee, 2004]. For example, Hanna [1999] proposed intelligent process control architecture based on fuzzy Petri nets with a feed forward neural network for modelling product quality in a CNC machining centre. The proposed methodology uses the input machining parameters; such as spindle speed, feed rates and tool diameter to simulate the quality of the surface roughness and identifying it as high, medium or low. Although the modelling of quality in this approach is still relying on experimental results obtained from different milling operations conducted on a CNC machining centre, its main value relies on the possibility of extending the application of the same methodology to model the quality at the manufacturing system level.

The variation propagation approach attempts to investigate how the variation propagates through the system and predicts the end of line variation in the product quality characteristics. This approach is mainly based on the stream of variation theory developed by Hu [1997]. Variation propagation approach has been used to predict the quality for different application. Mantripragada and Whitney [1999] and Jin and Shi [1999] used it for modelling and controlling variation in assemblies. Huang, et al. [2000] applied it for multi-process machining. Camelio et al. (2003) used this approach in fault diagnosis in fixturing of compliant parts. The problem with the variation propagation approach is that it needs detailed modelling of the processes.

2.10. THE IMPACT OF MANUFACTURING SYSTEM DESIGN ON QUALITY

Inman *et al.* [2003] have recently explored the intersection of two important fields of research: Quality and manufacturing system design. They argued that the production system used to manufacture a product does indeed affect its quality. They also provided evidence from the automotive Industry in order to support their argument. They also pointed out that there is a lack of attention in literature to the impact of production system design on product quality and suggested several future research issues, related to the manufacturing system design and quality, which are important to industry. Some of these research issues are studying the impact of each of the following on quality: Ergonomics, line or machine speed, plant layout, number and location of inspection stations, Buffer location and size, Batch size, level of automation, and flexibility. Some of the proposed issues are partially explored and just an extension of the research is required, however others are largely unexplored.

The Impact of Flexibility on Quality

For this section, an intensive survey of the literature has been conducted in order to identify the most significant research that studied the impact of flexibility or the impact of flexible manufacturing systems on the production quality. The result of that survey reveals that there is only very few research work in the literature that have tried to investigate that relation [Chen and Adam,1991, ElAhmedy,1993, Eckstein,1994, Manneh, 1996]. Inman *et al.* [2003] stated: "the issue of flexibility's impact on quality is very important but largely unexplored".

Chen and Adam [1991] presented a study on the impact of flexible manufacturing systems on productivity and quality. In general, it has been reported in literature that flexible manufacturing systems are widely claimed to positively impact productivity and quality. Therefore, their focus was mainly directed to investigate whether the often stated or claimed potential FMS benefits do really widely exist, or they are simply stated to exist without documentation or evidence. To do so, they summarized and examined several published case studies. Their results concerning quality reveal that there is a modest empirical relationship between FMS and quality improvement. They also noticed that quality in most of the studied projects has not been addressed and they related that to any of the following reasons: quality improvement was not measured; no improvement having been achieved, or quality measures indicated some negative FMS impacts. Hence, they suggested a proposition to be thoroughly tested; which measures the FMS impacts in terms of the cost of quality. From their work, it can be recognized that one cannot conclude what the relationship between FMS implementation and quality improvement is. Their results can only be accepted as indicative one rather that conclusive.

ElAhmedy [1993] investigated the impact of the level of advanced manufacturing technologies (AMTs) in business units -in terms of the use of computer integrated manufacturing, group technology, flexible manufacturing systems- on four aspects of quality; which are quality costs, market and customer, total employee involvement, and quality techniques. They conduct the research by using hypothesis testing with analysis of variance to determine whether there are statistically significant differences in those four aspects of quality among business units with different levels of AMTs. He reported that the higher the levels of AMTs, the more likely that business unit will outperform their counterparts with low levels of AMTs. It should be pointed out that these results are based only on empirical study and it only considers the above mentioned four aspects of quality.

The Impact of System Configuration (Layout) on Quality

Based on engineering observations and the preliminary study of a few selected systems, Webbink and Hu [2005] concluded that parallel systems usually result in larger variations than the serial ones. Hu [1997] developed the concept of "stream-of-variation theory" and studied the performance difference of different assembly configurations (i.e., serial or parallel) by combining engineering structural models and statistical analysis to predict and diagnose the dimensional variation of multi-leveled automotive body assembly. Suri et al. [1998] presented a generalized variation propagation model to predict the end-of-line variation and discussed the variation stack-up in serial and parallel systems. Zhong [2000 and 2002] focuses on modelling the variation propagation for machining systems with different configurations. The author presented a methodology to predict the product geometric quality for machining systems with different configurations. The methodology considers the kinematic and static variations by modelling the system level variation propagation using methods such as Homogeneous Matrix Transformation (HTM), Finite Element Methods (FEM), Monte Carlo Simulation and Object-Oriented techniques. The results of this research are relevant and can be incorporated into developing the proposed metric for assessing the product quality as it is affected by the system configuration.

Research Work on Other Aspects That Affect Quality

The relation between human factors and quality is one of the important issues for the following research work [Drury, 2000a, and b], [Ortner, 2000], [Drury and Kim, 2001], and [Baines and Kay, 2002]. Also introduced is the relation between quality and collaborative work, and team implementation [Field and Sinh, 2000], and [Van Oyen *et al.*, 2001].

Also relevant is the research work concerned with learning, forgetting, individual workers differences, workers training, and assignment as well as worker attributes in manufacturing environment [Eckstein, 1994], [Askin and Huang, 1997], [McCreey and Krajewski, 1999], [Needy *et al.*, 2000], [Hopp and Van Oyen, 2001], [Nembhard, 2001], [Buzacott, 2002], [Jaber and Bonney, 2003], and [Urbanic and ElMaraghy, 2003] is also important to identify the relation between those aspects and the product quality.

2.11. LITERATURE REVIEW OUTCOMES

Despite the many existing tools for assessing the product quality in manufacturing systems, there is not much in the research that is concerned with studying the impact of a certain manufacturing system design on the resulting product quality; especially, at the system development stage [Nada et al. 2004]. Most of the measures used in the literature can be estimated using data from systems that are already in the operating mode. Even the methodologies that are used for designing the product for quality, its application in the literature at the manufacturing system level is very limited. In the early stages of manufacturing systems development, the system designer will be faced with many of configuration alternatives. From the quality point of view, the designer should have an insight of how his decisions could affect the product. Therefore, the relationship between the quality and the different system parameters should be well defined and quantifiable and integrated to provide the system designer with the tools that can help in comparing different system design options based on the resulting product quality.

3. CONCEPTUAL FRAMEWORK FOR PROACTIVE ASSESSMENT OF QUALITY

3.1. THE OVERALL PROPOSED FRAMEWORK

As a response to frequent changes in customer requirements, frequent reconfigurations of manufacturing systems are expected in order to cope with those changes. A need for reconfiguring a manufacturing system might arise due to changes in product(s) design, changes in product mix variety, as well changes in capacity. In the context of this research, a manufacturing system configuration is defined by the set of design parameters that can be can varied, and based on that, the system design alternative that satisfy the functionality and capacity requirements can be selected. In this research, the manufacturing system design parameters are called configuration parameters. Changes in the design of a manufacturing system are expected to affect different performance measures including the resulting product quality.

In this chapter, a conceptual framework is proposed for the proactive assessment of the expected quality level that can be achieved using a typical system configuration. This framework, as shown in Figure 3.1, is the outcome of extensive review of the literature concerning the relation between manufacturing system design and quality. In addition to the direct relations between manufacturing system design parameters and the resulting output quality, it has been found that changes in the product(s) design, product mix, as well as changes in the capacity are expected to be associated with changes in complexity in terms of product complexity, system complexity, and task complexity on the operator's level. Several researchers [Hickley, 1993], [Beiter et al., 2000], [Shibata, 2002], and [Shibata et al., 2003] have investigated the correlation between complexity and quality in terms of defect rates. The outcomes of their research indicated that complexity has a strong positive correlation with the occurrence of defects. In the methodology known as "Assembly Quality Methodology", Shibata [2002] and Shibata et al. [2003] proposed assessing the assembly complexity in terms of assembly time estimates as well as measures for ease of assembly. Using empirical data, the correlation between the assembly complexity and the defect rate can be quantified. In order to use the assembly quality methodology to predict the defect rate for a new product, the facility should be calibrated using sets of products in order to empirically quantify the effect of the facility on the occurrence of defects. As a result, this method cannot be applied during the manufacturing system development stage. In the meanwhile, insights from literature indicate that the complexity of the system design itself is positively correlated with the occurrence of defects, but these are only based on observations and there is no research that quantifies such a correlation [Kim, 1999].

Therefore, in the framework illustrated in Figure 3.1, different system configuration parameters or attributes have been identified. As a result of human involvement in manufacturing, a number of these parameters could affect the operators' performance in terms of the probability of the occurrence of errors, and hence the output quality will be affected. Based on that, the configuration parameters have been classified to system related parameters and worker related parameters. It has been found that the output quality as well as the system complexity could be affected by each individual system related parameters. In addition, the output quality as well as the task complexity could be affected by each individual worker related parameters. Literature has been searched for publications that addressed the relations between configuration parameters and complexity as well as quality. In Figure 3.1, the dashed links indicates that the relation has not been studied in the literature or it is not well established. On the other hand, relations addressed in the literature are represented using sold lines associated with number(s) above each line referring to the citation listed in Table 3.1.

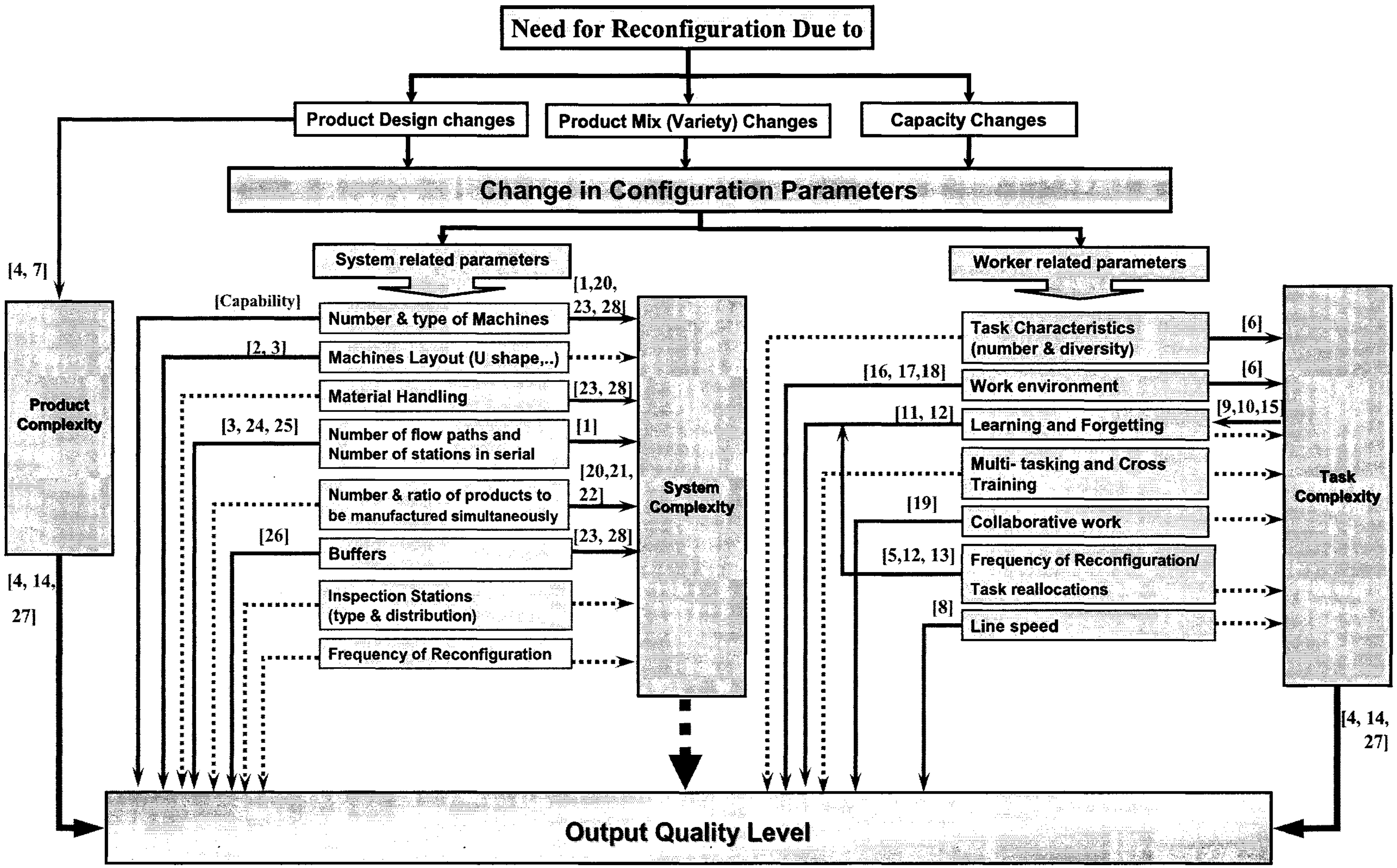


Figure 3.1 Conceptual Overall Framework for Quality Assessment

Table 3.1 References listed in Figure 3.1

[1] Kim, 1999	[10] Nembhard, and Osothsilp, 2002	[22] Frizelle, 1997
[2] Cheng, et al., 2000	[11] Badiru, 1995	[23] ElMaraghy, H., et al., 2005
[3] Zhong, 2002	[13] Jaber, and Bonney, 2003	[24] Zhong, W., *et al.*, 2000
[4] Shibata, et al., 2003	[14] Hinckley, 1993	[25] Webbink and Hu, 2005
[5] Urban, 1998	[15] Kvalseth, 1978	[26] Kim, and Gershwin, 2005
[6] ElMaraghy, W. and Urbanic, 2004	[16] Baines and Kay, 2002	[27] Shibata, 2002
[7] ElMaraghy, W. and Urbanic, 2003	[17] Drury, 2000	[28] Kuzgunkaya, and ElMaraghy, H.
[8] Lin, et al., 2001	[18] Eklund, 1995	
[9] Nembhard, and Uzumeri, 2000	[19] Field, 1997	
	[20] Deshmukh, *et al.*,1998	
	[21] Deshmukh, *et al.*,1992	

In the proposed framework, it is illustrated that there are two types of links between the configuration parameters and the resulting quality. One is the direct links between each configuration parameter and the resulting quality level. In considering those direct links, the relations between each configuration parameter and quality should be investigated, quantified, and integrated in order to map the configuration parameters into output quality level. It should be highlighted, here, that this direct link represents the approach to be used in this research.

The other link is an indirect one, in which complexity will be used as an intermediate link between configuration parameters and quality. Considering that indirect link, it is recommended that quality could be assessed in terms of product complexity, system complexity, and task complexity as affected by product design, system related configuration parameters, and worker related design parameters, respectively. It should be mentioned that this indirect link, that proposes the prediction of quality in terms of complexity, is not addressed in this research except for the effect of task characteristics on the errors due to human involvement in manufacturing.

In the next section, the roadmap for predicting product quality in terms of configuration parameters will be illustrated and stated to Chapter 4, 5, and 6.

3.2. APPROACH CONSIDERED IN THIS RESEARCH

Manufacturing system configuration parameters including the overall capability of processes, machine operations and manual operations, the number of serial stations, the number of flow paths, the level of mistake proofing implementation, the allocation of inspection stations, the level of Jidoka implementation, the inspection error, as well as the buffer size do affect the resulting product quality. These can be modelled to enable the system designer to assess different system configurations in terms of quality as well as to predict the expected output quality level at the early stages of system development. To achieve this target, the roadmap presented in Figure 3.2 is followed in this dissertation to develop a Configuration Capability Indicator that is capable of mapping manufacturing system configuration parameters into an expected output quality level. The set of considered configuration parameters is explained in more details in Chapter 4 and 5. These parameters include the overall capability of processes needed to produce the product under consideration. These processes might include machine operations as well as manual operations. For machine operations, process capability databases can be used to obtain the capabilities of individual operations. For manual operations, a model for assessing the probability of errors due to human involvement in manufacturing tasks is developed in Chapter 6 using multi-attribute utility approach. The output of this model can be used as a measure for the yield of manual operations and also can be used to assess the expected inspection error as will be explained in more detail in Chapter 5. As shown in Figure 3.2, the Analytic Hierarchy Process (AHP) is used in Chapter 4 in order to develop the Configuration Capability Indicators (CCI) in terms of the considered configuration parameters. The CCI developed using AHP is a relative measure that can be used to compare a set of configuration alternatives based on the resulting output quality. In addition, the fuzzy logic inference is used in Chapter 5 to predict the configuration capability in terms of sigma capability and compare it to the benchmark Six Sigma Capability.

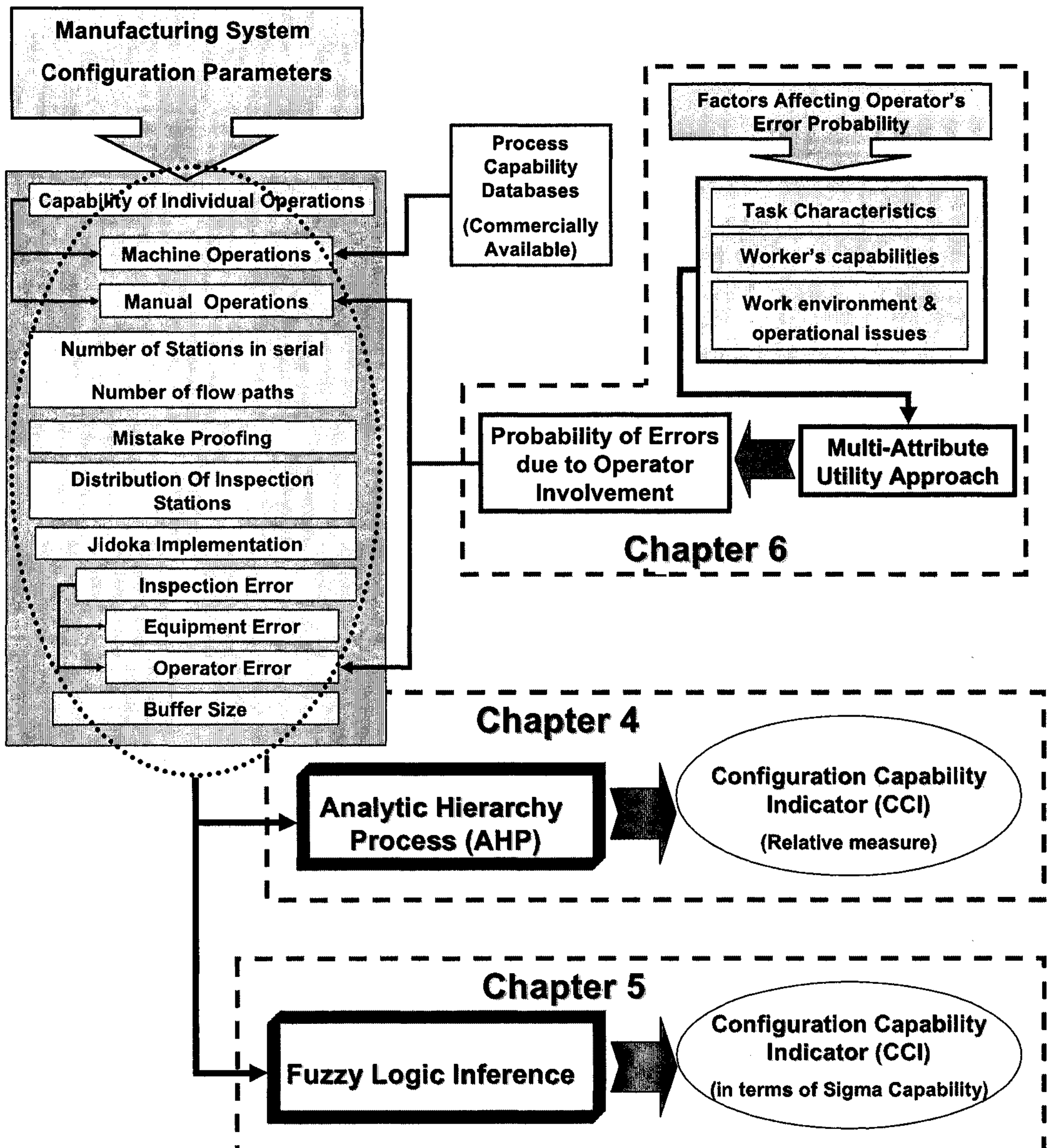


Figure 3.2 Roadmap for Developing Configuration Capability Indicator

4. AHP MODEL FOR QUALITY BASED ASSESSMENT OF MANUFACTURING SYSTEM DESIGN ALTERNATIVES

4.1. INTRODUCTION

In this chapter, the Analytic Hierarchy Process (AHP) is used in developing a model for comparing different system configurations based on quality. This model considers the defect prevention capability of a given system configuration as well as the defect detection capability. The defect prevention capability is assessed based on the overall capabilities of processes, the number of flow paths, the number of serial stations as well as the implementation of mistake proofing techniques. The defect detection capability is influenced by the distribution of inspection stations, the capabilities of inspection equipment, the implementation of Jidoka, as well as the buffer size.

4.2. ANALYTIC HIERARCHY PROCESS (AHP)

The analytic hierarchy process (AHP) is a widely-used technique for comparing alternatives with respect to an overall objective. The AHP is based on the natural human ability to make sound judgments about problems. It facilitates decision-making by organizing perceptions, feelings, judgments and memories into a framework that exhibits the forces influencing a decision. The AHP was developed by Saaty [1980, 1990, 1994] and it has many applications in various areas which include systems engineering, operations research and management science, conflict management, capital budgeting, strategic business planning and marketing, and resource planning [Vaidya and Kumar, 2006]. The AHP relies on the ability of the decision maker to decompose the main problem into a hierarchy of smaller decision problems that consist of different objective and subjective factors that work together to influence the overall goal. The overall result of using the AHP is a priority vector that provides a ranking of the different alternatives under consideration.

The application of AHP involves three major steps. The first step is related to selecting the evaluation criteria and constructing the hierarchy. Secondly, the relative importance (priority) of criteria/alternatives is identified through pairwise comparisons. Finally, synthesizing these priorities to obtain each alternative's overall priority and selecting the one with the highest priority. The following subsections illustrate these steps according to Saaty [1980].

4.2.1. STRUCTURING THE HIERARCHY

Structuring the hierarchy requires experience with the various aspects that influence the overall goal. The hierarchy must be designed so that these alternatives are accurately evaluated based on their ability to achieve the overall goal. The hierarchy starts at the top by clearly stating the goal of the problem. Directly beneath this goal are the primary criteria to be considered for decision making. As illustrated in Figure 4.1, the overall goal is listed at the top of the hierarchy and is broken down into the key criteria that directly influence the goal above them. These criteria can be further broken down into sub-criteria. In general, there is no limit to the size and number of levels within the hierarchy, although, as a practical matter, there are usually only two or three levels of criteria and sub-criteria beneath the overall goal. Ideally, the hierarchy should be large enough to capture the important criteria involved in the decision-making process but small enough for the problem to remain manageable and meaningful. At the bottom level of the hierarchy, the alternatives are listed beneath the sub criteria and are connected to each one. Lines extending from each sub-criterion down to all of the alternatives can be observed. This implies that the decision maker compares all the alternatives with respect to each sub-criterion.

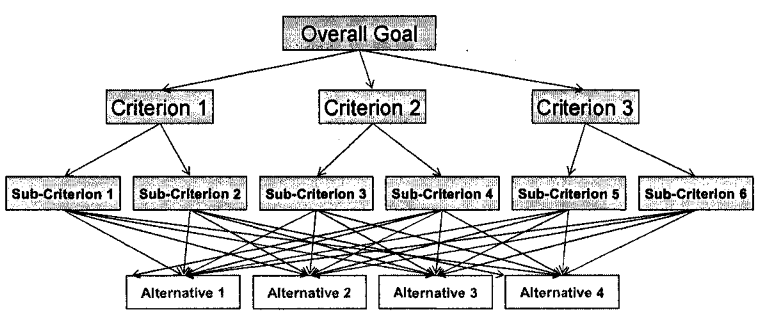


Figure 4.1 Structuring the Hierarchy for developing AHP model [Saaty 1980]

4.2.2. PAIRWISE COMPARISONS AND PRIORITY VECTOR

The analytic hierarchy process relies on pairwise comparisons to evaluate the importance of the criteria, sub-criteria, and alternatives. Saaty [1980] pointed out that making judgments based on pairwise comparisons enhance the formulation of the problem so that it can be handled more easily. In this step, the decision maker has to construct a matrix of pairwise comparisons of elements where the entries indicate the strengths with which one element dominates another using a method for scaling of weights of the elements in each of the hierarchy levels with respect to an element of the next higher level. The comparison process moves from the top of the hierarchy down to the lowest level. The criteria beneath the goal are pairwise compared, followed by the sub-criteria beneath each criterion. At the bottom of the hierarchy, the alternatives are then compared relative to the sub-criteria. The decision maker can express preferences between each pair of elements verbally as equally important, moderately more important, strongly more important, very strongly more important, and extremely more important. These descriptive preferences would then be translated into numerical values 1, 3, 5, 7, 9, respectively, with 2, 4, 6 and 8 as intermediate values for comparisons between two successive qualitative judgments. Reciprocals of these values are used for the corresponding transposed judgments. A typical pairwise comparison matrix of order n can be expressed as in Equation (4.1).

$$A = \begin{bmatrix} 1 & a_{12} & a_{13} & \cdots & a_{1n} \\ \frac{1}{a_{12}} & 1 & a_{23} & \cdots & a_{2n} \\ \frac{1}{a_{13}} & \frac{1}{a_{23}} & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ \frac{1}{a_{1n}} & \frac{1}{a_{2n}} & \cdots & \cdots & 1 \end{bmatrix}, \tag{4.1}$$

where

a_{ij} : decision maker's judgement on the relative importance of factor i to factor j and it can be calculated as in Equation (4.2).

$$a_{ij} = w_i / w_j \,, \tag{4.2}$$

w_i : weight of factor i, and

$$a_{ji} = 1/a_{ij} \,. \tag{4.3}$$

The goal of AHP is to use the pairwise comparison matrices to establish the values for the weights of the criteria and alternatives. In this context, the concept of consistency of the comparison matrix should be explained. A matrix is said to be consistent if all its elements a_{ij} respect the transitivity and reciprocity rules. The transitivity rule is satisfied if $a_{ik} . a_{kj} = a_{ij}$, for all i, j, k. The reciprocity rule is satisfied if $a_{ji} = 1/a_{ij}$ for all i, j. Let's represent the weight vector as $w = [w_1 \quad w_2 \quad \cdots \quad w_n]^T$, perfectly consistent pairwise comparison matrix has a rank of one, and this allows us to extract a priority vector by solving the following eigenvalue problem:

$$Aw = nw \quad . \tag{4.4}$$

Given a perfectly consistent pairwise comparison matrix "A", the right eigenvector of "A" is composed of a set of weights that are derived directly from the comparison ratios. Normalizing this eigenvector so that its elements sum to one gives a unique set of weights for the alternatives.

In a typical practise, the decision maker is not perfectly consistent in making pairwise comparisons. Therefore, the AHP considers that and it allows a small amount of inconsistency in making comparisons. Inconsistencies take place when $a_{ik} . a_{kj} \neq a_{ij}$. The presence of inconsistencies implies that each (i, j) entry of A is actually an approximation to the ratio of the weight of alternative i to the weight of alternative j. Thus, A is no longer of rank one, and more than one nonzero eigenvalue might exist. In cases associated with inconsistencies, Saaty [1980] proposed determining the weight vector by solving the following eigenvalue problem:

$$A\hat{w} = \lambda_{\max} \hat{w}, \tag{4.4}$$

where $\hat{w}$ is an approximation to the underlying exact priority vector, and $\lambda_{\max}$ is the maximum eigenvalue of A. Saaty [1980] has shown that $\lambda_{\max} \geq n$, with equality holding in the perfectly consistent case. Whenever λ_{max} is close to n, it is found that $\hat{w}$ is a relatively good approximation to w. Therefore, it is critical to assess the level of inconsistency in the pairwise comparison matrix. To do so, the following terms can be defined and calculated according to Saaty [1980] as follows:

Coefficient of Inconsistency (CI): it represents the deviation from perfect consistency, and it can be calculated as in Equation (4.5).

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{4.5}$$

Coefficient of Random Inconsistency (CRI): it is the average CI for randomly generated reciprocal matrices. The CRI values for different order of the matrix are given in Table 4.1 [Saaty, 1980].

Table 4.1 Values of Coefficient of Random Inconsistency (CRI) [Saaty, 1980]

Matrix order (n)	1	2	3	4	5	6	7	8	9
CRI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45

Inconsistency Ratio (IR): it is the ratio of the Coefficient of Inconsistency (CI) to the Coefficient of Random Inconsistency (CRI) as in Equation (4.6).

$$IR = \frac{CI}{CRI} \tag{4.6}$$

Saaty [1980] indicated that for when $IR < 0.1$, the level of inconsistency is acceptable and the weight vector is acceptable. Otherwise, the comparison matrix needs to be revised.

In order to avoid inconsistency in judgement while generating the pairwise comparison matrix, the different types of elements in the matrix are illustrated in Figure (4.2); these include [Ishizaka and Lusti, 2004]:

The ***comparisons on the principal diagonal*** which compare an alternative with itself. This is represented by entries of "1 s along the diagonal

The ***independent comparisons*** which are not linked to other comparisons by the transitivity or the reciprocity rule. The first diagonal above the principal diagonal can be chosen for performing those independent comparisons.

The ***transitive comparisons*** which can be deduced with the transitivity rule from the first diagonal entered in the independent comparisons phase.

The ***reciprocal comparisons*** which can be deduced using the reciprocity rule.

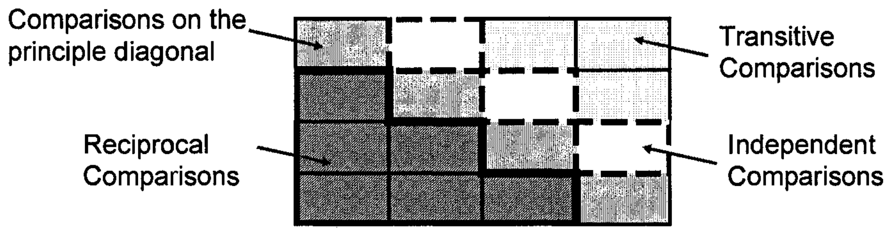


Figure 4.2 Different types of entries in the pairwise comparison matrix

4.2.3. SYNTHESIS AND RANKING OF ALTERNATIVES

The final step in the AHP implementation involves synthesizing the priorities assessed in the previous stages to obtain the overall priority for each alternative and then ranking the alternatives based on that overall priority. The overall priorities of the alternatives are determined by means of a linear additive function, in which the relative priorities for an alternative are multiplied by the priorities of the corresponding criteria and then aggregated over the all criteria.

4.3. MODEL DEVELOPMENT

The objective here is to use the AHP approach to help in assessing different system configurations based on their expected output product quality. This can be achieved through the development of a relative measure called the "Configuration Capability Indicator" (CCI). This measure assesses the configuration capability in achieving high levels of product quality. This measure can be assessed based on two major criteria: the ability of system to prevent the defects occurrence and its ability in detecting defects. The defect prevention and detection capabilities are assessed in terms of the system design criteria illustrated in Figure 4.3.

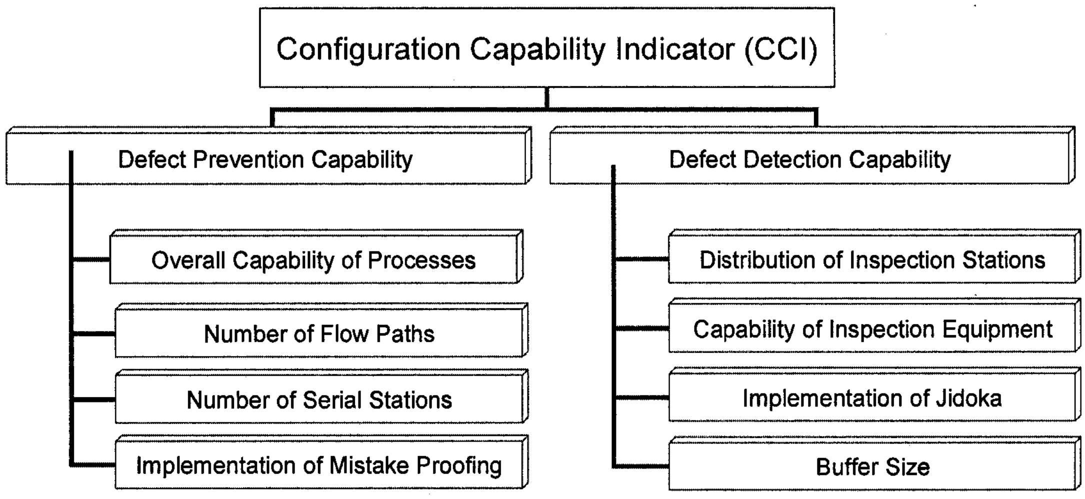


Figure 4.3. Criteria Used for Quality Assessment Using AHP

4.3.1. CRITERIA FOR ASSESSING DEFECT PREVENTION CAPABILITY (DPC)

4.3.1.1. Overall Capability of Processes (OCP)

This model assumes the availability of process capability databases where the capabilities of individual processes can be easily obtained at the early stages of manufacturing system development. The rolled throughput yield is used as a measure for assessing the overall capability of processes which can be also expressed in terms of sigma capability and it ranges from zero to 6. The higher the value of the sigma capability level the better the overall capability of processes. The rolled throughput yield is calculated as in Equation (4.7) [Priest and Sanchez, 2001]:

$$Y_{RT} = \prod_{i=1}^{P_T} Y_i \,, \tag{4.7}$$

where

Y_{RT} : Rolled throughput yield of a product and it represents the fraction of product units that pass through all the stations without rework or scrap,

Y_i : Yield of an individual process i, $i = 1,2,\cdots,P_T$,

P_T : Total number of processes.

4.3.1.2. Number of Flow Paths (NFP)

The number of lines a product through passes during manufacturing (parallel processing) has a significant impact on the output quality. Webbink and Hu [2005] indicated that assessing the impact of the number of flow lines on the end of line variability necessitates a case-based detailed modelling. However, he concluded that the general trend is that the increase in the number of flow paths is associated with an increase in the standard deviation of the output quality.

4.3.1.3. Number of Serial Stations (NSS)

The number of stations in series, which the product passes through using different set-ups, affects the end of line variability [Webbink and Hu, 2005]. In this research the number of stations in series will be used as a measure of variability as it accounts for variability due to variation stack-up.

4.3.1.4. Implementation of Mistake Proofing (IMP)

Shigeo Shingo [1986] formalized a new approach to quality control. He called it "poka yoke", which translated from Japanese, means "mistake proofing". Shingo believed that defects could simply be eliminated in the first place instead of relying on measures taken after-the-fact. Shingo found that defects arise from errors, therefore, discovering and eliminating errors at their source will help prevent defects down the line. Poka Yoke devices are not just a theoretical concept. They are being used successfully in hundreds of companies throughout the world and their effectiveness in preventing the occurrence of errors has been proven [Tsou and Chen, 2005]. In this research the percentage of processes that are equipped with mistake proofing devices will be used as a measure of the level of mistake proofing implementation.

4.3.2. Criteria for Assessing Defect Detection Capability (DDC)

In order to assess the system capability in detecting defects, the following criteria are considered.

4.3.2.1. Distribution of Inspection Stations (DIS)

One of the decisions that should be taken during the design of the manufacturing system is the number and location of inspection stations. The distribution of inspection stations has a significant effect on how fast the defect can be detected. It mainly affects the time between defect occurrence and defect detection. The early detection of defects can help in stopping the propagation of defective items to down stream operations as well as taking actions to stop the generation of more defects.

In this research, the distribution of inspection stations will be assessed based on where inspection activities are performed. Inspection can be performed at the end-of-line, in-process, after each station or within every station. A measure is proposed for assessing the allocation of inspection stations, which is assigned values that range from “0 to “1 . The “0 value represents the best case where inspection is integrated with each production station. The “one” value represents the case of end of line inspection. The values of that measure can be assigned subjectively, or using the relative measure proposed in Equation 5.8, which assesses the allocation of inspection stations based on the average number of processes performed before inspection as well as the total number of inspection stations and total number of processes.

4.3.2.2. Capability of Inspection Equipment (CIE)

This criterion will assess the capability of inspection equipment in performing a specific inspection task. It depends mainly on the specifications of the inspection task with respect to the accuracy and repeatability of the inspection equipment. This criteria is measured in terms of sigma capability as in the overall capability of processes.

4.3.2.3. Implementation of Jidoka (IJ)

"Jidoka" means, in the production context, not allowing defective parts to go from one work station to the next. The implementation of Jidoka has a significant effect on the instantaneous detection of errors and can drastically reduce the rates of defective parts [Mayne et al. 2001]. It specifically refers to machines or to the production line itself being able to stop automatically in abnormal conditions (for example, when a machine breaks down or when defective parts are produced). In Japanese 'jidoka' simply means automation, which according to their philosophy means "automation with a human touch" and implies that machines have a human-like ability to sense when something goes wrong [Miltenburg, 2001]. In this research the percentage of processes that are equipped with sensing devices, capable of detecting the occurrence of defects, will be used as a measure of the level of Jidoka implementation.

4.3.2.4. Buffer Size

Buffer size also affects the time between making the defect and detecting it. Smaller buffer sizes lead to a smaller gap between making the errors and detecting them. Kim and Gershwin [2005] addressed the harmful effect of the buffer size on the system yield. They reported that when there is quality information feedback between two production stations, the system yield is a function of the buffer size and they demonstrated that the system yield decreases as the buffer size increases. This is because larger buffer sizes lead to larger delays between making the errors and detecting them.

4.3.3. Pairwise Comparisons and Results Synthesis

After constructing the Hierarchy, a set of matrices of pairwise comparisons is generated as indicated in Section 4.2.2. Matrix entries indicate the strengths with which one element dominates another using a method for scaling of elements' weights in each of the hierarchy levels with respect to an element in the next higher level. In this research, the preferences are individually assigned based on understanding of the problem and using insights from literature. However, this can be done more accurately by consulting a team of engineers and experts or through conducting a questionnaire. After deriving the local priorities for the criteria and the alternatives through pairwise comparisons, the priorities of the criteria were synthesized to calculate the overall priorities for the decision alternatives. The AHP software *Expert Choice* [2004] has been used to perform the pairwise comparisons and to obtain the relative weights for different criteria. The pairwise comparisons for defect prevention, defect detection and configuration capability indicator criteria are illustrated in Tables 4.2, 4.3, and 4.4, respectively. Inconsistency Ratio (IR) for each pairwise comparison matrix is shown in each table. As indicated by Satty [1980] if the IR value is less than 0.10, the comparison matrix is generally considered acceptable. The obtained priority levels for defect prevention criteria, defect detection criteria, and configuration capability indicator criteria are also illustrated in Figures 4.4, 4.5, and 4.6, respectively.

Table 4.2. Pairwise Comparison and Priority for Defect Prevention Criteria

	OCP	NFP	NSS	MPI	Priority
Overall Capability of Processes (OCP)	1	5	8	2	0.536
Number of Flow Paths (NFP)		1	2	1/3	0.108
Number of Serial Stations (NSS)			1	1/5	0.060
Mistake Proofing Implementation (MPI)				1	0.296
					IR= 0.0

Table 4.3 Pairwise Comparison and Priority for Defect Detection Criteria

	DIS	CIE	JI	BS	Priority
Distribution of Inspection Stations (DIS)	1	2	1/2	4	0.283
Capability of Inspection Equipment (CIE)		1	1/3	2	0.152
Jidoka Implementation (JI)			1	6	0.490
Buffer Size(BS)				1	0.076
					IR= 0.0

Table 4.4 Pairwise Comparison and Priority for CCI Criteria

	DPC	DDC	Priority
Defect Prevention Capability (DPC)	1	3	0.750
Defect Detection Capability (DDC)		1	0.250
			IR= 0.0

For defect prevention criteria, the model has been designed to assign higher weights for the overall capability of processes and mistake proofing implementation as they are considered dominant factors for preventing the occurrence of defects. On the other hand, the dominant factors for defect detection capability the implementation of Jidoka and the distribution of inspection stations. On the higher layer of the hierarchy, the defect prevention capability is the dominant factor compared to defect detection capability as the preference is always given to preventing the occurrence of defects rather than allowing their occurrence and then detecting them.

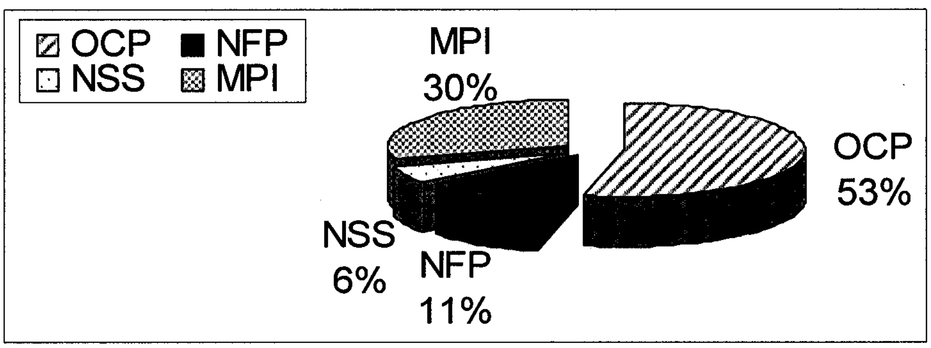


Figure 4.4 Priority Levels for Defect Prevention Criteria

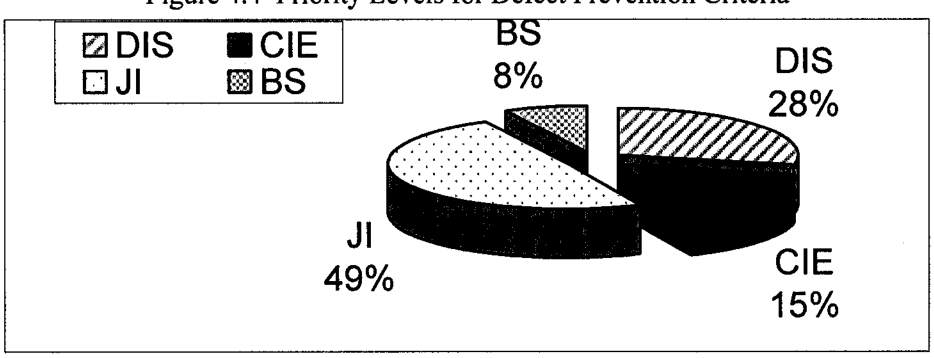


Figure 4.5 Priority Levels for Defect Detection Criteria

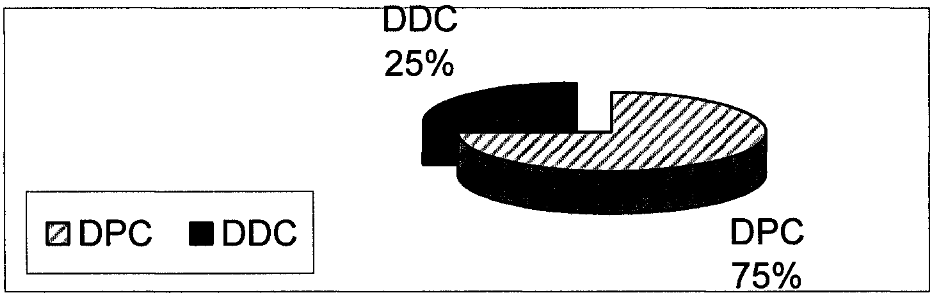


Figure 4.6 Priority Levels for Configuration Capability Indicator Criteria

4.4. APPLICATION (GEARBOX HOUSING)

The application of the developed model is illustrated using a case study concerned with the design of a manufacturing system for machining of the gearbox housing shown in Figure 4.7 [Zhang et al. 2002]. Three different configuration alternatives, shown in Figure 4.8, will be considered. Any of these three configurations can be used in the machining of the gearbox shown in Figure 4.7, but at different costs and production rates. In this research, the main concern is to assess these configurations from the quality point of view and this assessment can later be incorporated with other selection criteria to support the configuration selection decision making.

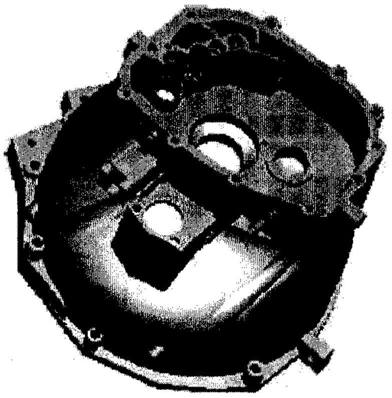


Figure 4.7 Gear Box Housing Considered for Application [Zhang et al., 2002]

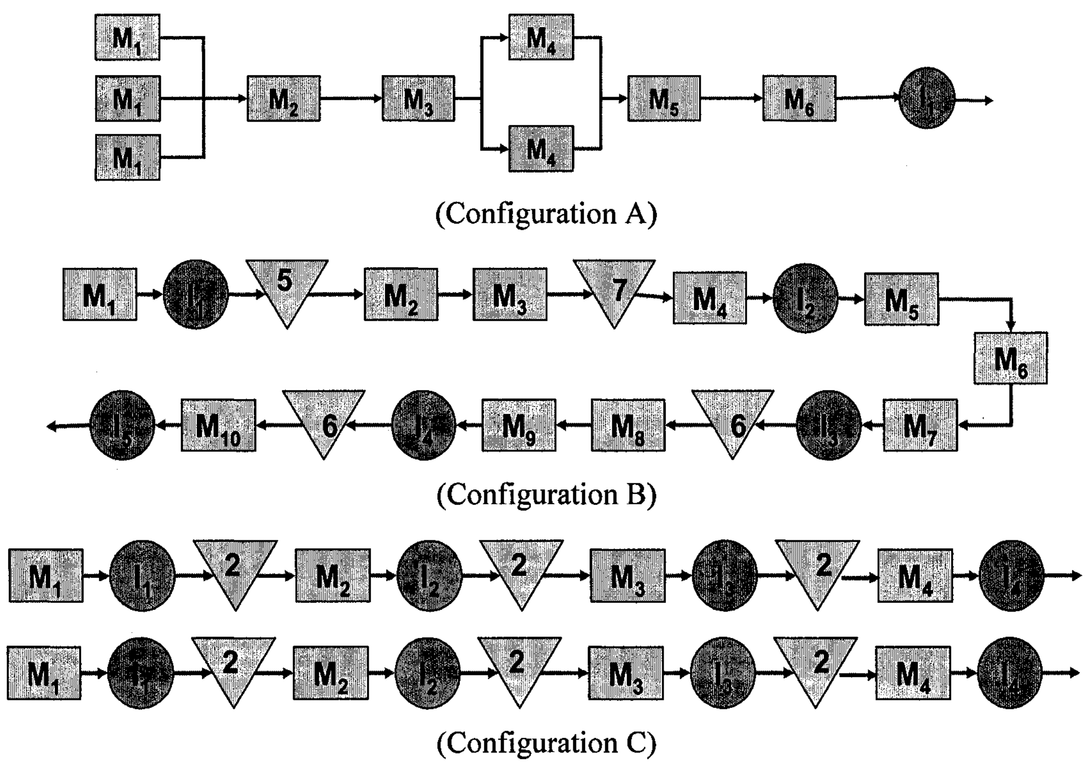


Figure 4.8 Manufacturing System Configuration Alternatives for Gear Box Housing

The considered system configurations are automatic transfer lines and the machines used in these systems are 4-axis horizontal milling machines. The developed model will be used to compare the different configurations by computing the relative Configuration Capability Indicator (CCI) for each alternative.

The data for each configuration alternative is given in Table 4.5. The three configurations have been assessed with respect to each evaluation criterion. The assessment starts with each criterion in the lowest layer in the hierarchy by performing pairwise comparisons among configurations with respect to each criterion.

4.5. RESULTS AND DISCUSSION

The results obtained with respect to defect prevention criteria are shown in Table 4.6. These results have been synthesized and the rank for Defect Prevention Capability (DPC) has been obtained as follows:

DPC (Configuration A) = 0.129,

DPC (Configuration B) = 0.293, and

DPC (Configuration C) = 0.578.

These results indicate that Configuration C has the highest defect prevention capability relative to Configuration A and B. This is because configuration C has a higher overall capability of processes (4.2 σ) as opposed to the other two configurations (3.7 σ for Configuration B and 3.2 σ for Configuration A). In addition, the level of mistake proofing implementation in Configuration C (75%) is higher than the other two alternatives (50% for Configuration B, and 30% for Configuration A). Also, Configuration C has relatively low number of flow paths (2) as well as low number of serial stations (4), whereas Configuration B has one flow path and (10) serial stations and Configuration A has (6) flow paths and (6) serial stations.

Similarly, the results obtained with respect to the defect detection criterion are shown in Table 4.7. These results have been synthesized and the rank for Defect Detection Capability (DDC) has been obtained as follows:

DDC (Configuration A) = 0.189,

DDC (Configuration B) = 0.344, and

DDC (Configuration C) = 0.467.

Also, Configuration C has the highest defect detection capability relative to the other two configurations. This is mainly due to the use of inspection after each production station. These results for the defect detection criteria as well as defect prevention evaluation criteria are illustrated in Figure 4.9. This Figure represents a radar chart, in which the values for all evaluation criteria are plotted for each configuration to visually display their relative values.

Table 4.5 Specifications of Configuration Alternatives for the Gearbox Housing Case Study

	Configuration A	**Configuraion B**	**Configuration C**
Overall Capability of Processes	3.2 σ	3.7 σ	4.2 σ
Number of Flow Paths	6	1	2
Number of Serial Stations	6	10	4
Mistake Proofing Implementation	In 30% of the operations mistake proofing devices are used	In 50% of the operations mistake proofing devices are used	In 75% of the operations mistake proofing devices are used
Distribution of Inspection Stations	As shown in Figure 3 (end-of-line)	As shown in Figure 3 (In-process)	As shown in Figure 3 (After each station)
Capability of Inspection Stations	Average = 3 σ	Average= 4 σ	Average= 4 σ
Jikdoka Implementation	2 machines out of 9 are equipped with sensors of error detection (22.22%)	5 machines out of 10 are equipped with sensors of error detection (50%)	4 machines out of 8 are equipped with sensors of error detection (50%)
Buffer Size	As shown in Figure 3 (no buffer)	As shown in Figure 3 (with average size=6)	As shown in Figure 3 (with average size=2)

Table 4.6 Results of Assessing Different Alternatives With Respect to Defect Prevention Criteria

	Configuration A	Configuration B	Configuration C
Overall Capability of Processes (OCP)	0.143	0.286	0.571
Number of Flow Paths (NFP)	0.082	0.603	0.315
Number of Serial Stations (NSS)	0.315	0.82	0.603
Mistake Proofing Implementation (MPI)	0.08	0.236	0.682

Table 4.7 Results of Assessing Different Alternatives With Respect to Defect Detection Criteria

	Configuration A	Configuration B	Configuration C
Distribution of Inspection Stations (DIS)	0.058	0.278	0.663
Capability of Inspection Equipment (CIE)	0.200	0.400	0.400
Jidoka Implementation (JI)	0.200	0.400	0.400
Buffer Size(BS)	0.582	0.109	0.309

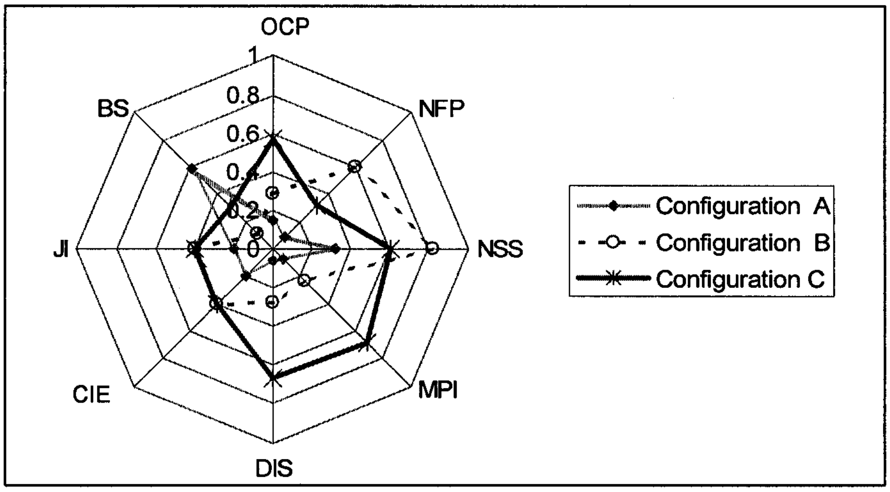


Figure 4.9. Results of Evaluation Criteria for Different Configuration Alternatives

By synthesizing the results for defect prevention capability and defect detection capability, the Configuration Capability Indicator (CCI) for each alternative can be obtained. The results indicate the following:

CCI (Configuration A) = 0.144,

CCI (Configuration B) = 0.306, and

CCI (Configuration C) = 0.55,

From these results, it can be concluded that Configuration C is the best alternative from a quality point of view as shown in Figure 4.10.

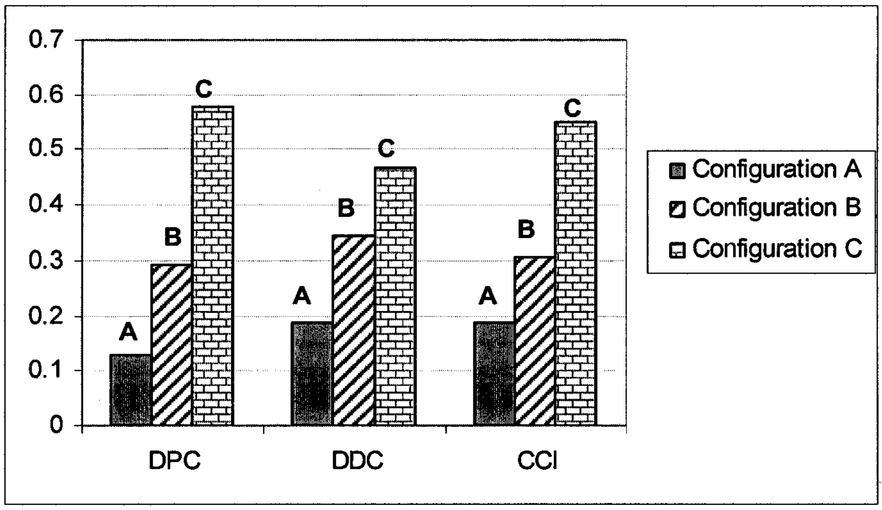


Figure 4.10. Quality-Based Comparison of the Configuration Alternatives

Sensitivity analysis can be easily performed using the developed model to investigate the impact of the relative importance of the evaluation criteria. For instance, Figure 4.11 illustrates the results obtained above; in which the weight for Defect Prevention Capability (DPC) equals 0.75 and Defect Detection Capability (DDC) equals 0.25. In this case the rank of the configurations is: Configuration C is best, and then Configuration B, and the worst is Configuration A. If the weights for DPC and DDC are changed and a higher weight is assigned to DDC, it is expected that Configuration B and C will start to be equally preferred. Figure 4.12 illustrates this case when the weight for DDC is 0.8 and for DPC is 0.2.

However, the weight for DPC should always be much greater than the weight for DDC. This is because it is always preferable to prevent the occurrence of defects rather than detecting them. Further sensitivity analysis can be performed with respect to the sub-criteria as needed. For instance, the weight assigned to the overall capability of processes with respect to the implementation of mistake proofing can be changed in order to explore their impact on the defect prevention capability of different system configurations.

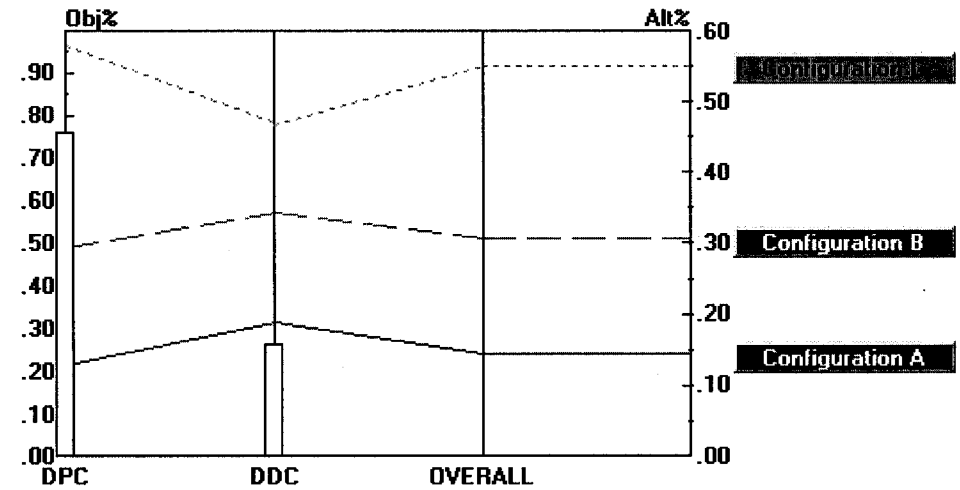


Figure 4.11 Ranking of the Different Configurations When the Wight for DPC =0.75 and for DDC=0.25

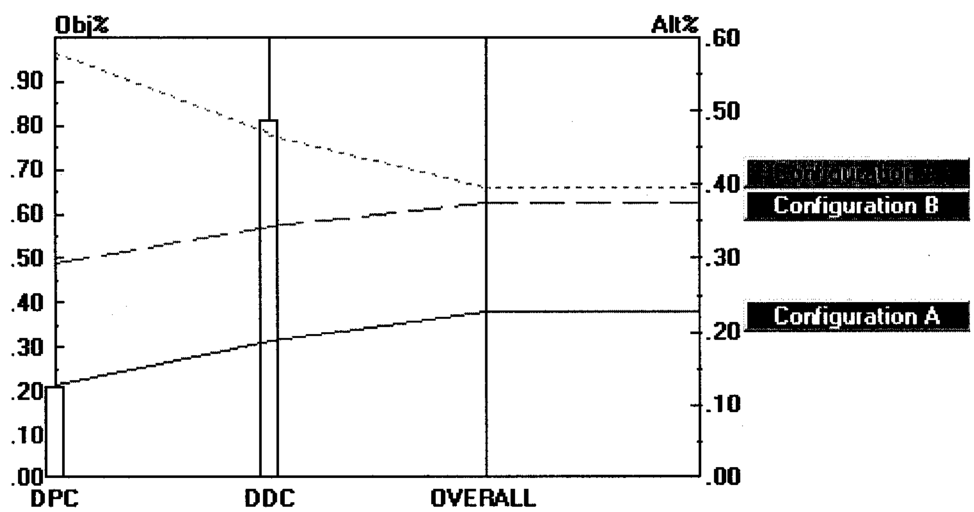


Figure 4.12 Ranking of the Different Configurations When the Wight for DPC = 0.2 and for DDC= 0.8

One of the limitations of using the AHP to assess the configuration capability is that the final ranking can be perturbed by introducing new alternative(s). In such a situation, the comparison matrix that is used to assess the alternatives with respect to the sub-criteria has to be regenerated. In addition, using such a model, sensitivity analysis can be easily performed to assess the impact of changing the weights of the criteria and sub-criteria. However, investigating the impact of changing any of the alternatives characteristics cannot be achieved using sensitivity analysis. This is because any changes in any of the alternatives characteristics will result in a new alternative, and based on that the new set of alternatives should be considered for re-evaluation. This necessitates reconstructing the pairwise comparison matrices that assess the different alternatives with respect to the evaluation criteria.

In addition, AHP is limited to providing a relative rank for the considered set of alternatives. Therefore, the obtained measure is valid only within that set of alternatives as it can compare them and provide a relative assessment based on their considered characteristics. Although such a relative measure can help the decision maker in selecting the best alternative among the considered set of alternatives, it will not provide the decision maker with insights about the absolute performance of the selected alternatives. For instance, one of the scenarios could include a set of alternative that all will result in a poor output quality. Such an AHP model will still provide a rank for these alternatives and the decision maker will not be aware that even the best configuration is not capable of achieving the organization quality targets. Moreover, AHP depends on the additive aggregation of priorities. This requires the assumption that all criteria must be independent, which not the case is all the time. For instance, the importance of the buffer size, as an evaluation criterion that assesses the gap between making errors and detecting them, decreases when inspection is performed after each production station. However, the AHP model assigns a constant weight for the buffer size regardless of the allocation of the inspection stations. Therefore, in the next chapter, a fuzzy logic inference model is developed to handle these shortcomings.

4.6. SUMMARY

This chapter proposed the use of AHP for comparing different system configurations based on quality. The evaluation criteria used in the developed model include some of the critical system design parameters that have a direct impact on the resulting product quality. A case study for the machining of a gearbox housing has been presented to illustrate the use of the model.

The developed model is capable of providing the decision maker with a relative Configuration Capability Indicator (CCI) that is based on assessing the configuration defect prevention as well as defect detection capabilities. The configuration defect prevention capability is assessed based on the overall capabilities of processes, implementation of mistake proofing, variability due to mixing or stack-up of variation as affected by the number of parallel and serial stations. The configuration defect detection capability is assessed in terms of distribution and capabilities of inspection stations, the implementation of Jidoka, as well as the buffer size. Despite the importance of the system capability in detecting defects, it is recommended that more attention should be given to the defect prevention capability. This is because preventing the occurrence of defects always has a higher preference over tracking and detecting the defects; especially from the productivity and cost perspectives. The proposed model considers these issues and is capable of integrating the different system design criteria concerned with defect prevention and detection to provide the system designer with a relative configuration capability indicator. In addition, the limitations have been highlighted and discussed.

5. FUZZY LOGIC INFERENCE SYSTEM FOR QUALITY PREDICTION IN MANUFACTURING SYSTEMS DESIGN

5.1. INTRODUCTION

The prediction of quality at the early stages of manufacturing systems design and development can support the manufacturing system configuration decision making. Therefore, it can significantly enhance the manufacturer's competitiveness through achieving higher quality levels at lower costs in a responsive manner. It has been reported in the literature, as shown in Chapter 2, that system design and configuration do affect the quality of products. Unfortunately, the information available about the impact of manufacturing system design on quality is associated with uncertainties, vagueness, and incompleteness.

In this chapter a Configuration Capability Indicator (CCI) that is capable of mapping the manufacturing system configuration parameters into an expected product quality level has been developed. A hierarchical Fuzzy Inference System (FIS) is used for modeling the ill-defined relation between manufacturing system design parameters and the resulting product quality. The proposed CCI aims at predicting the system's output quality based on the manufacturing system's defect prevention capability as well as defect detection capability. The hierarchical fuzzy inference system is designed to predict the product quality level that could be achieved as a function of the manufacturing system configuration parameters. The considered system parameters, as illustrated in Figure 5.1, include the number of flow paths contributing to the manufacturing of the same product, the number of serial stations using different set ups, the overall capabilities of processes including manual operations, the implementation of mistake proofing techniques, the allocation of inspection stations, the expected inspection error including equipment errors as well as errors due to human involvement in inspection tasks, the implementation of Jidoka, as well as the buffer size.

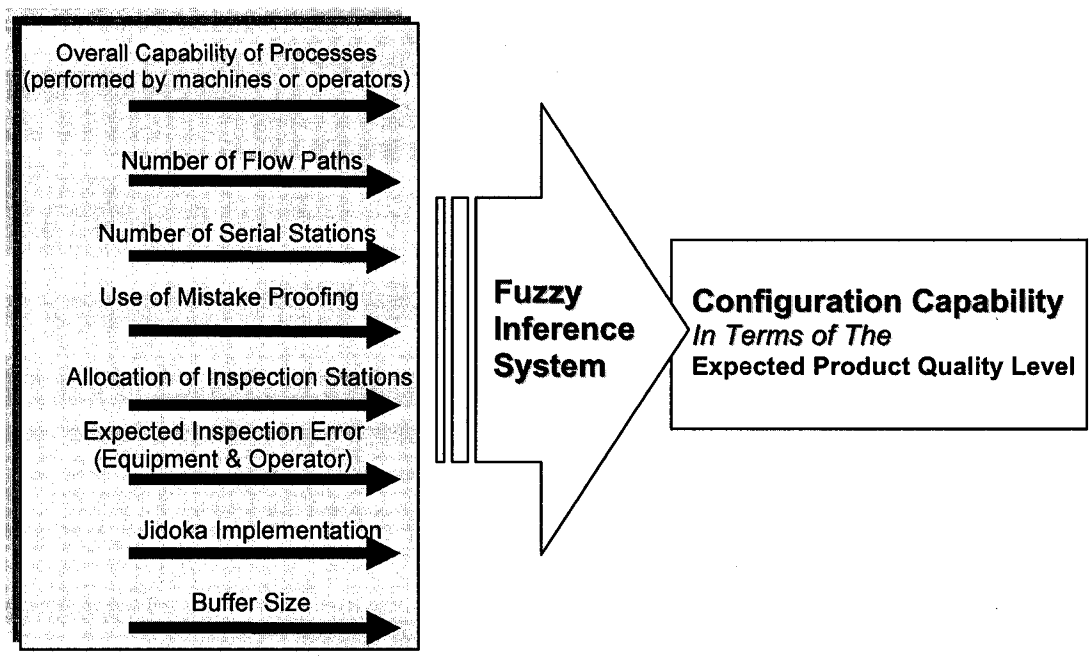


Figure 5.1 The Set of Configuration Parameters Used in Quality Prediction.

5.2. FUZZY LOGIC

Fuzzy logic is a powerful problem-solving methodology with several applications in different fields. Fuzzy logic provides a simple way to draw definite conclusions from vague, ambiguous or imprecise information. In a sense, fuzzy logic resembles human decision making with its ability to work from approximate data and find precise solutions.

Unlike classical logic that requires deep understanding of a system, exact equations, and precise numeric values, Fuzzy logic incorporates an alternative way of thinking, which allows modeling complex systems using a higher level of abstraction originating from our knowledge and experience. Fuzzy Logic allows expressing this knowledge with subjective concepts, which are mapped into exact numeric ranges.

Fuzzy set theory is a mathematical tool for describing impreciseness, vagueness and uncertainty. A fuzzy set is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership. The notion of fuzzy set was introduced first by Lotfi Zadeh in 1965 [Zadeh, 1965]; he later developed many of the methods of fuzzy logic based on this simple notion. It took a couple of decades for the rationale of fuzzy sets to be understood and applied by other scientists. The traditional way of representing element u of a set A is through the characteristic function:

$$\mu_A(u) = \begin{cases} 1 & \textit{if u is an element of the set A} \\ 0 & \textit{if u is not an element of the set A} \end{cases} \quad . \tag{5.1}$$

That is, an object either belongs or does not belong to a given set. This is the general definition of sets according to the classical or crisp set theory. In fuzzy sets, an object can belong to a set partially. The degree of membership is defined through a generalized characteristic function called the membership function:

$$\mu_A(u): \quad U \rightarrow [0,1] \quad , \tag{5.2}$$

where U is called the universe of discourse, and A is a fuzzy subset of U. The values of the membership function are real numbers in the interval [0, 1], where 0 means that the object is not a member of the set and 1 means that it belongs entirely. Each value of the function is called a degree of membership, which resembles the degree to which an element u belongs to a fuzzy set A.

5.2.1. Fuzzy Inference System Design

The process of designing a Fuzzy Inference System (FIS) involves the design of the input and output fuzzy variables as well as the set of fuzzy rules that map the input into output. The fuzzy variable design, as illustrated by Berkan and Trubatch [1997], is mainly concerned with determining the number of membership functions and their location on the universe of discourse as the first step in fuzzy variable design. The second step is concerned with selecting the shape, height, and overlap of each membership function. Membership functions can take many forms such as: triangular, trapezoidal, Gaussian curve, etc as shown in Figure 5.2 . The design of membership functions can be achieved through subjective evaluation, physical measurement, converted frequencies or probabilities, as well as learning and adaptation [Berkan and Trubatch, 1997]. After designing the fuzzy variables, the knowledge of the relationship between inputs and outputs of fuzzy systems are expressed as a set of *if-then* rules to form the *rule-base* of

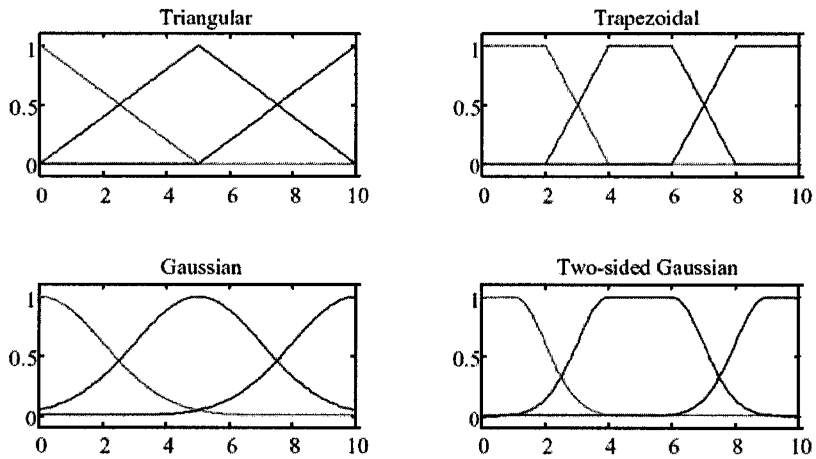


Figure 5.2. Common Shapes of Fuzzy Membership Functions [Jang et al., 1997]

the fuzzy system. Knowledge acquisition for rules development can be done through experts, engineering judgment, data sets, textbooks and literature information, observations and empirical studies, as well as common sense. Fuzzy *if-then* rules and fuzzy reasoning are the backbone of fuzzy inference system. A single fuzzy *if-then* rule states the following:

$$\textit{If } u_1 \textit{ is } A \textit{ and } u_2 \textit{ is } B \textit{ then } u_0 \textit{ is } C, \tag{5.3}$$

where A, B and C are linguistic values defined by fuzzy sets on the universes of discourse U_1, U_2 and U_0 respectively. The *if-part* of the rule "u_1 *is A and* u_2 *is B*" is called the *antecedent* or *premise*, while the *then-part* of the rule "u_0 *is C*" is called the consequent or conclusion.

The general inference process, as shown in Figure 5.3, proceeds in the following steps [Yen and Langari, 1999]:

Fuzzification: The fuzzification process is simply converting the input from its original crisp nature to a fuzzy form ready for inference process.

Inference: In which, the truth value for the premise of each rule is computed, and applied to the consequent part of each rule. This results in one fuzzy subset to be assigned to each output variable for each rule; this part is known also as implication. The two most popular fuzzy inference systems are Mamdani's method [Mamdani and Assilian, 1975], and Takagi–Sugeno's Method [Takagi and Sugeno, 1985]. These two methods have been widely deployed in various applications. The differences between these two fuzzy inference systems lie in the consequents of their fuzzy rules. In Mamdani's fuzzy inference system, the rule antecedents and consequents are defined by fuzzy sets. However, in Takagi–Sugeno's Method the consequent of a fuzzy rule is constituted by a weighted linear combination of the crisp inputs rather than a fuzzy set.

Aggregation: In the aggregation process all of the fuzzy subsets assigned to each output variable are combined together to form a single fuzzy subset for each output variable.

Defuzzification: It is optional and is used when it is useful to convert the fuzzy output set to a crisp number. There are several defuzzification methods. Two of the more common techniques are the Centroid and Maximum methods. In the Centroid method, the crisp value of the output variable is computed by finding the variable value of the center of gravity of the membership function for the fuzzy value. In the Maximum method, one of the variable values at which the fuzzy subset has its maximum truth value is chosen as the crisp value for the output variable.

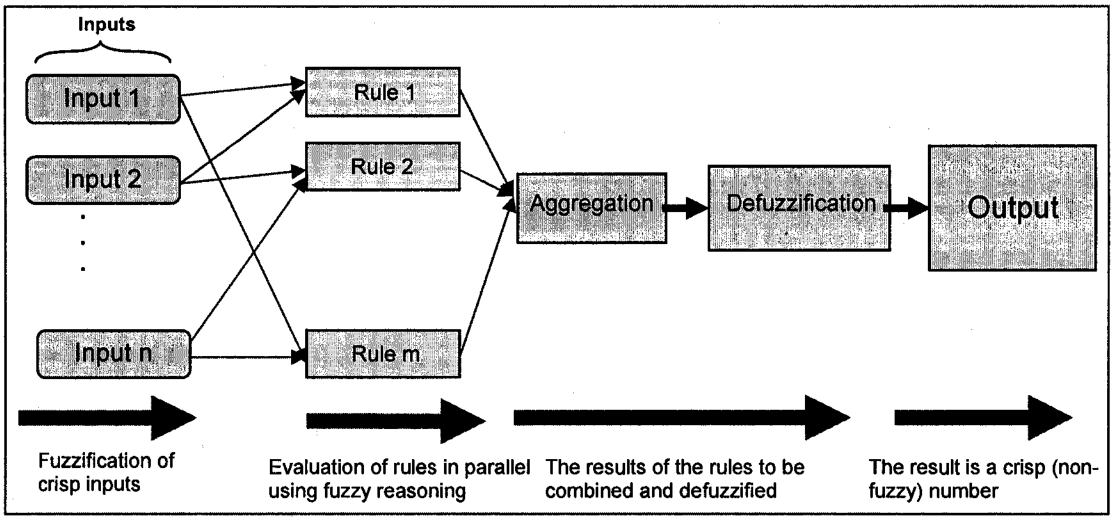


Figure 5.3. Fuzzy Inference Process [Yen and Langari, 1999]

5.2.2. Hierarchical Fuzzy Inference System

One of the most important issues in the design of fuzzy inference systems is how to reduce the number of rules and their corresponding computation requirements. In conventional fuzzy inference systems, shown in Figure 5.4, the number of fuzzy rules grows exponentially with the number of input variables. Specifically, a single output fuzzy logic system with "n" input variables and "m" membership functions defined for each input variable requires "m to the power of n" number of fuzzy rules. This is called rule explosion problem.

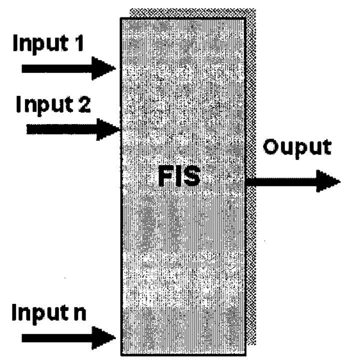


Figure 5.4. A Conventional Single Layer Fuzzy Inference System

To overcome this problem, the hierarchical fuzzy system was proposed by Raju et al. [1991]. Such system consists of a number of hierarchically connected low-dimensional fuzzy systems. Figure 5.5 shows a typical example of hierarchical fuzzy systems. It was proved by Wang [1998 and 1999] that the number of rules in the hierarchical fuzzy system increases linearly with the number of input variables. It greatly reduces the number of rules compared with the standard fuzzy system. Despite their small rule base and structure constraints, the hierarchical fuzzy systems are proven in [Wang, 1998] to be universal approximators for the three-input case. Wei and Wang [2000] extended that result to the general high-dimensional case. They reported that the hierarchical fuzzy systems do provide a good candidate for solving high-dimensional problems.

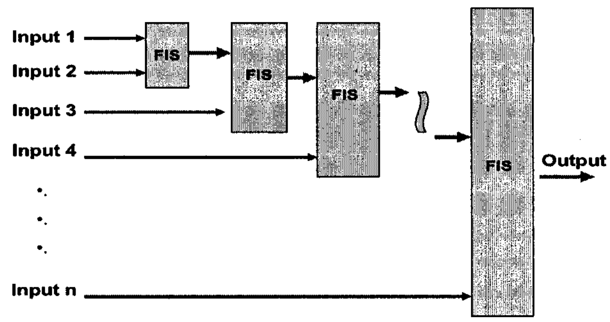


Figure 5.5. A Typical Hierarchical Fuzzy Inference System [adapted from Wang 1999]

5.3. MODEL DEVELOPMENT

In this research, the hierarchical structure is used in designing a fuzzy inference system for quality prediction in terms of manufacturing system configuration parameters. The developed fuzzy inference system consists of five sub-systems in three layers as illustrated in Figure 5.6. The overall procedure used to develop this model is listed in Section B1 in Appendix B.

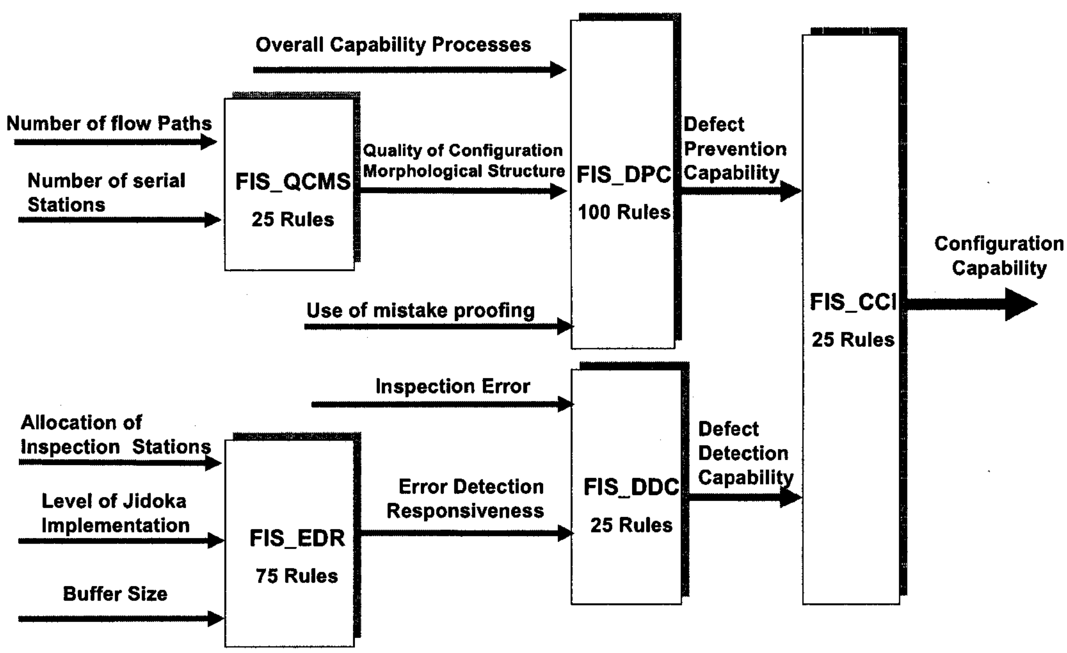


Figure 5.6. The Structure of the Proposed Hierarchical Fuzzy Inference System for Predicting Product Quality level in a Given Manufacturing System

At the highest level, the configuration capability is predicted using the fuzzy inference system Configuration Capability Indicator (FIS_CCI); which is assessed based on the system's Defect Prevention Capability (DPC) as well as Defect Detection Capability (DDC). The Defect Prevention Capability is assessed using a fuzzy inference system (FIS_DPC) that has three inputs. The first input for FIS_DPC represents the overall capability of processes performed by machines or manually by human operators. The second input for FIS_DPC represents the Quality of Configuration Morphological Structure (QCMS). This fuzzy variable is predicted using fuzzy inference system (FIS_QCMS) and it accounts for the variability in the system resulting from variation stack up as well as variation associated with parallel processing. The third input to (FIS_DPC) accounts for the use of mistake proofing devices. The Defect Detection Capability is assessed using a fuzzy inference system (FIS_DDC). The defect detection capability is mainly assessed based on the accuracy of error detection as well as the responsiveness in error detection; which are the two inputs for FIS_DDC. The Error Detection Responsiveness (EDR) is assessed using FIS_EDR; which has three inputs. The first one is the allocation of inspection stations. The second represents the use of signalling devices that allow the process to be stopped in case of error occurrence. The last one is the buffer size.

The use of the hierarchal structure in designing the fuzzy inference system significantly reduced the number of the required rules to only 250 rules. If the conventional single layer structure has been used to develop this model a total of 187,500 rules will be needed, which is the product of the number of fuzzy sets for all input values. Specifically, in this case, 5 sets for No. of flow paths × 5 sets for No. of serial stations × 4 sets for overall capability of processes × 5 sets for mistake proofing × 5 sets for inspection error × 3 sets for allocation of inspection stations × 5 sets for level of Jidoka implementation × 5 sets for buffer size will result in a total of 187,500 rules.

In the design of this hierarchal fuzzy inference system, the inputs to the system are clustered and grouped such that the outputs of the intermediate layers can provide the user with a meaningful quality measures such as defect prevention capability and defect detection capability. This can help in identifying the improvement opportunities and in investigating the sensitivity of the final quality measure to the changes to be made in the parameters considered for improvement.

In this research, Mamdani's fuzzy inference system is used in the implication process. According to Mamdani, the rules antecedents and consequents can be represented as fuzzy sets. Using fuzzy sets is appropriate for the considered application because they can handle the subjectivity associated with quality assessment. Rules based on Mamdani's approach can be expressed, for two inputs, as:

$$\textit{if } X \textit{ is } A_{iq} \textit{ and } Y \textit{ is } B_{jq} \textit{ then } Z \textit{ is } C_{kq} \tag{5.4}$$

where A, B, and C are fuzzy sets and X, Y, and Z are fuzzy variables divided into i, j, and k fuzzy sets, respectively; and their relation is described by the rule q, $q = 1, 2, \cdots, n$, where n is the number of rules. In the rules, the connector "and" can be replaced by "or" depending on the requirements of the physical model. The connectors "and" and "or" are evaluated by standard operations of intersection and union, respectively. A simplified version of fuzzy inference process according to Mamdani using "min" operator is illustrated in Figure 5.7. In this illustration, two rules are considered and formed as in relation (5.4) as follows:

$$\text{Rule 1: } \textit{if } X \textit{ is } A_{21} \textit{ and } Y \textit{ is } B_{21} \textit{ then } Z \textit{ is } C_{11} \tag{5.5}$$

$$\text{Rule 2: } \textit{if } X \textit{ is } A_{12} \textit{ and } Y \textit{ is } B_{22} \textit{ then } Z \textit{ is } C_{22} \tag{5.6}$$

As shown in Figure 5.7, when using the "min" operator, the output membership function is clipped off at the minimum height corresponding to the rule premise's computed degree of truth.

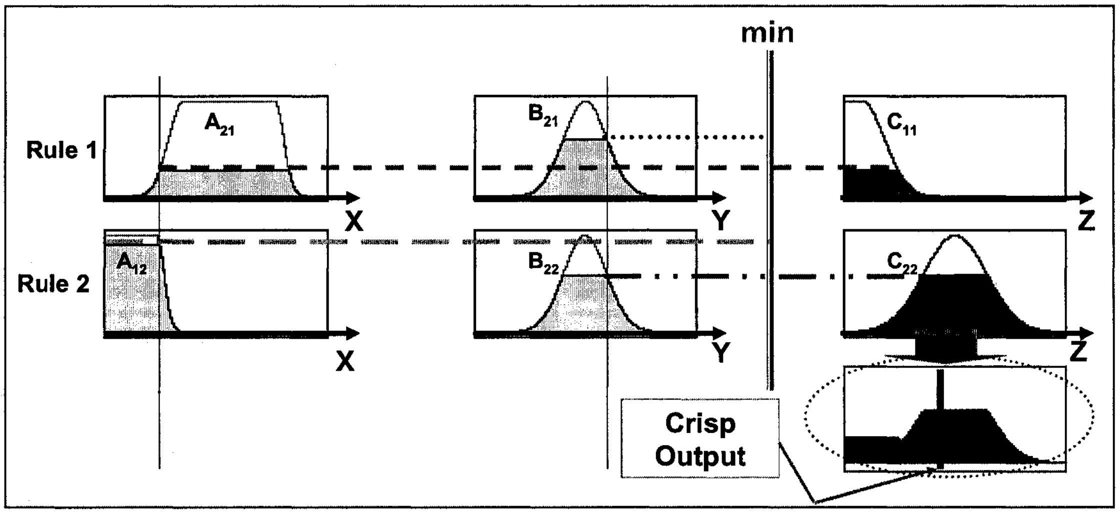


Figure 5.7. Mamdani Fuzzy Inference System adapted from [Ross, 2004]

In the following subsections, the design details for each fuzzy inference system are illustrated. It has been reported earlier in Section 5.2 that there are several methods for the design of fuzzy variables and membership functions as well as rule derivation. Despite the differences between these methods, according to Berkan and Trubatch [1997], they follow two main approaches. One is the data-driven approach that depends on availability of data sets that can be used during the design process. The other is the linguistic design approach which mainly depends on the understanding of the problem. Because of the lack of data, this research is based on the linguistic design of the fuzzy variables and uses the related literature to aid in the design of variables and rule derivation. The fuzzy inference systems, presented in the following sections, have been designed according to the following specifications:

- The fuzzy inference process follows Mamdani's approach.
- The "min" and "max" operators are used to express the fuzzy intersection and union (i.e. "and" and "or"), respectively.
- The centroid method, Ross [2004], is used for the defuzzification
- The shape of the membership function follows Gaussian distribution curves. The simple Gaussian curve and the two-sided Gaussian curve have been used, as these represent smooth curves that are capable of expressing the most-likely value and the most-likely range, respectively. It is worth mentioning that the shape of

membership function does not significantly affect the performance of the inference system compared with the effect of the number, location, and overlap of the functions [Ross, 2004].

- The used software is the Matlab Fuzzy Logic Toolbox as well as the Matlab Simulink [The Math Works, 2002] to integrate the subsystems using fuzzy logic controllers.

5.3.1. The Design of the First Layer in the Hierarchical FIS

As shown in Figure 5.6, the first layer "lowest level" in the hierarchical fuzzy inference system for quality prediction has two fuzzy inference systems. One is concerned with assessing the Quality of Configuration Morphological Structure and the other with assessing the Error Detection Responsiveness.

5.3.1.1. FIS Design For Assessing The Quality Of Configuration Morphological Structure

Different structures of system configuration, in terms of the number of flow paths as well as serial stations, affect the end of line variability. Zhong [2002] and Zhong *et al.*, [2002] demonstrated that different configurations could result in different performance in terms of the resulting product quality. Figure 5.8 illustrates the impact of number of parallel flow lines on the end of line dimensional quality.

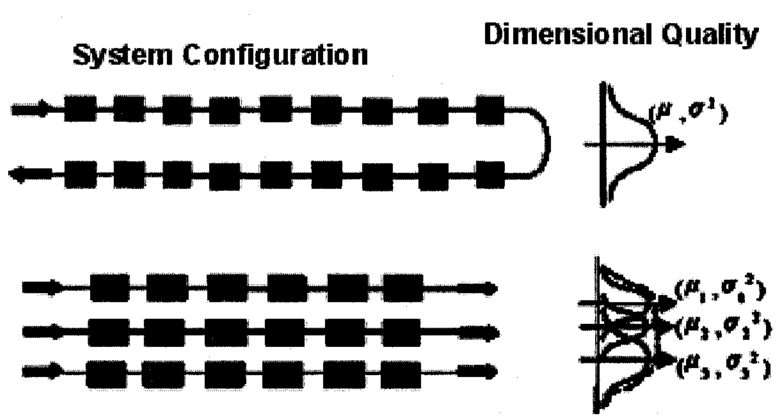


Figure 5.8. The effect of Parallel Processing on the end of line variability [Zhong, 2002]

In this research, the quality of the morphological structure of a manufacturing system configuration refers to how the system layout design contributes to the variability of the manufactured product. It accounts for variability due to variation stack-up as well as variation due to parallel processing. The stream of variation approach has been used in the literature to predict quality in machining systems and assembly systems as well [Hu, 1997], [Hung et al., 2002], [Zhong et al., 2002], and [Webbink and Hu, 2005]. The implementation of that approach necessitates detailed modeling of the processes. Webbink [2003] reported that the level of variation produced by a system is impossible to be predicted as a function of system configuration alone because many other factors contribute directly to this measure of system performance. Although, the impact of system configuration on quality may not be easily predictable for all cases, Webbink and Hu [2005] concluded that general trends can be derived as an aid in the selection of system configuration. Therefore, the use of stream of variation in quality prediction is limited by the need of in-depth study and analysis on a case-by-case basis.

The general trends and conclusions reached by researchers in that field are used in developing the fuzzy inference system for assessing the quality of configuration morphological structure. Thorough review of the research work that studies the impact of system configuration on quality [Zhong et al., 2002], and [Webbink and Hu, 2005] reveals that two main dominant system design related parameters affect the end of line variability. These are the number of flow paths and the number of serial stations. The general trend that they have concluded is that the increase in the number of flow paths increases the standard deviation of the output product and this is due to the effect of mixing. In addition, the increase in the number of serial stations increases the standard deviation and this is due to the stack-up effect. They also indicted that the variability due parallel processing has a more dominant adverse effect on the overall variability compared to the variability due to the stack-up effect.

The developed fuzzy Inference System for assessing the Quality of the Configuration Morphological Structure (QCMS) is illustrated in Figure 5.9. Two fuzzy variables have been designed to represent the system inputs. The first one represents the number of flow paths that contribute to the manufacture of the same product, i.e. parallel processing, and its universe of discourse ranges from 1 to 20, and is divided to five fuzzy sets whose linguistic values are "low", "low-medium" "medium", "medium-high", and "high". These fuzzy sets are defined by the fuzzy membership function shown in Figure 5.10. Similarly, the other fuzzy input represents the number of serial stations and its universe of discourse ranges from 1 to 20; which it is divided into five fuzzy sets as shown in Figure 5.11. It should be highlighted here that the number of serial stations accounts for the variation stack-up. Therefore, in the implementation of the model only the number of serial stations that affect the variability should be considered.

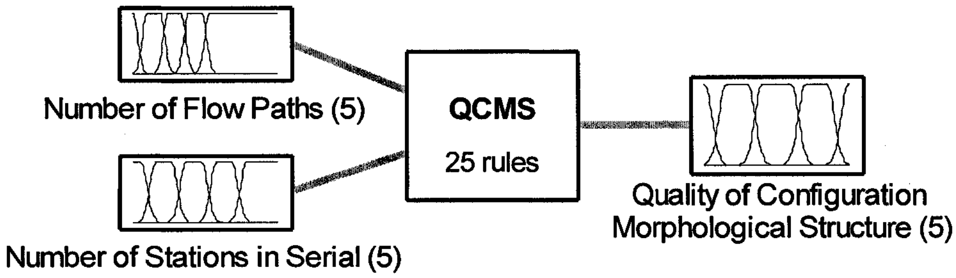


Figure 5.9. Fuzzy Inference System for Assessing Quality of the Configuration Morphological Structure (QCMS)

The output of this FIS represents the quality of configuration morphological structure. A fuzzy variable that represent this measure is designed with a universe of discourse ranges from 0 to 1. The fuzzy sets of this variable and their membership functions are shown in Figure 5.12. It should be noted that in Figure 5.9, the numbers between parentheses "( )" represent the number of fuzzy sets associated with each fuzzy variable and the number of rules equal to the product of the number of fuzzy sets for all the input variables. Therefore, twenty-five fuzzy rules are used to identify the relation between the inputs and the output of this fuzzy inference system as listed in Table A-1 in Appendix A. Examples of these rules are:

- "***If*** (No. of Flow Paths is Low) ***and*** (No. of Serial stations is Low) ***then*** (Quality of Configuration Morphological Structure is High)",

- "***If*** (No. of Flow Paths is Low) ***and*** (No. of Serial stations is Low-Med) ***then*** (Quality of Configuration Morphological Structure is High)",
- "***If*** (No. of Flow Paths is Low) ***and*** (No. of Serial stations is Med) ***then*** (Quality of Configuration Morphological Structure is High)".

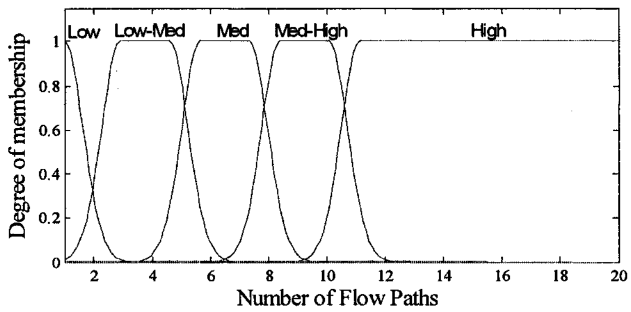


Figure 5.10. Number of Flow Paths Membership Function

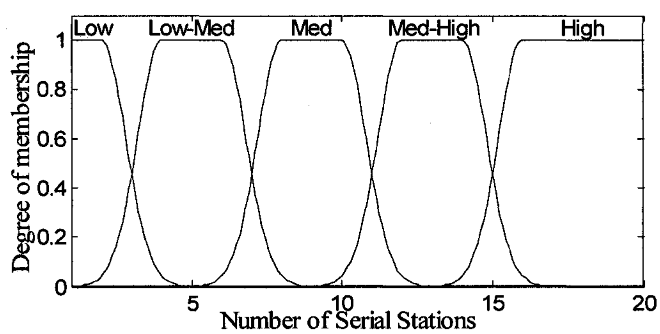


Figure 5.11. Number Serial Stations Membership Function

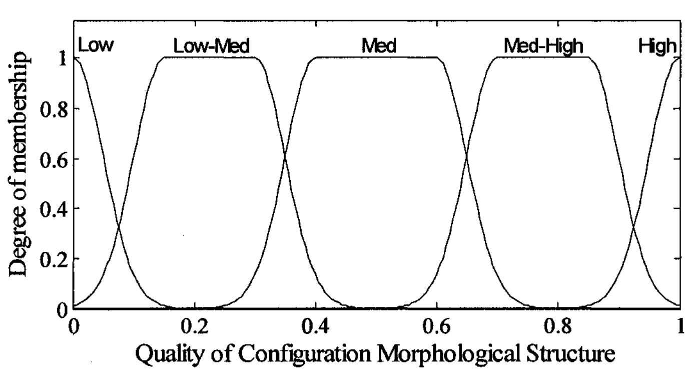


Figure 5.12. Quality of Configuration Morphological Structure Membership Function

5.3.1.2. FIS Design for Assessing the Error Detection Responsiveness (EDR)

The system responsiveness in error detection assesses the extent to which the system is capable of detecting errors as early as possible. The time between the occurrence of errors and detecting them can significantly affect the propagation of errors and defect rates as well as the manufacturing resource used in performing more processes on a part that will be rejected at the end. In this section, the design of a fuzzy inference system for assessing the system responsiveness in detecting errors is illustrated. Error Detection Responsiveness (EDR) is assessed based on three parameters as shown in Figure 5.13. The inputs to this fuzzy inference system are the allocation of inspection stations, the level of Jidoka implementation, and the buffer size.

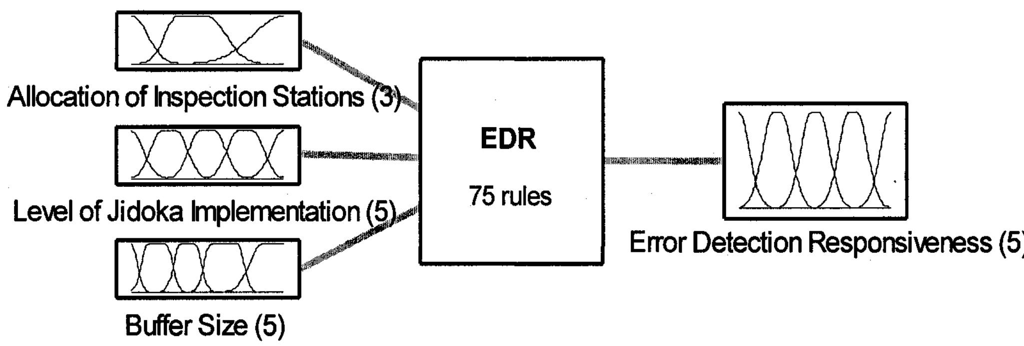


Figure 5.13. Fuzzy Inference System for Assessing EDR

Allocation of Inspection Stations

Considering the first input used in assessing the error detection responsiveness; that is the allocation of inspection stations. In order to assess the extent to which the allocation of inspection stations could help in the early detection of errors, a measure is proposed for assessing the location of inspection stations relative to production processes. To mathematically express that measure, let's define:

P_T : Total number of processes

n_I : The number of inspection stations

I_i : Inspection station number i, $i = 1, 2, \ldots, n_I$

P_{I_i} : The number of processes performed before inspection station I_i

AP : Average number of processes performed before inspection

AIS : A measure for assessing the allocation of inspection station

The measure proposed for assessing the allocation of inspection stations, AIS, is assigned values that range from "0 to "1 . The "0 value represents the best case where inspection is integrated with each production station. The "one" value represents the case of end of line inspection. The values for AIS can be assigned subjectively. However, a relative measure for AIS can be estimated as a function of the average number of processes performed before inspection as well as the total number of inspection stations and total number of processes.

The number of processes performed before inspection is assessed as a weighted average of the number of processes before each inspection station.

$$AP = \sum_{i=1}^{n_I} \left(\frac{P_{I_i}}{P_T} \right) P_{I_i} \tag{5.7}$$

The expression in Equation (5.7) calculates the weighted average for P_{I_i}, with the weights represented as the ratio between the number processes before inspection station I_i and the total number of processes. In this expression, if the weights are not used, the average AP will only account for the ratio between the total number of processes and the number of inspection stations. This means that the expression will not consider how early or late the inspection is performed.

The proposed measure for assessing the allocation of inspection stations, AIS, is calculated as the average number of processes performed before inspection relative to the total number of processes as shown in Equation (5.8)

$$AIS = \begin{cases} 0 & \text{if } AP = 1 \\ \dfrac{AP}{P_T} & \text{elsewhere} \end{cases} \tag{5.8}$$

To illustrate the use of this measure, consider the set of production and inspection stations shown in Figure 5.14.

For the scenario illustrated in Figure 5.14 (a),

$P_T = 15$, $n_I = 3$,

$P_{I_1} = 3, P_{I_2} = 3, P_{I_3} = 9$,

Using these values in equations 5.7, and 5.8, we obtain $AIS = 0.44$

For the scenario illustrated in Figure 5.14 (b),

$P_T = 15$, $n_I = 1$,

$P_{I_1} = 15$,

Using these values in equations 6.2, and 6.3, we obtain $AIS = 1$

For the scenario illustrated in Figure 5.14 (c),

$P_T = 15$, $n_I = 7$,

$P_{I_1} = 1, P_{I_2} = 2, P_{I_3} = 3, P_{I_4} = 1, P_{I_5} = 2, P_{I_6} = 2, P_{I_7} = 4$,

Using these values in equations 6.2, and 6.3, we obtain $AIS = 0.173$

For the scenario illustrated in Figure 5.14 (d),

$P_T = 15$, $n_I = 4$,

$P_{I_1} = 6, P_{I_2} = 3, P_{I_3} = 2, P_{I_4} = 4$,

Using these values in equations 1, and 2, we obtain $AIS = 0.288$

For the scenario illustrated in Figure 5.14 (e)

$P_T = 15$, $n_I = 2$,

$P_{I_1} = 6, P_{I_2} = 9$,

Using these values in equations 6.2, and 6.3, we obtain $AIS = 0.52$

A fuzzy variable for representing the allocation of inspection stations is designed with a universe of discourse from 0 to 1 and is divided into three fuzzy sets whose linguistic values are "Intensive in-process", "in-process", and "end-of-line" based on the value of the AIS, as shown in Figure 5.15. In other words, the inspection is considered as "Intensive in-process", "in-process", or "end-of-line" based on the average number of processes to be performed before inspection relative to the total number of processes. The lower the value of the fuzzy variable, the more intensive the inspection is.

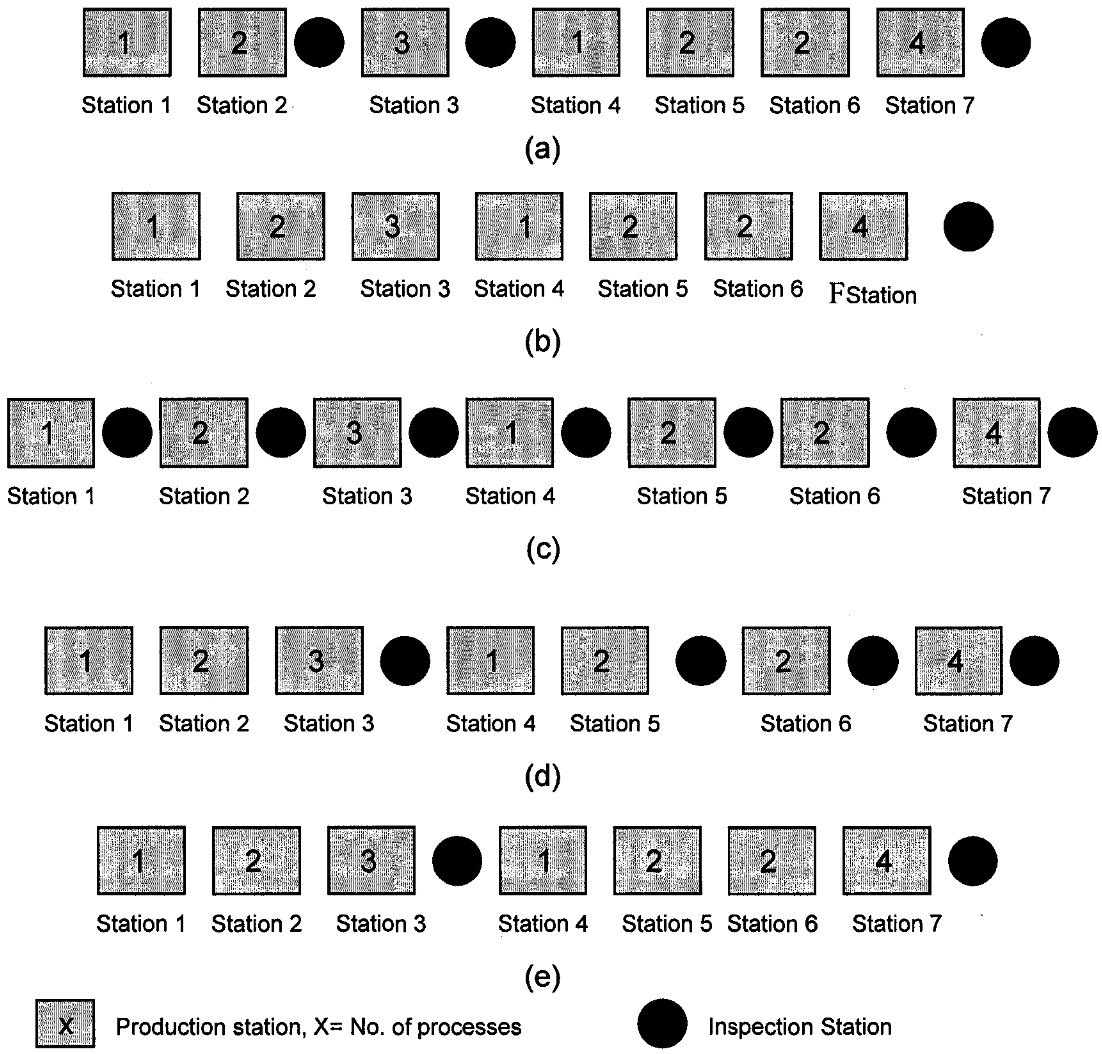


Figure 5.14. Cases for Illustrating the Use of the Proposed Allocation of Inspection Stations Measure

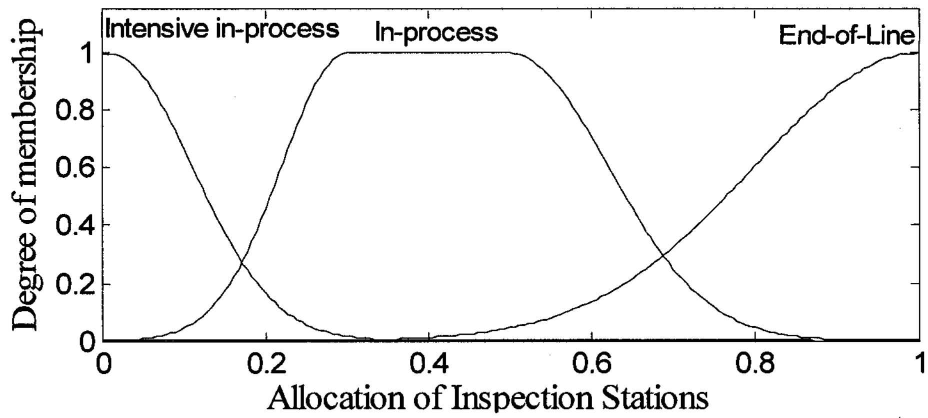


Figure 5.15. Allocation of Inspection Stations Membership Function

Jidoka Implementation

The second input to the FIS_EDR is the level of Jidoka implementation in the manufacturing system. Jidoka means, in the production context, not allowing defective parts to go from one workstation to the next. The implementation of Jidoka has a significant effect on the instantaneous detection of errors and can drastically reduce the defective rates [Mayne et al., 2001]. It specifically refers to machines or the production line itself being able to stop automatically in abnormal conditions (for example, when a machine breaks down or when defective parts are produced). In Japanese 'jidoka' simply means automation, which according to their philosophy "automation with a human touch" and implies that machines have a human-like ability to sense when something goes wrong [Miltenburg, 2001]. In order to assess the level of Jidoka implementation in the manufacturing system, a fuzzy variable that represents the percentage of the production stations equipped with Jidoka to the total number of stations is introduced. Its universe of discourse ranges from 0 to 1. The "0 value represents that 0% of the stations are equipped with Jidoka and the value "1 represents that 100% of the stations are equipped with Jidoka. The fuzzy variable is divided into five fuzzy sets with the membership functions illustrated in Figure 5.16.

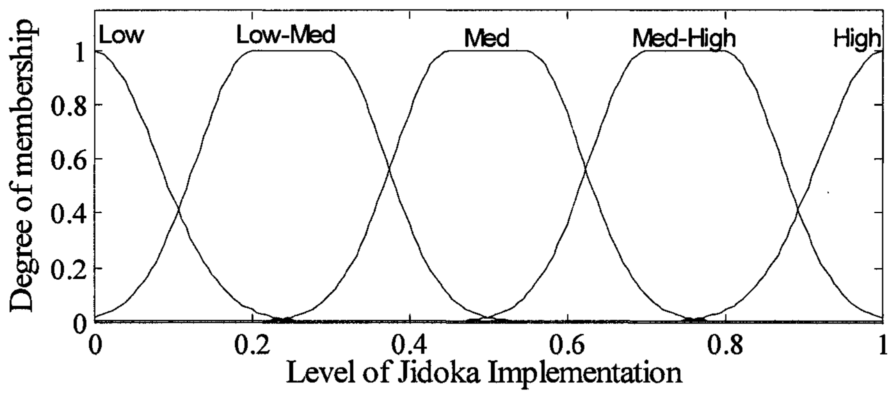


Figure 5.16. Level of Jidoka Implementation Membership Function

Buffer Size

The third input to the FIS_EDR is the buffer size. Lean manufacturing professionals recommend reducing inventory on the factory floor because the reduction of work-in-process (WIP) reveals the problems in the production line [Black, 1991]. In this research, the Buffer is considered in assessing the system responsiveness in error detection as it affects the time between making the defect and detecting it. Smaller buffer sizes leads to a smaller gap between making the errors and detecting them. Kim and Gershwin [2005] addressed the harmful effect of buffer size on the system yield. They reported that, when there is quality information feedback between two production stations, the system yield is a function of the buffer size and they demonstrated that the system yield decreases as the buffer size increases. This is because larger buffer sizes lead to longer delays between making errors and detecting them. The trends that they have obtained have been used in designing the buffer size fuzzy variable as well as in the rule derivation. In the design of the fuzzy variable that represents the buffer size, a weighted average of the buffer sizes between stations will be used; with higher weights assigned to buffers that are located after station performing operations with low capability. The universe of discourse has been selected based on the range of the buffer that Kim and Gershwin [2005] used in their work. The universe of discourse for buffer size is from zero to fifty as shown in Figure 5.17. The number of fuzzy sets is five with “low”, “low-medium”, “medium”, “medium-high”, and “high” as linguistic values. Kim and Gershwin [2005] demonstrated in their results different rates for the decrease of yield as buffer increases. Their demonstrations have been used to help in decisions related to the design of fuzzy sets including their number, location and overlap.

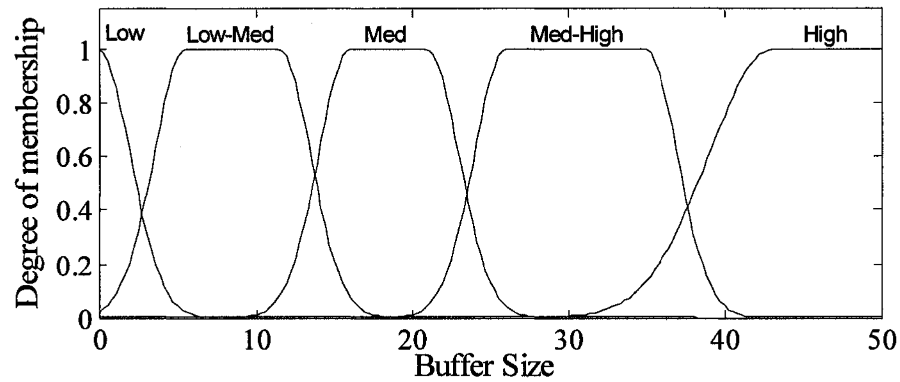


Figure 5.17. Buffer Size Membership Function

Output Variable and Rules for The FIS For Assessing EDR

The output of this EDR fuzzy inference system is a measure for the error detection responsiveness. A fuzzy variable that represents this measure is designed with a universe of discourse ranges from 0 to 1. The fuzzy sets of this variable and their membership functions are shown in Figure 5.18.

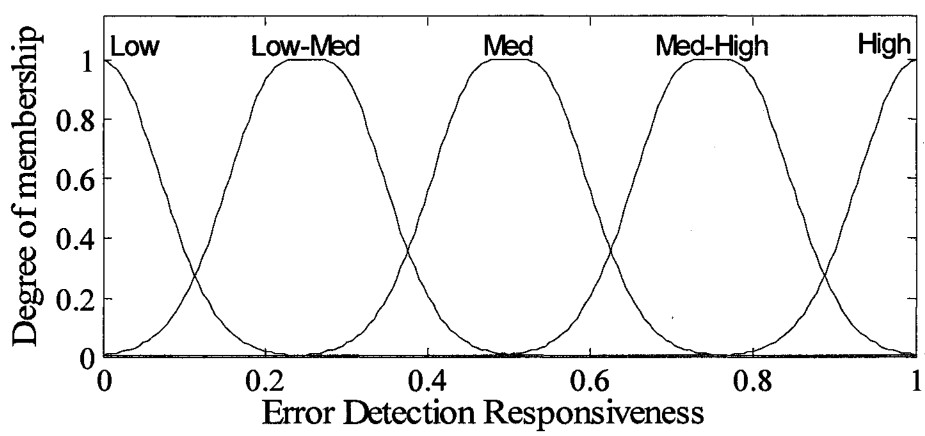


Figure 5.18. Error Detection Responsiveness Membership Function

The set of fuzzy rules used in assessing the Error Detection Responsiveness (EDR) in terms of the considered three inputs involves 75 rules as illustrated in Table A-2 in Appendix A. A sample of these of these rules is as follows:

- "***If*** (Allocation of Inspection Stations is Intensive in process) ***and*** (Level of Jidoka Implementation is High) and (Buffer Size is Low) ***then*** (Error Detection Responsiveness is High)",
- "***If*** (Allocation of Inspection Stations is Intensive in process) ***and*** (Level of Jidoka Implementation is High) ***and*** (Buffer Size is Low-Med) ***then*** (Error Detection Responsiveness is High)",
- "***If*** (Allocation of Inspection Stations is Intensive in process) ***and*** (Level of Jidoka Implementation is High) ***and*** (Buffer Size is Med) then (Error Detection Responsiveness is High)".

5.4. THE DESIGN OF THE SECOND LAYER IN THE HIERARCHICAL FIS

As shown in Figure 5.6, the second layer in the hierarchical fuzzy inference system for quality prediction has two fuzzy inference systems. One is concerned with assessing the Defect Prevention Capability (DDC) and the other with assessing the Error Detection Capability.

5.4.1.1. FIS Design For Assessing The System Defect Prevention Capability (DPC)

The system's defect prevention capability assesses to what extent the system is capable of producing products that conform to specification and with minimal deviation from the design targets as well as how the quality is designed into the system to prevent the generation of defects.

In this section, the design details of a fuzzy inference system for assessing the system's defect prevention capability are illustrated. Defect Prevention Capability (DPC) is assessed based on three parameters as shown in Figure 5.19. These are the overall capability of processes, the quality of configuration morphological structure, and level of mistake proofing implementation.

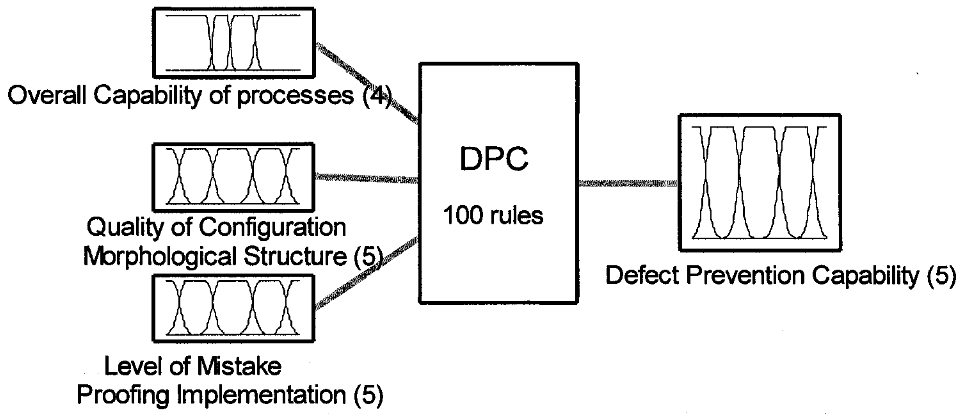


Figure 5.19. Fuzzy Inference System for Assessing DPC

Overall Capability of Processes

In order to estimate a value for the overall capability of processes at the system design stage, the availability of process capability databases is very critical. Process capability databases uses historical data to predict the "sigma capability" for a part based on the specific manufacturing process used to produce the feature. The sigma capability determined by the database is based not only on the particular manufacturing process but also based on other factors that influence the process such as the material type, size of the feature, tolerance, etc. Fiore [2005] pointed out that the historical data needed to build process capability databases comes from the data generated from previous similar products produced by the company. He also indicated that, in cases where data is not available, commercially available tools are available. These contain a library of ready to use capability data. The data used by such commercial tools is based on common manufacturing processes used throughout industry. In this study, it will be considered that the process capabilities for individual machine operations can be obtained at the early stages of design using process capability databases. However, for manual operations the model developed in Chapter 6 can be used to assess the probabilities of errors in performing manual tasks. The overall capability of processes can be calculated as follows:

- For each machine operation with certain specifications, databases can be used to obtain the sigma capability level. Assuming that the process follows a normal distribution, the sigma capability can then be converted into its associated first time yield value using tables for area under the standard normal distribution curve or using the Excel function "NORMSDIST" [Ledolter and Burrill, 1999].
- For each manual operation, the developed model described in Chapter 6 can be used to assess the probability of errors. The yield for such operations can be expressed in terms of the probability that the operator successfully performed the operation, which can be obtained as (1-Probability of errors).
- To predict the quality for all of the processes, the rolled throughput yield is calculated as in Equation (5.9) [Priest and Sanchez, 2001]:

$$Y_{RT} = \prod_{i=1}^{P_T} Y_i \ , \tag{5.9}$$

  where

  Y_{RT} : Rolled throughput yield of a product and it represents the fraction of product units that pass through all the stations without rework or scrap,

  Y_i : Yield of an individual process i, $\quad i = 1, 2, \cdots, P_T \quad$,

  P_T : Total number of processes.

- After calculating the rolled throughput yield, the obtained value should be converted back into its associated sigma level using tables for the area under the standard normal distribution curve or using the Excel function "NORMSINV". This will represent the overall sigma capability level. Tennant [2000] reported that such a computed value "the Z-score" represents the long term sigma capability level and in order to obtain the short term sigma capability level, 1.5σ should be added to the long term sigma capability.

In designing the fuzzy variable that assesses the overall capability of processes, the ratio between the calculated short-term sigma capability level and the targeted six-sigma capability level will be used. Therefore, the fuzzy variable universe of discourse ranges from "0 as the worst case to "1 which represents the case of six sigma capability. The universe of discourse is divided into four fuzzy sets with linguistic values "Incapable", "barely-capable", "capable", and "highly-capable" as shown in Figure 5.20.

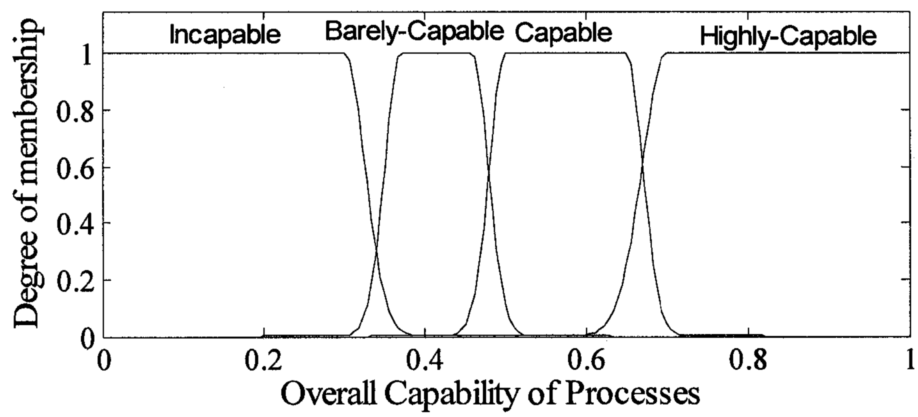


Figure 5.20. Overall Capability Membership Function

Other Inputs to The FIS for Assessing DPC

The second input for the fuzzy inference system for assessing DPC is the quality of the configuration morphological structure. This variable has been assessed in the first layer as in section 5.3.1.1. However, the third input represents the level of the implementation of mistake proofing. A fuzzy variable is designed to assess the level of mistake proofing implementation and it is expressed as the ratio of processes with mistake proofing devices to the total number of processes that is liable to produce faulty actions. Figure 5.21 illustrates the design of this variable.

Output Variable and Rules for The FIS for Assessing DPC

The output of this fuzzy inference system is a measure for the system's defect prevention capability. A fuzzy variable that represent this measure is designed with a universe of discourse ranges from 0 to 1. This fuzzy variable is divided to five fuzzy sets with linguistic values "low", "low-medium", medium", "medium-high", and "high". The fuzzy sets of this variable and their membership functions are shown in Figure 5.22.

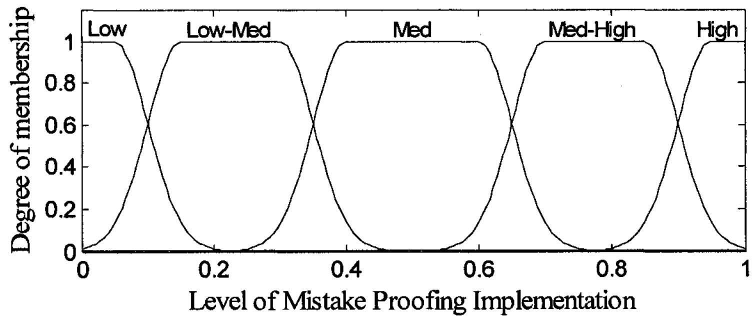


Figure 5.21. Level of Mistake Proofing Membership Function

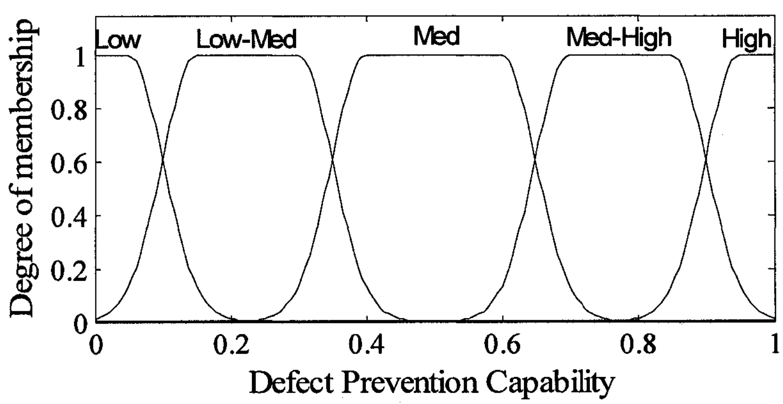


Figure 5.22. Defect Prevention Capability Membership Function

A set of one hundred fuzzy rules is used to predict the defect prevention capability based on the considered three inputs. These rules are illustrated in Table A-3 in Appendix A. Examples of these rules are:

"***If*** (Overall Capability of Processes is Highly-Capable) ***and*** (QCMS is High) ***and*** (Level of Mistake Proofing Implementation is High) ***then*** (DPC is High)",

"***If*** (Overall Capability of Processes is Highly-Capable) ***and*** (QCMS is High) ***and*** (Level of Mistake Proofing Implementation is Med-High) ***then*** (DPC is High)",

"***If*** (Overall Capability of Processes is Highly-Capable) ***and*** (QCMS is High) ***and*** (Level of Mistake Proofing Implementation is Med) ***then*** (DPC is High)".

It has been considered in designing the rules, illustrated in Table A-3 in Appendix A, that in cases where the relative capability measure of the overall capability of processes indicates that the system is "In-Capable", the result for the defect prevention capability will be "low" regardless of the values of the other two inputs.

5.4.1.2. FIS Design for Assessing the System Defect Detection Capability (DPC)

The system's defect detection capability assesses to what extent the system is capable of detecting defects in an accurate and responsive manner. In this section, the design details of a fuzzy inference system for assessing the system defect detection capability will be illustrated. Defect Detection Capability (DDC) is assessed based on two parameters as shown in Figure 5.23. The inputs to this fuzzy inference system are the inspection error and the error detection responsiveness.

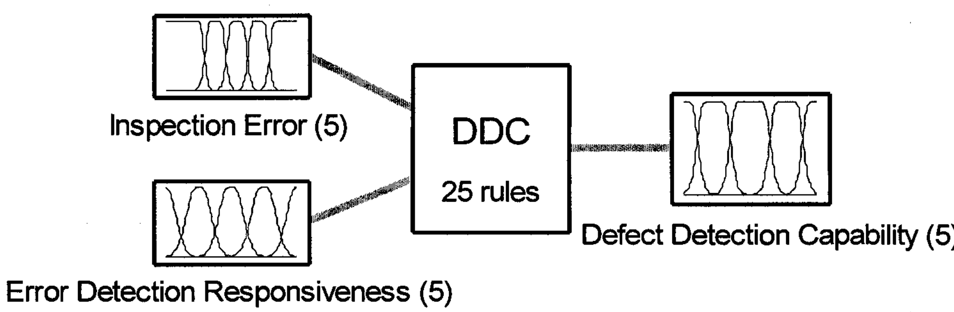


Figure 5.23. Fuzzy Inference System for Assessing Defect Detection Capability

In this research, the inspection error is estimated by the average error probabilities of different inspection tasks.

Let's define:

$p(HE)_i$: Probability of human error in performing inspection task i, $i = 1, 2, \cdots, n_I$

$p(EE)_i$: Probability of equipment error in performing inspection task i, $i = 1, 2, \cdots, n_I$

$p(E)_i$: Probability of error in performing inspection task i, $i = 1, 2, \cdots, n_I$

n_I : Number of inspection tasks

$AIEP$: Average Inspection Error Probability

It can be reasonably assumed that the two events "human error occurrence" and "equipment error occurrence" are independent and the inspection task will fail if either one of them failed to perform the job. Therefore, the error probability for task i , $p(E)_i$, can be expressed using the union of the two events as in Equation (5.10):

$$p(E)_i = p(HE \cup EE)_i = p(HE)_i + p(EE)_i - p(HE)_i . p(EE)_i \quad (5.10)$$

The values for human error probabilities in performing inspection tasks can be estimated using the approach proposed in Chapter 6. For the equipment, subjective probability values will be used based on the capabilities of the inspection equipment in performing tasks with certain specifications. These values for equipment error probabilities can be assumed based on historical data.

Therefore, for n inspection tasks, the average inspection error probability can be calculated as follows:

$$AIEP = \frac{\sum_{i}^{n} p(E)_i}{n} \quad (5.11)$$

A fuzzy variable is designed to assess the inspection error in terms of the average inspection error probability. Because the probability can take very small values as well as large values near "1 , the linear scale will not be appropriate in representing the error probabilities. To overcome this problem, the inspection error is expressed in terms of a logarithmic measure of the average inspection error probability as follows:

$$Inspection\,Error = -\log(AIEP) \quad (5.12)$$

According to equation (5.12), the fuzzy variable that represents the inspection error has been designed with a universe of discourse ranges from "0 to "6 ; the "0 represents the highest value for the average inspection error probability which is "1 , and the "6 represents the lowest value for average inspection error probability which is 10^{-6} as shown in Figure 5.24.

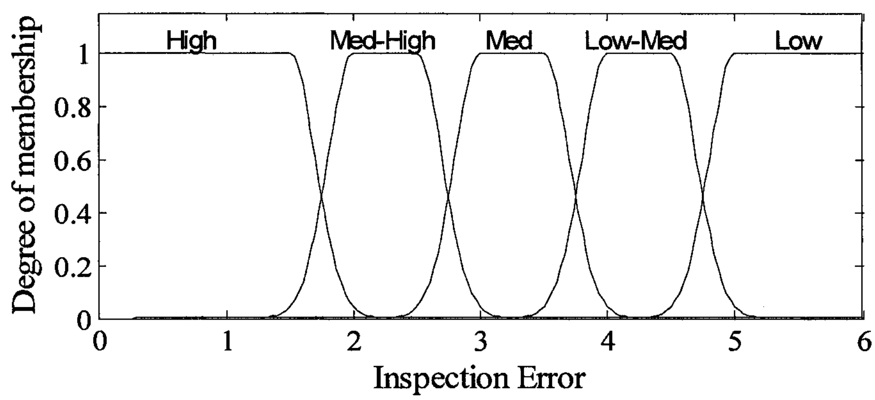


Figure 5.24. Inspection Error Membership Function

The other input to this fuzzy inference system is the error detection responsiveness and it has been discussed in details in Section 5.3.1.2. The output variable for fuzzy inference system represents a measure of the system's defect detection capability. This output variable has been designed similar to the defect prevention variable illustrated in Figure 5.22. The set of fuzzy rules that has been used is illustrated in Table A-4 in Appendix A. Examples of these rules are:

- "***If*** (Inspection Error is Low) ***and*** (EDR is High) ***then*** (DDC is High)"
- "***If*** (Inspection Error is Low) ***and*** (EDR is Med-High) ***then*** (DDC is High)"
- "***If*** (Inspection Error is Low) ***and*** (EDR is Med) ***then*** (DDC is Med-High)"

5.4.2. THE DESIGN OF THE HIGHEST LEVEL IN THE HIERARCHICAL FIS

As shown in Figure 5.6, the highest layer in the hierarchical fuzzy inference system consists of only one fuzzy inference system. This fuzzy inference system assesses the configuration capability in terms of the expected product quality based on the defect prevention capability as well defect detection capability as shown in Figure 5.25.

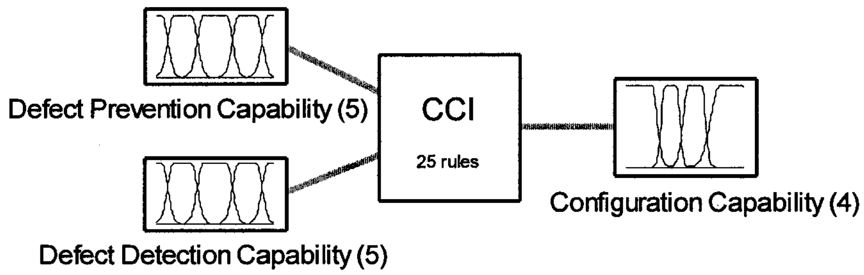


Figure 5.25. Configuration Capability Indicator (CCI) Fuzzy Inference System

The output of this fuzzy inference is a Configuration Capability Indicator that is designed to represent the approximate sigma quality level of the product to be manufactured using that system configuration. The universe of discourse for the CCI ranges from 1 to 6. The fuzzy variable representing the configuration capability is divided into four fuzzy sets and their linguistic values are "unacceptable", "acceptable", "good", and "excellent" as shown in Figure 5.26. The set of fuzzy rules used in designing the CCI fuzzy inference system is illustrated in Table A-5 in Appendix A. Examples of these rules are:

- "If (DPC is High) and (DDC is High) then (Configuration Capability is Excellent)",
- "If (DPC is High) and (DDC is Med-High) then (Configuration Capability is Excellent)",
- "If (DPC is High) and (DDC is Med) then (Configuration Capability is Excellent)".

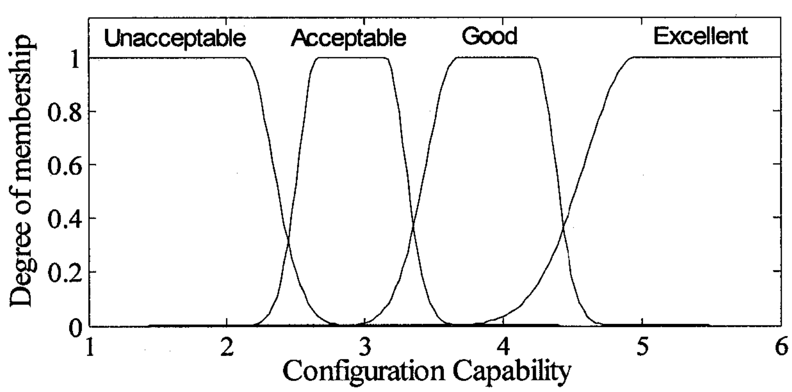


Figure 5.26. Configuration Capability Membership Function

5.5. INTEGRATION OF THE DEVELOPED FUZZY INFERENCE SYSTEMS

The developed fuzzy inference systems, using the Matlab Fuzzy Logic Toolbox [The MathWorks, 2002], have been integrated into one model using Matlab Simulink [The MathWorks, 2002]. In the developed Simulink model, fuzzy logic controllers are used to represent the developed fuzzy inference systems. The different layers of the hierarchical system are linked together as shown in Figure 5.27

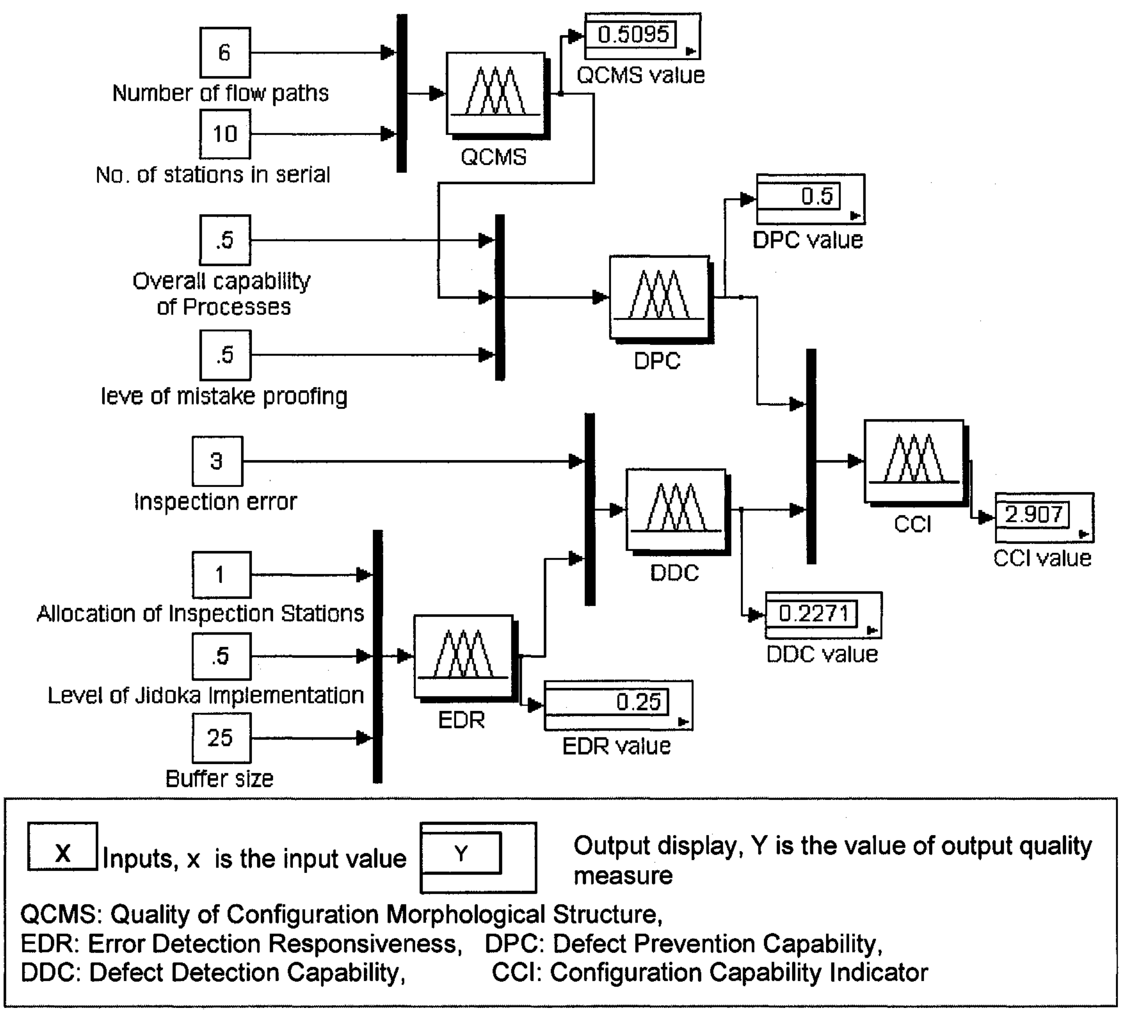


Figure 5.27. Matlab Simulink Model for Fuzzy Inference Systems Integration

Integrating the model that way assists in getting the final results for the configuration capability easily and quickly. It takes few seconds to run the model on a PC using Pentium 4 processor. This facilitates the use of the model in testing several cases with minimal effort. In the meantime, the results for the intermediate fuzzy inference systems are still accessible and displayed in a comprehensible way.

5.6. SIX SIGMA CONFIGURATION CAPABILITY ZONE FOR MULTI-PRODUCTS

The developed fuzzy inference system can help in assessing the expected capability level for a system configuration in manufacturing a typical product in terms of sigma capability. Cases in which more than one product are produced by the system configuration; the configuration capability should be assessed for each individual product first. Then, in order to assess the overall capability of the system configuration, a configuration capability zone is suggested to be constructed and compared to the benchmark six sigma capability, as shown in Figure 5.28. The proposed capability zone can be used in identifying the set of products that do not satisfy the organization targeted quality levels. This can help in investigating improvement opportunities for enhancing the quality of the products that doesn't satisfy the targeted quality levels. Improvement opportunities can be modifications in the product design, manufacturing system design, as well as investigating other options such as outsourcing. Also, the overall configuration capability $(CCI)_{Overall}$ can be assessed as in Equation (5.13)

$$(CCI)_{Overall} = \sum_{i=1}^{n_p} w_{product\ i} * (CCI)_{product\ i} \tag{5.13}$$

where:

$(CCI)_{product\ i}$: Configuration Capability Indicator for $product\ i$, $i = 1,...n_p$,

n_p: Number of products in the product family to be produced using the system configuration

$w_{product\ i}$: weight for $product\ i$; which represent its relative importance with respect to the other products

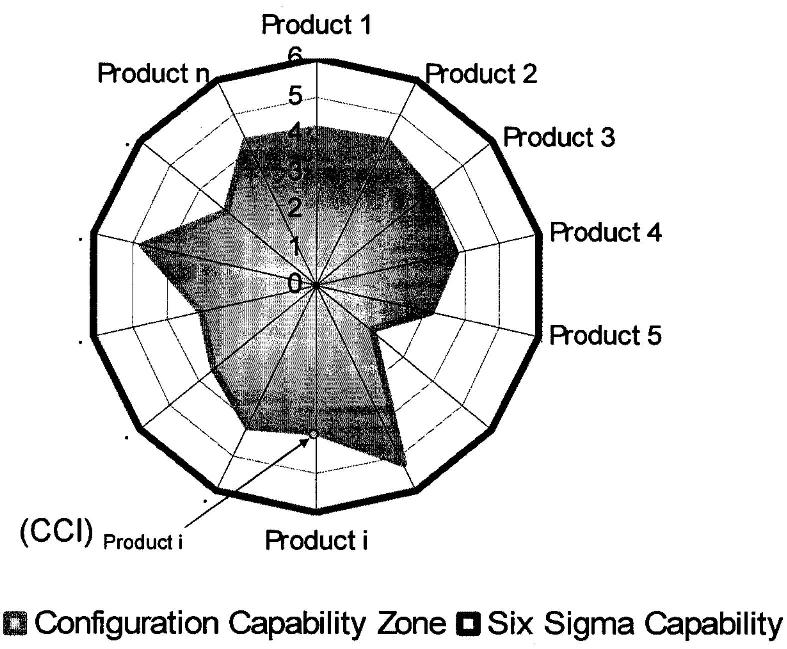
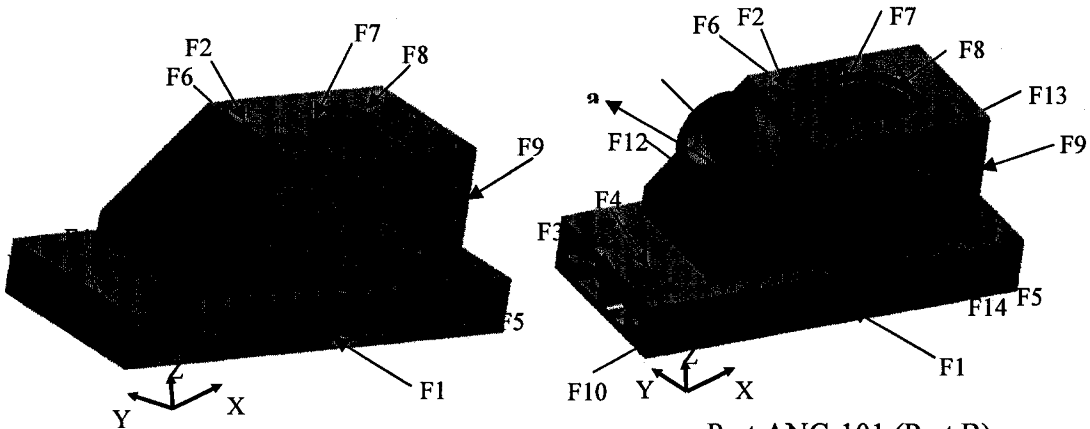


Figure 5.28. Configuration Capability Zone Compared to Benchmark Six Sigma Capability

5.7. CASE STUDIES FOR ILLUSTRATION AND VERIFICATION

5.7.1. CASE STUDY-1 (TEST PART ANC-90 AND ANC-101)

This case study has been introduced by Youssef and ElMaraghy [2006]. In their case study, they presented a set of optimal system configurations for producing a family of products that consists of two example parts shown Figure 5.29. Part B is a test part [Computer Aided Manufacturing- International (CAM-I), 1986 test part ANC-101] which has been widely used in the literature, and part A (ANC-90) is a basic part that was developed as a variant of part B. Part B has five more features than part A and it is to be produced with a rate of 180 parts/hour, however part A is to be produced with a rate of 120 parts/hour.



Part ANC-90 (Part A)

Part ANC-101 (Part B)

Figure 5.29. Two Test Parts Used by Youssef and ElMaraghy [2006]

Two of the corresponding manufacturing system configurations proposed by Youssef and ElMaraghy [2006] have been considered. These two configurations have been modified by adding buffers and inspection stations to be more suitable for illustrating the use of the developed model for quality prediction. The first considered configuration alternative called "scenario 1 is illustrated in Figure 5.30. This configuration has eight production stages and three inspection stations. Reconfigurable machines are used in this configuration; M1 and M8 are 3-axis reconfigurable horizontal milling machines with one spindle, M2, M3, and M4 are 3-axis reconfigurable horizontal milling machines with 2, 3, and 4 spindles, respectively. M5 is a 4-axis reconfigurable horizontal milling machine with one spindle. However, M6 and M7 are reconfigurable drilling press with 3 spindles. Human operators in this system are only responsible for loading and unloading the parts. However, the tool exchange is automated. For configuration scenario 1, the data concerned with the production processes required for part A and part B and their capabilities in terms of sigma levels are given in Table 5.1, and Table 5.2, respectively. The inspection tasks are automated and they are mainly concerned with dimensional checks using coordinate measuring machines (CMM) with the expected equipment error probabilities 3×10^{-5} for all the inspection tasks.

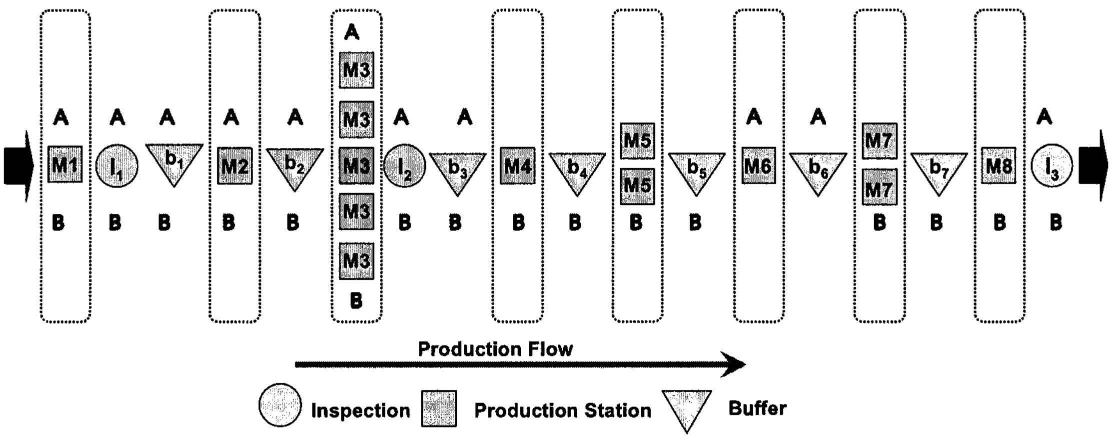


Figure 5.30. System Configuration (Scenario 1)-Case Study 1 (Test Part ANC-90 and ANC-101), adapted from [Youssef and ElMaraghy ,2006]

Table 5.1 Part A Production Processes and Their Associated Sigma Capabilities for Scenario 1

Operation	Machine	Feature	Description	Process Capability in terms of Sigma level
OP1	M1	F1	(Milling) Planar surface	3.9
OP2		F2	(Milling) Planar surface	3.9
OP3	M2	F3	(Drilling) Four holes arranged as a replicated feature	3.6
OP4		F4	(Milling) A step	4.1
OP12		F9	(Milling) A step	4.1
OP5		F5	(Milling) A protrusion (rib)	4.1
OP6		F6	(Milling) A protrusion (rib)	4.1
OP7	M3	F7a	(Drilling) A compound hole	3.9
OP8		F7b	(Reaming) A compound hole	4.1
OP9		F7c	(Boring) A compound hole	4.2
OP10	M6	F8'a	(Drilling)Six holes arranged in a Replicated feature	3.9
OP11		F8'b	(Tapping)Six holes arranged in a Replicated feature	4.2

Table 5.2. Part B Production Processes and Their Associated Sigma Capabilities for Scenario 1

Operation	Machine	Feature	Description	Process Capability in terms of Sigma level
OP1	M1	F1	(Milling) Planar surface	3.9
OP2	M2	F2	(Milling) Planar surface	3.9
OP4		F4	(Milling) A step	4.1
OP12		F9	(Milling) A step	4.1
OP5	M3	F5	(Milling) A protrusion (rib)	4.1
OP6		F6	(Milling) A protrusion (rib)	4.1
OP7		F7	(Drilling) A compound hole	3.9
OP8			(Reaming) A compound hole	4.1
OP9			(Boring) A compound hole	4.1
OP13	M4	F10	(Milling) Two pockets arranged as a replicted feature	3.1
OP18		F13	(Milling) A pocket	3.1
OP14	M5	F11	(Milling) A boss	3.1
OP15			(Drilling) A boss	3.2
OP16		F12	A compound hole (Reaming)	3.3
OP17			A compound hole (Boring)	3.6
OP10	M7	F8	(Drilling)Nine holes arranged in a Replicated feature	3.9
OP11			(Tapping)Nine holes arranged in a Replicated feature	4.2
OP3	M8	F3	(Drilling) Four holes arranged as a replicated feature	3.6
OP19		F14	A compound hole (Reaming)	3.3
OP20			A compound hole (Boring)	3.3

Scenario 2, represents a different configuration alternative that is shown in Figure 5.31. This configuration uses nine production stages and the inspection is integrated with each production unit. In this scenario, the same two parts are produced using the same type of machines but with more implementation of mistake proofing devices.

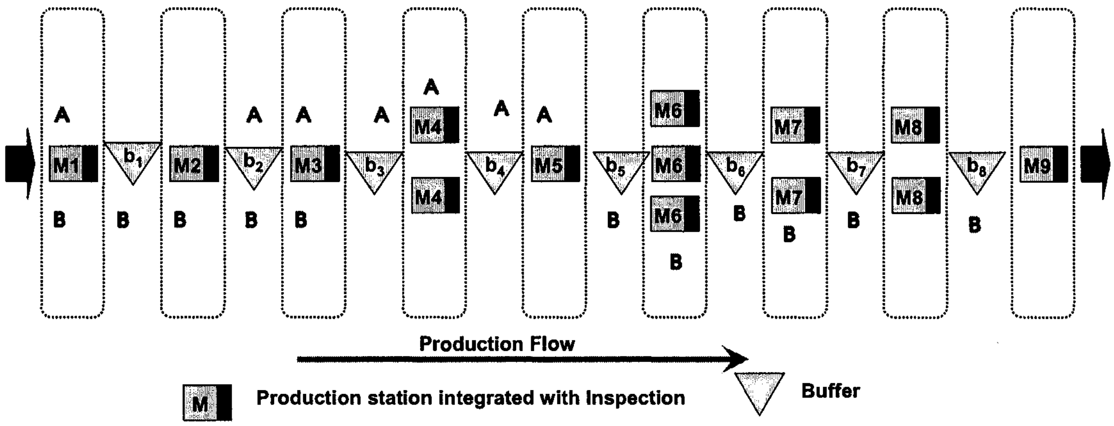


Figure 5.31. System Configuration (Scenario 2)-Case Study 1 (Test Part ANC-90 and ANC-101), adapted from [Youssef and ElMaraghy ,2006]

To calculate the overall capability of processes relative to six-sigma capability, the procedure explained in Section 5.3.2.1 has been implemented using a spreadsheet. As a sample of how overall capabilities have been calculated, Table 5.3 shows the results obtained for product B using configuration scenario 2. Equations 6.2-6.3 have been used to calculate the measure that assesses the allocation of inspection stations. Equations 6.5-6.7 have been used to calculate the measure that assesses the inspection error. A summary of the inputs to the developed model for part A and B in the scenario 1 and 2 is given in Table 5.4.

This data has been used as input to the developed fuzzy inference system to assess the configuration capability in producing the two parts A and B using the considered two configuration scenarios illustrated in Figure 5.30 and Figure 5.31. The results obtained for the intermediate quality measures as well as the final Configuration Capability Indicator (CCI) for each product using different configuration scenario are listed in Table 5.5. A sample of the Matlab output report for Part A using configuration scenario 1 is presented in Section B2 in Appendix B.

Table 5.3. Overall Capability Results Obtained for Prat A (Scenario 1)

Operation	Sigma Capability	Yield
OP1	3.9	0.999952
OP2	3.9	0.999952
OP3	3.6	0.999841
OP4	4.1	0.999979
OP12	4.1	0.999979
OP5	4.1	0.999979
OP6	4.1	0.999979
OP7	3.9	0.999952
OP8	4.1	0.999979
OP9	4.2	0.999987
OP10'	3.9	0.999952
OP11'	4.2	0.999987
Rolled Throughput yield		0.999518
Overall Sigma Capability		3.301117
Short-term Sigma Capability		4.801117
Short-term Sigma Capability/ 6 Sigma		**0.800186**

Table 5.4. Summary of Model Inputs for Case Study-1(Test Part ANC-90 and ANC-101)

Configuration Parameter	Scenario 1		Scenario 2	
	Part A	Part B	Part A	Part B
No. of flow paths	5	20	2	6
No. serial stations	4	7	4	6
Overall capability of processes	0.8	0.67	0.8	0.67
Level of mistake proofing	0.6	0.6	0.7	0.7
Inspection error	4.5	4.5	4.5	4.5
Allocation of inspection stations	0.6	0.47	0	0
Level of jidoka implementation	0.5	0.5	0.5	0.5
Buffer size	5	13	5	13

Table 5.5. Results for Case Study-1(Test Part ANC-90 and ANC-101)

Quality Measure	Scenario 1		Scenario 2	
	Part A	Part B	Part A	Part B
Quality of Configuration Morphological Structure (QCMS)	0.64	0.05	0.79	0.52
Error Detection Responsiveness (EDR)	0.64	0.65	0.90	0.90
Defect Prevention Capability (DPC)	0.78	0.40	0.889	0.75
Defect Detection Capability (DDC)	0.67	0.69	0.83	0.83
Configuration Capability Indicator (CCI)	**3.89**	**3.59**	**4.52**	**4.35**

These results indicate that configuration scenario 2, shown in Figure 5.31, has a higher estimated capability in producing both "part A" and "part B" compared to configuration scenario 1. Using configuration scenario 2, the system is capable of producing "part A" with expected "4.52 Sigma" capability level and "part B" with expected "4.35 Sigma" capability level. The higher capabilities associated with the use of configuration 2 as opposed to configuration 1 can be attributed to improvements of some configuration design parameters. These parameters include defect prevention related parameters as well as defect detection related ones. In this case, study, it should be pointed out that the two configuration scenarios are using individual processes with the same capabilities and the overall capability is the same for the two scenarios.

The improvement in defect prevention capability for configuration scenario 1 is due to improvements in two parameters. The first one is the use of lower number of flow paths (2 flow lines for part A as opposed to 5 flow lines in scenario 1 and 6 flow lines for part B as opposed to 20 flow lines in scenario 1); which decreases the end of line variability associated with parallel processing. The second one is the increase of mistake proofing implementation (70% as opposed to 60% in scenario 1), which has the effect of decreasing defective rates associated with mistakes. On the other hand, the improvement in defect detection capability is mainly due to improvements in error detection responsiveness, which resulted from the integration of inspection stations with all production stations.

In addition, regardless of the configuration scenario to be used, the results show that the capability associated with producing "Part A" is higher that "Part B" in the two considered scenarios. This can be interpreted as follows: "Part B" has more features than

"Part A". Therefore, more processes are needed to produce it and this directly affects the rolled throughput yield used in calculating the overall capability of processes. Table 5.6 indicates that as the number of parts or the number of production steps needed to produce a product increases; the overall yield decreases and this effect became more significant when using individual processes with low individual capabilities. This can be directly linked to the framework presented in Chapter 3; in which the complexity of the product is considered one of the main parameters affecting the resulting quality. The results obtained, here, directly support the proposed framework and indicate that the increase in product complexity adversely affects the resulting product quality. In such a case, in order to achieve higher quality levels, not only highly capable processes should be used, but also the product complexity should be minimized during the design stage. In addition, the number of processes should be minimized by eliminating the non-value added steps.

Table 5.6. Relation Between Number of Parts or Process Steps and Overall Yield Using Different Sigma Level Capabilities [adapted from Gorge, 2003]

	OVERALL YIELD vs SIGMA (Distribution Shifted $\pm1.5\sigma$)			
# of Parts (Steps)	$\pm3\sigma$	$\pm4\sigma$	$\pm5\sigma$	$\pm6\sigma$
1	93.32%	99.379%	99.9767%	99.99966%
7	61.63	95.733	99.839	99.9976
10	50.08	93.96	99.768	99.9966
20	25.08	88.29	99.536	99.9932
40	6.29	77.94	99.074	99.9864
60	1.58	68.81	98.614	99.9796
80	0.40	60.75	98.156	99.9728
100	0.10	53.64	97.70	99.966
150	---	39.38	96.61	99.949
200	---	28.77	95.45	99.932
300	---	15.43	93.26	99.898
400	---	8.28	91.11	99.864
500	---	4.44	89.02	99.830
600	---	2.38	86.97	99.796
700	---	1.28	84.97	99.762
800	---	0.69	83.02	99.729
900	---	0.37	81.11	99.695
1000	---	0.20	79.24	99.661
1200	---	0.06	75.88	99.593
3000	---	---	50.15	98.985
17000	---	---	1.91	94.384
38000	---	---	0.01	87.880
70000				78.820
150000				60.000

Use for Benchmarking

Source: Six Sigma Research Institute Motorola University, Motorola, Inc.

5.7.2. CASE STUDY-2 (CYLINDER HEAD PART FAMILY)

This case study considers the system configuration that has been proposed by Tang, *et al.* [2003] to produce a part family consists of the two cylinder heads shown in Figure 5.32. They named the parts as "Left-hand" that requires 84 manufacturing tasks, and "Right-hand" that requires 80 manufacturing tasks. The proposed system configuration to produce that part family is shown in Figure 5.33; it consists of eight stages and each stage consists of a set of reconfigurable machine tools.

Figure 5.32. Cylinder Head Part Family [Tang, et al. 2003]

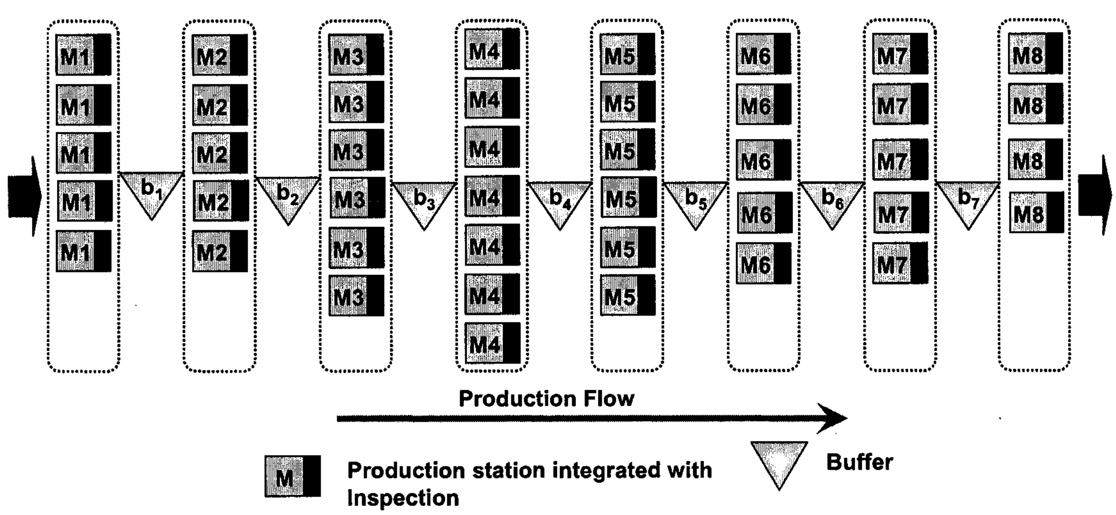


Figure 5.33. System Configuration -Case Study 2 (Cylinder Head Part Family), Adapted From [Tang et al. 2003]

For this case study, two different scenarios will be considered. In the two scenarios, the same system configuration illustrated in Figure 5.33 is used to produce the product family illustrated in Figure 5.32. However, the difference between the two scenarios is due to the specifications of the family of products. In scenario 2, changes in customer requirements regarding the dimensional tolerances of the products are expected. Therefore, scenarios 2 is associated with tighter tolerances and hence, lower process capabilities. A summary of the inputs to the developed model for quality prediction for the two cylinder heads "Left-hand" and "Right-hand" in the scenario 1 and 2 is listed in Table 5.7.

Table 5.7. Summary of Model Inputs for Case Study-2 (Cylinder Head Part Family)

Configuration Parameter	Scenario 1		Scenario 2	
	Left-hand	Right-hand	Left-hand	Right-hand
No. of flow paths	630,000	630,000	630,000	630,000
No. serial stations	8	8	8	8
Overall capability of processes	0.67	0.8	0.35	0.5
Level of mistake proofing	0.6	0.6	0.6	0.6
Inspection error	3	3	3	3
Allocation of inspection stations	0	0	0	0
Level of jidoka implementation	0	0	0	0
Buffer size	2	2	2	2

Data in Table 5.7 has been used as input to the developed fuzzy inference system to assess the configuration capability in producing the two cylinder heads named as "Left-hand" and "Right-hand" using the considered two configuration scenarios. In this case, as the number of flow lines is greater than the maximum value of the universe of discourse, the input concerned with the number of flow paths will be used as the worst-case scenario. The results obtained for the intermediate quality measures as well as the final Configuration Capability Indicator (CCI) for each the cylinder heads using different configuration scenario are listed in Table 5.8.

Table 5.8. Results for Case Study-2 (Cylinder Head Part Family)

Quality Measure	Scenario 1		Scenario 2	
	Left-hand	Right-hand	Left-hand	Right-hand
Quality of Configuration Morphological Structure (QCMS)	0.037	0.037	0.037	0.037
Error Detection Responsiveness (EDR)	0.5	0.5	0.5	0.5
Defect Prevention Capability (DPC)	0.41	0.53	0.22	0.27
Defect Detection Capability (DDC)	0.49	0.49	0.49	0.49
Configuration Capability Indicator (CCI)	**2.78**	**2.91**	**1.69**	**1.72**

The results for case study-2 indicate that configuration scenario 1 is capable of producing the two cylinder heads with higher expected quality levels than configuration scenario 2. Configuration scenario 1 can produce the "Left-hand" cylinder head at "2.78 Sigma" capability level and the "Right-hand" cylinder head at "2.91 Sigma" Capability level, whereas Configuration scenario 2 can produce the "Left-hand" cylinder head at "1.69 Sigma" capability level and the "Right-hand" cylinder head at "1.72 Sigma" Capability. The lower quality levels associated with the use of configuration scenario 2 as opposed to configuration scenario 1 is due to the use of processes with lower capabilities. These unacceptable quality levels are expected to arise in scenarios in which the configuration is incapable of satisfying the design requirements.

Relationship between Quality and Complexity

According to Suh's definition of complexity [2005], this represents another dimension for the relation between quality and complexity. He pointed out that in any engineering design the functional requirements need to be satisfied within their specified ranges (design range or specification limits). However, the actual performance of the system that is designed to produce the product (system range) may or may not fully lie inside the design range. When the system range is not fully inside the design range, the functional requirements cannot be satisfied at all times and in such cases, the task or the system appears to be complex. Therefore, he defined complexity as *a measure of uncertainty in achieving the functional requirements*. As illustrated in Figure 5.34 and according to Suh's definition of complexity, the complexity of the system illustrated in

Figure 5.34 (a) is zero because the system range fully lies inside the design range. However, the complexity of the system illustrated in Figure 5.34 (b) is finite because the system range does not fully lie inside the design range. This complexity perspective is highly related to the process capability concept. The process capability assesses the extent to which the process is capable of satisfying the requirements. In other words, process capability also measures the relationship between specification limits and process variability; in terms of mean and standard deviation. Figure 5.35 illustrates the relation between the distribution of the process and the specification limits at different levels of process capability. At higher capability levels, the distribution of the process fully lies inside specification limits. From quality perspective, the area under the probability density curve that lies outside the specification limits is used as a measure for the defective rate. For a six sigma capability with process mean shifted by 1.5 Sigma from the design target, defects measured by parts per million (ppm) reach 3.4 ppm as shown in Figure 5.35 [Tennant, 2000]. From this discussion, it can be concluded that highly capable configuration scenarios represent low complexity according to Suh's complexity point of view.

The configuration parameters considered for predicting the Configuration Capability Indicator (CCI) are not function of time. For example, the possible deterioration of process capability with time is not considered. According to Suh's [2005] classes of complexity, the obtained capability can be represented as a case of time-independent real complexity. This is because time-independent real complexity measures the probability of successfully satisfying functional requirements and it is not a function of time [Suh 2005].

However, when the system is in the operating mode, quality could be affected by other parameters that are function of time such as the deterioration of equipment through its lifetime, or the gradual deterioration of quality due tool wear. In such cases, the system tends to have a time-dependent combinatorial complexity. Suh [2005] stated that a system can have a time-dependent combinatorial complexity when the system range changes with the time as shown in Figure 5.36. He also illustrated that if the system range drifts away from the design range, the system performance cannot be predicted. These cases in on-line quality control are identified as “the system is out of control”.

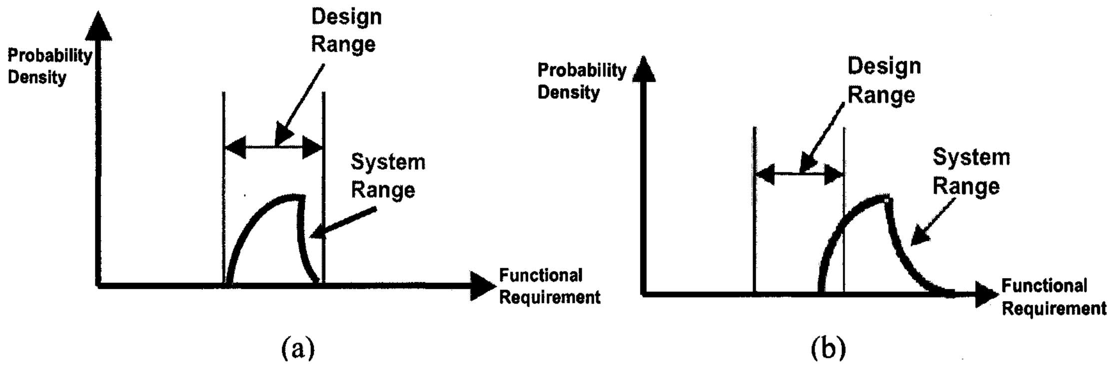


Figure 5.34 (a) The System Range Fully Lie Inside the Design Range; (b) The System Range Does not Fully Lie Inside the Design Range [Suh, 2005]

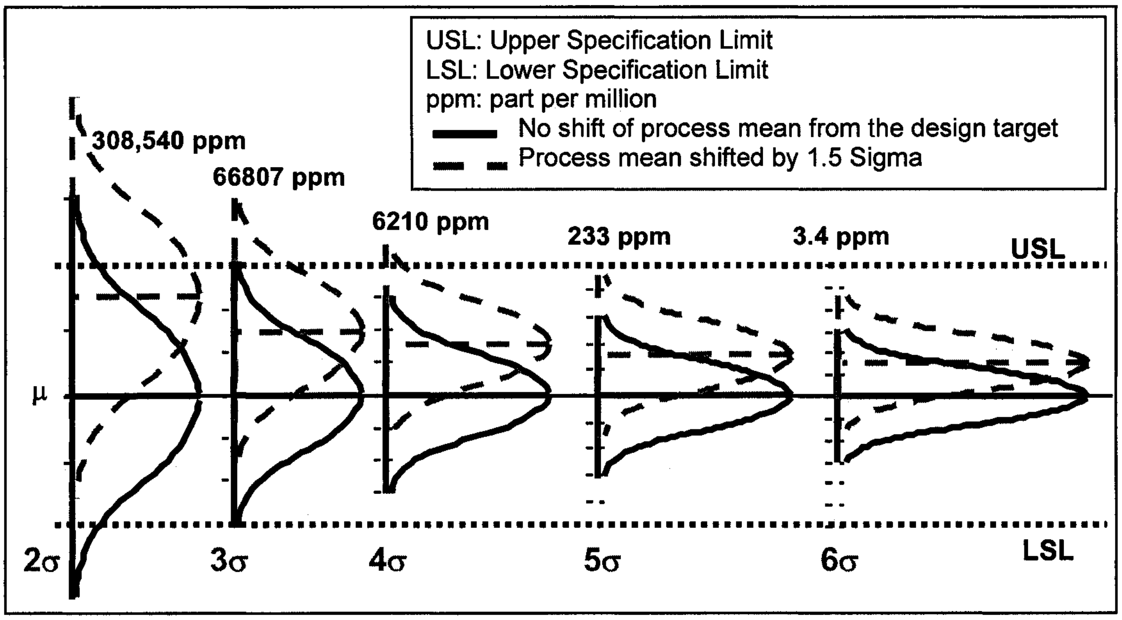


Figure 5.35. Relation between Process Variability and Specification Limits at Different Sigma Capability Levels [Tennant, 2000]

Suh [2005] emphasized that complexity can be significantly reduced when a system with time-dependent combinatorial complexity is transformed to a system with periodic complexity; where periodic complexity is defined as the complexity that exists only in a finite time period. To achieve periodic complexity or to ensure that the system operate stably for along time, functional periodicity must exist in the system or must be built into the system. He stated that functional periodicity is the period set by a repeating set of functional requirements. In case of manufacturing quality, the use of periodic maintenance and change of tools according to information related to relations between quality and tool life can help in transforming time-dependent combinatorial complexity to periodic complexity. In addition, the of on-line quality control programs can play the role of introducing functional periodicity into the system by using control charts to monitor the process and readjust the system when detecting out of control signals.

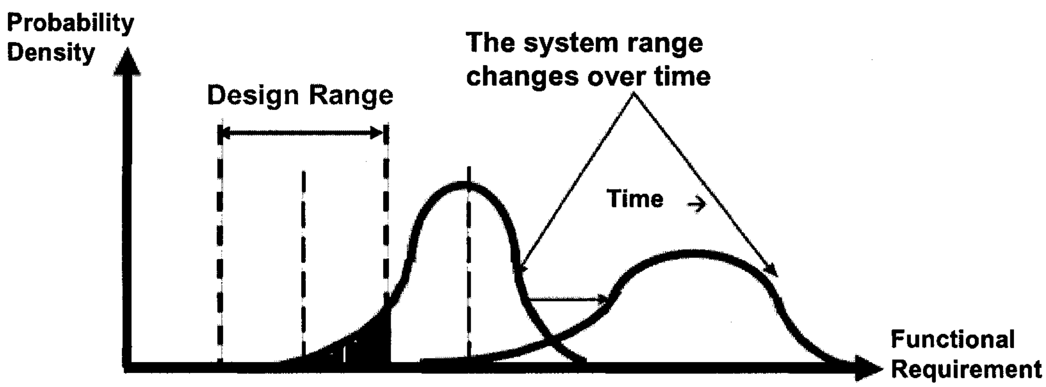


Figure 5.36. Time Dependent Combinatorial Complexity [Suh, 2005]

Based on this discussion and linking quality to complexity, higher quality levels can be achieved by following two main approaches. The first is reducing the time-independent real complexity which can be achieved by designing the system with high capability level. The model in this research will help the system designer in assessing the expected capability level at the early stages of system development. The second approach is to transform time-dependent combinatorial complexity into periodic complexity by the appropriate use of on-line quality control tools.

5.7.3. CASE STUDY-3 (GEAR BOX HOUSING MACHINING)

This case study has been presented by Zhang *et al.* [2002]; it is concerned with the design of a manufacturing system for machining of the gearbox housing shown in Figure 5.37. The authors proposed the configuration scenario presented Figure 5.38 (a), two more design scenarios have been considered as shown in Figure 5.38 (b and c). Any of these three configurations can be used in the machining of the gearbox hosing, but at different costs and production rates. The considered system configurations are automatic transfer lines and the machines used in these systems are 4-axis horizontal milling machines. A summary of the inputs to the developed model for quality prediction for the considered three scenarios is listed in Table 5.9.

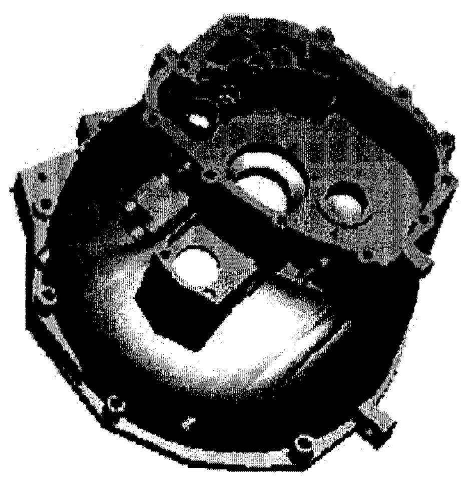


Figure 5.37. Gearbox Housing [Zhang et al. 2002]

The data listed in Table 5.9 has been used as input to the developed fuzzy inference system to assess the configuration capability in machining the gearbox housing using the considered three configuration scenarios illustrated in Figure 5.38. The results obtained for the intermediate quality measures as well as the final Configuration Capability Indicator (CCI) are listed in Table 5.10 and are shown in Figure 5.39.

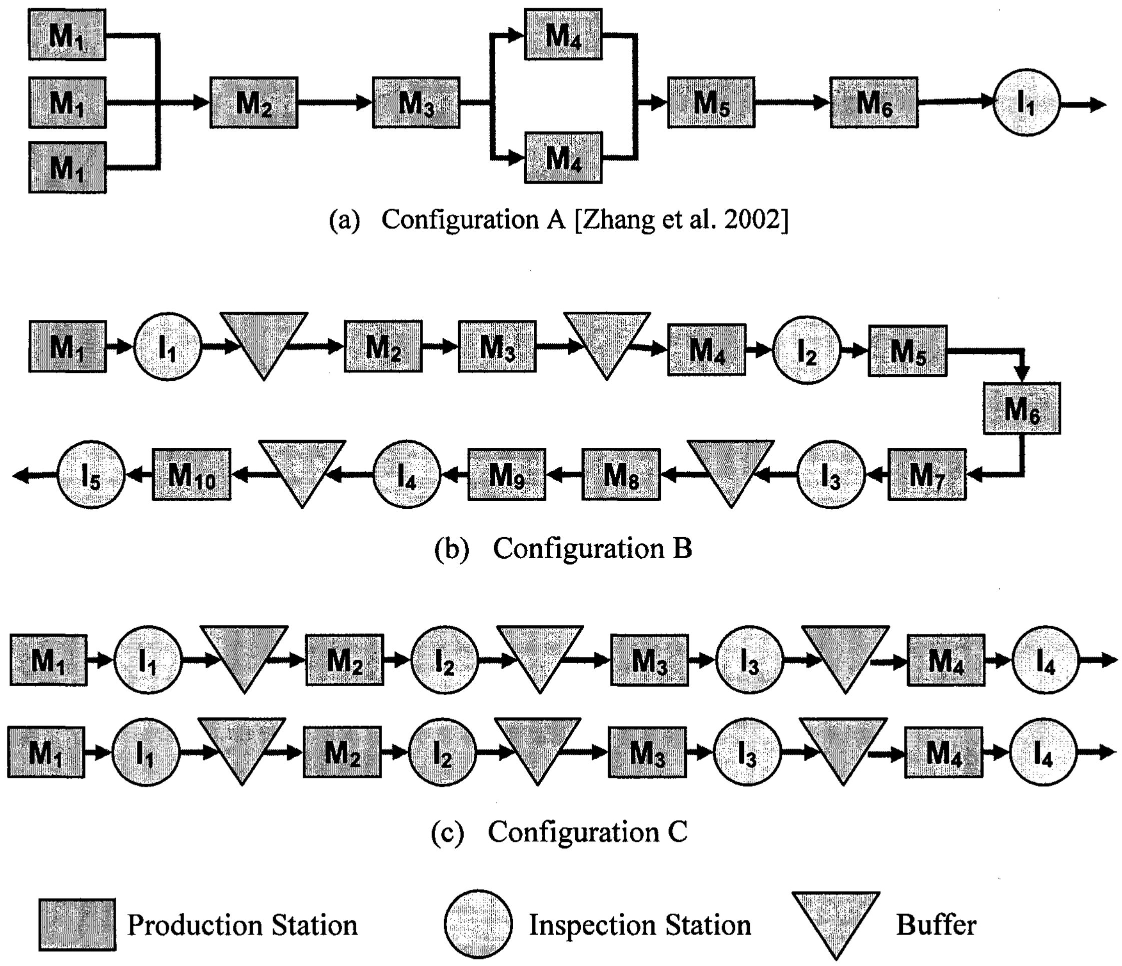


Figure 5.38 System Configuration Scenarios for Case Study-3 (Gear Box Housing Machining)

Table 5.9. Summary of Model Inputs for Case Study 3

Configuration Parameter	Configuration A	Configuration B	Configuration C
No. of flow paths	6	1	2
No. of serial stations	6	10	4
Overall capability of processes	0.53	0.62	0.70
Level of mistake proofing	0.30	0.50	0.75
Inspection error	3	4	4
Allocation of inspection stations	1	0.50	0
Level of jidoka implementation	0.22	0.50	0.50
Buffer size	0	6	2

Table 5.10. Results for Case Study-3

Quality Measure	Configuration A	Configuration B	Configuration C
Quality of Configuration Morphological Structure (QCMS)	0.52	0.90	0.80
Error Detection Responsiveness (EDR)	0.17	0.71	0.88
Defect Prevention Capability (DPC)	0.27	0.63	0.90
Defect Detection Capability (DDC)	0.22	0.76	0.80
Configuration Capability Indicator (CCI)	**1.72**	**3.89**	**4.73**

These results indicate that configuration C is best from the quality point of view, configuration B, and configuration A is the worst. Configuration C is capable of machining the gearbox housing at "4.73 Sigma" capability level. However, the capability level for configuration B is "3.89 Sigma" and capability level for configuration scenario A is "1.72 Sigma" which represents unacceptable quality level. Configuration C "best scenario" is characterizes by relatively higher defect prevention capability due to high overall capability of processes, high level of mistake proofing implementation as well as low variability due to parallel processing and variation stack-up. It also has a relatively high defect detection capability through the integration of inspection with production stations, relatively low inspection errors, moderate use of Jidoka as well as low buffer size. On the other hand, configuration A "worst scenario" has low defect prevention capability because of low capability of the overall processes, and low implementation of mistake proofing. It also has a low defect detection capability because the end-of-line inspection and low implementation of Jidoka.

In Configuration C, it should be highlighted that the increase of buffer size will not adversely affect its defect detection capability because the inspection stations are integrated with the production stations. This is because there will be no delay between the occurrence of defects and their detection during the inspection. Therefore, the Error Detection Responsiveness (EDR) fuzzy inference system is designed such that in cases with highly intensive in-process inspection the buffer size has no effect on the error detection responsiveness. Also, in case of end-of-line inspection, it is assumed that there is no quality information feedback and therefore the buffer has no effect on quality. This is because the end-of-line inspection is always targeting at sorting the conforming and non-conforming items and no quality information are fed back to the downstream operations for corrective actions.

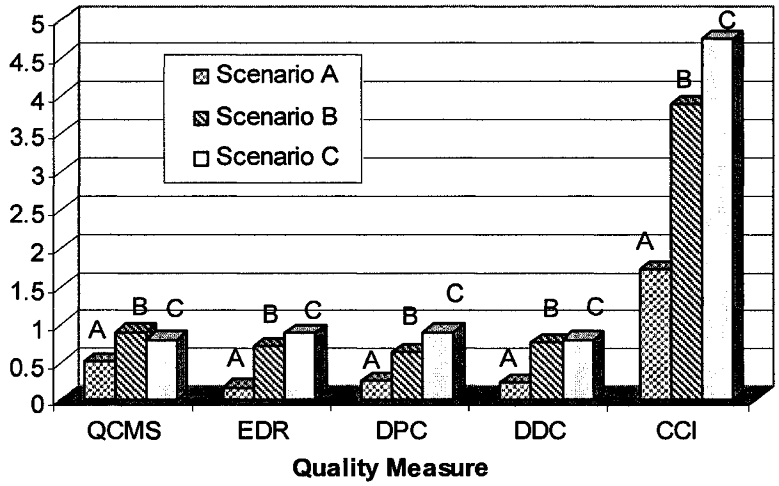


Figure 5.39 Results for Case Study-3 (Gear box housing machining)

The relation between the Configuration Capability Indicator and buffer size for the three configuration scenarios considered in this case study is illustrated in Figure 5.40. This figure shows that the configuration capability is a function of buffer size only in scenario B, which represents a case of in-process inspection with quality information feedback.

The feedback of quality information to the downstream operations prevents the production of more defects and gives the chance to correct the operation before the production proceeds. Therefore, it is expected that the quality will be adversely affected by the increase of buffer size in the case of in-process inspection with quality feedback. However, in cases with intensive in-process inspection, the buffer size has no effect on the configuration capability. This is because the inspection is performed locally after or within each station and the part enters the buffer after being inspected. Therefore, the time between the occurrence of errors and detecting them, and hence the configuration quality, is not affected by the buffer size as shown in scenario C in Figure 5.40.

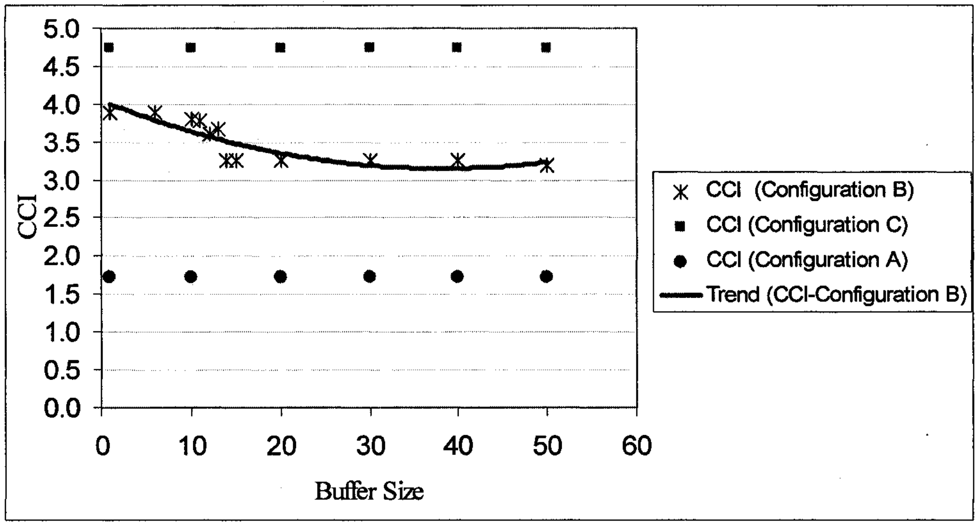


Figure 5.40. Relation between Configuration Quality Indicator (CCI) and Buffer Size for Different Configuration Scenarios of Case Study-3

For configuration scenario A, as it represents end-of line inspection with no quality information feedback, the configuration quality is not a function of the buffer size. The fuzzy rules related to buffer size have been designed based on the work done by Kim and Gershwin [2005]; as mentioned earlier in Section 6.3.1.2. The results obtained as illustrated in Figure 5.40 follow the same trend as the results obtained by Kim and Gershwin [2005] illustrated in Figure 5.41.

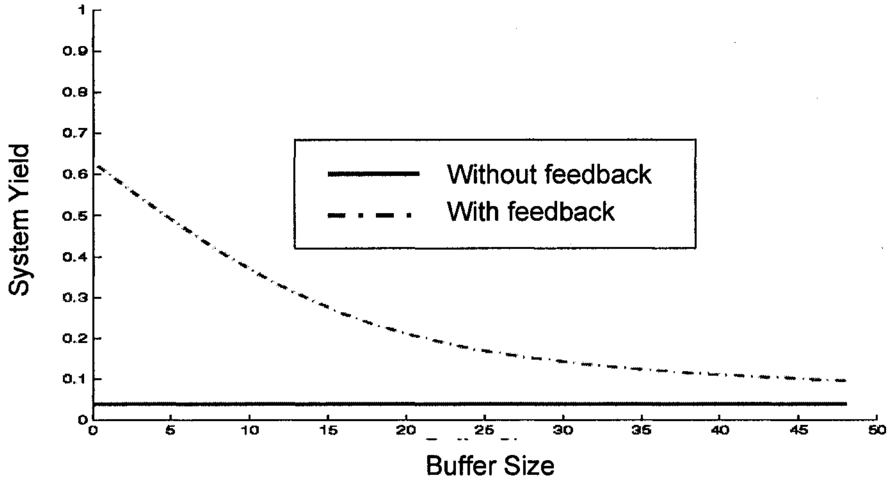


Figure 5.41. Relation between Buffer and System Yield [Kim and Gershwin, 2005]

Moreover, configuration scenario A can be improved to enhance its capability through improving its defect prevention capability and defect detection capability. Considering improving the defect prevention capability, the effect of increasing the level of mistake proofing implementation will be investigated along with improvements in the overall capability of processes as illustrated in Figure 5.42. In this figure, the Configuration Capability Indicator (CCI) values for configuration scenario A, B and C are highlighted. In addition, the CCI values for configuration scenario A are plotted against the level of mistake proofing implementation for overall capability of processes equals to 0.53 (which is the current value) and an improved value equals to 0.7.

It can be noticed that keeping the overall capability of processes at its current value (0.53) and increasing the implementation of mistake proofing implementation up to about 0.72 instead of 0.22 can help in improving the capability of scenario A and turns it out to be equivalent to configuration scenario B. However, by improving the overall capability of processes from 0.53 to 0.7, the same result can be obtained at level of mistake proofing implementation equals to 0.4. This illustrates the significant effect of the overall capability of processes as well as the implementation of mistake proofing in improving the configuration capability.

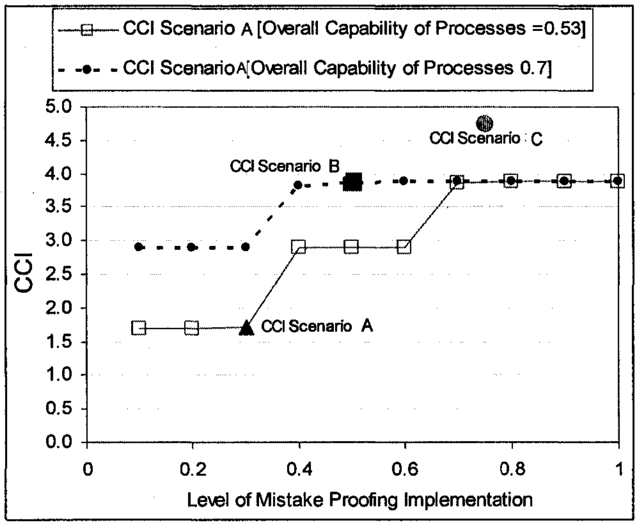


Figure 5.42. Effect of Mistake Proofing Implementation on CCI for Configuration A [Case Study-3 (Gear box housing machining)]

Further improvements to configuration A in both the level of mistake proofing implementation and the overall capability of processes have been considered to investigate their impact on the CCI and to explore whether it would be equivalent to the best case (scenario C) or not. The results obtained reveal that any further increases in both the mistake proofing implementation and overall capability of processes will not improve the CCI value. This is because of its very low defect detection capability. Therefore, improving the defect detection parameters has been investigated.

Using the current level of the overall capability of processes (0.53) and using the level of mistake proofing as 0.72, a set of improvements can turn Configuration A to be equivalent to Configuration C. These improvements involve performing the inspection locally within the production stations, decreasing the expected inspection errors by using more capable inspection equipment and inspectors so that the measure for inspection error improves from 3 to 4, and increasing the level of Jidoka implementation to 0.55.

It should be pointed out that this case study has been used in Chapter 4 to demonstrate the use of the developed AHP model. The results of this case study using the developed AHP model in Chapter 4 indicate that Configuration C is the best, then Configuration B, and the worst one is Configuration A as shown in Figure 4.10 in Chapter 4. Therefore, it can be concluded that both the AHP model and the fuzzy inference model reached the same conclusion. However, the values of Configuration Capability Indicator obtained using the two models are not numerically comparable. This is because in case of AHP, the CCI is a relative measure whereas the CCI value obtained using the fuzzy inference model is an absolute value.

5.7.4. Case Study-4 (Rack Bar Machining)

Reynal [1998] has introduced a case study that involves the machining of the rack bar illustrated in Figure 5.43. Such a rack bar is used in the rack and pinion steering gear that is used indirectly by the driver to control the direction of the front wheels in the automobile. Reynal [1998] made a comparison between Plant M and Plant L, shown in

Figure 5.44 and Figure 5.45 respectively, based on the rack bar component which is very similar in both plants.

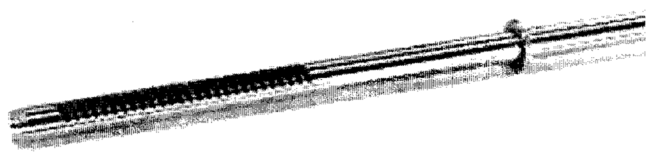


Figure 5.43. Typical Rack Bar Machined at Plant M and L [Reynal, 1998]

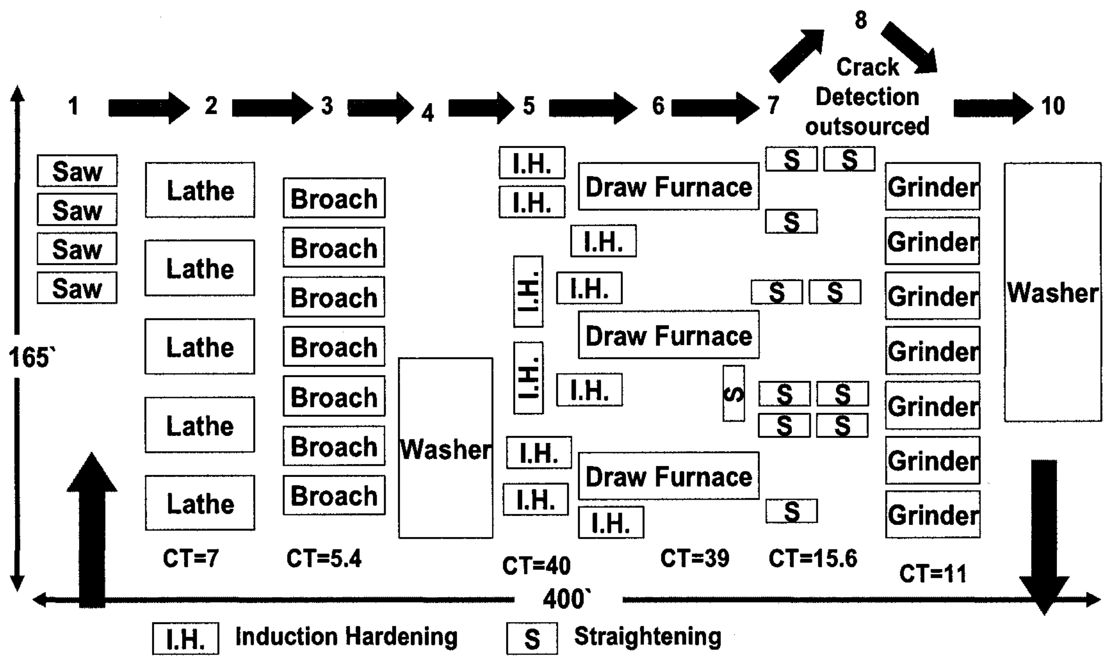


Figure 5.44 Rack Bar Machining System (Plant M) [Reynal, 1998]

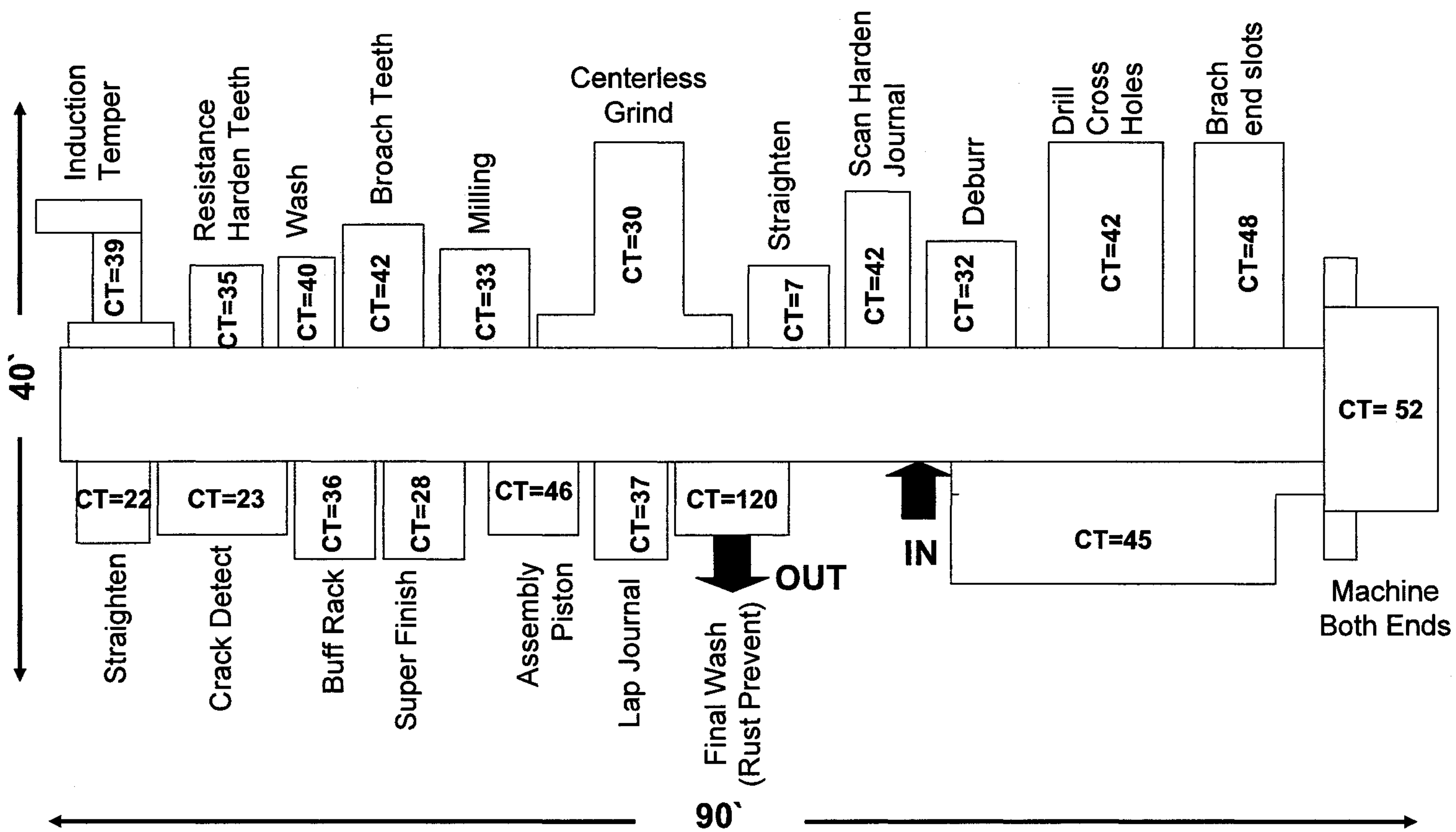


Figure 5.45 Rack Bar Machining System (Plant L) [Reynal, 1998]

Plant M starts by cutting the rack bar to the desired length from a long bar stock. After this process, the rack bar goes through nine other different processes. The rack bar is transferred from one machine to the other in batches using a forklift truck. There are 49 machines in the system with a capital investment of $29.5 Million. The total number of operators needed to operate the system is 28. The only inspections done on the rack bar are during the crack detection and straightening operations. On the other hand the machining of the rack bar at plant L is done using a U shaped cell as shown in Figure 5.44. Plant L receives incoming bar cut-to-length from suppliers. There are 21 different processes in the cell designed at Plant L. Most of the time, two or three operators are running the cell. The operators move the rack bar from one machine to the other. When the operator unloads the part from one machine and transfer it to the next machine, he can visually verify that there are no scratches, marks or any other defective characteristics. In some instances, the operator even places the part in a gage to perform a quality check.

In addition to the layout of the two plants, Reynal [1998] compared these two plants with respect to other criteria and the following results have been reported. It has been found that the level of work-in-process inventory at Plant M is almost 80 times of that in Plant L. Moreover, as opposed to Plant M, Plant L has implemented devices for prevention/detection of defects in most of the machines and operations performed in machining the rack bar. It can be also concluded that Plant M performs end of line inspection. However, the inspection at Plant M is almost after each station. Plant M is characterised by high number of flow lines as opposed to Plant M that has a single flow line. The number of serial stations in Plant L is 17 stations (excluding washing and inspection stations), and in Plant M is 6 stations (excluding washing and inspection stations).

The information provided about the output of the two plants indicates that the defect rate at Plant M is 70 times that of Plant L. The average defect rate at Plant L is given as 487.5 ppm (part per million). Therefore, the defect for Plant M can be calculated as ($70 \times 487.5 = 34{,}125$) ppm. Assuming that the distribution of the system's output follows normal distribution, these defect rates can be expressed in terms of sigma capability as 4.8 Sigma for Plant L and 3.32 Sigma for Plant M.

The developed model has been used to assess the Sigma capability levels for Plant M and L and the obtained results will be compared by the actual values for the sake of verification and validation. The data provided by Reynal [1998] is used to assess in specifying the model inputs for the two plants. A summary of these inputs is illustrated in Table 5.11. In case of Plant M, as the number of flow lines is greater than the maximum value of the universe of discourse, the input concerned with the number of flow paths will be used as the worst-case scenario. In addition, Plant L has no buffers and Plant M is assigned the worst-case scenario for the buffer size.

Table 5.11 Summary of Model Inputs for Case Study 4

Configuration Parameter	Plant L	Plant M
No. of flow paths	1	29,400
No. of serial stations	17	6
Overall capability of processes	(0.1-0.9)	(0.1-0.9)
Level of mistake proofing	1	0
Inspection error	4	4
Allocation of inspection stations	0	1
Level of jidoka implementation	1	0
Buffer size	0	50

It should also be highlighted that there is no data available for the capabilities of individual processes. As a result, the measure that assesses the overall capabilities of processes relative to six sigma capability can not be estimated due to the lack of data. Therefore, the configuration capability indicator will be predicted using the developed model at different values for overall capability of processes.

The obtained results are illustrated in Figure 5.46. It should be pointed out that the actual defect rate of both of the systems indicate that their capabilities is greater than 3 Sigma as indicated before (4.8 Sigma for Plant L and 3.3 Sigma for Plant M). This means also that the measure for overall capability is greater than 0.5 (i.e. 3 Sigma/6 Sigma).

Therefore, only smaller range for the overall capability of processes can be reasonably considered as highlighted in Figure 5.46.

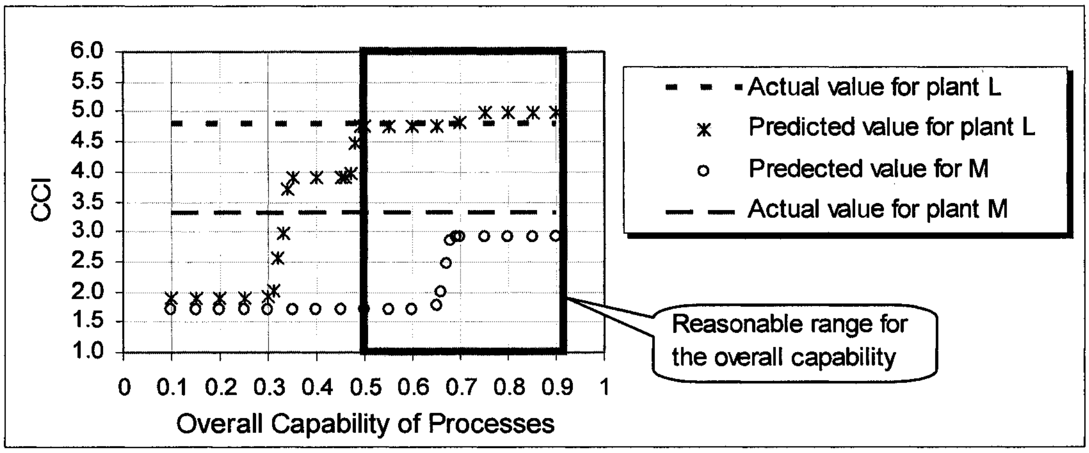


Figure 5.46 Predicted and Actual Configuration Capability for Plant L and Plant M

The results indicate that developed model provides a good prediction for the configuration capability. For Plant L, the actual value in terms of sigma capability is 4.8 Sigma. However, in the considered reasonable range, the predicted value for CCI ranges from 4.77 Sigma to 4.99 Sigma depending on the value of the overall capability of processes as shown in Figure 5.46. This result highlights that the developed model is capable of predicting the configuration capability with reasonable accuracy.

For Plant M, the actual value in terms of sigma capability is 3.3 Sigma. The predicted CCI for overall capability of processes greater than 0.68 is 2.9 Sigma, which is still considered a good estimate. However, for low values of overall capability of processes the developed model is expected to result in very low CCI for a system such Plant M. This is because Plant M has almost all the design features that adversely affect the quality including high variability due to parallel processing, no implementation of mistake proofing, high work in process inventory, as well as limited inspection at the end of the line. Therefore, it was expected that if all of these design characteristics accompanied by low capability of processes that the resulting CCI would be very low to indicate that the system is incapable and the quality level is unacceptable. This explains the very low values obtained for Plant M when the overall capability of processes decreases. The results also illustrate that when the overall capability of processes are low the CCI is low indicating that the system is incapable regardless of the values of the other configuration parameters. This can be seen in Figure 5.46; as it indicates the convergence between the predicted values for plant M and L associated to low values of the overall capability of processes.

5.8. SENSITIVITY ANALYSIS

In almost all of the case studies illustrated in the pervious section, the different presented scenarios have been associated with more than one change in the configuration parameters. Therefore, the estimated quality measures have been affected by the combined effect of changing those configuration parameters. Although a number of scenarios have been presented in Case Study-3 (Gearbox housing) for demonstrating the individual effect of buffer size and the level of mistake proofing implementation on the Configuration Capability Indicator (CCI), more sensitivity analysis are needed to demonstrate the individual effects of the other parameters. To do so, the value of each configuration parameter will be varied over its whole universe of discourse while the other parameters will be fixed as constants at their mean values; unless otherwise stated. These values will be used as inputs to the developed model and the outputs will be represented as two-dimensional figures to illustrate the effect of changing of each configuration parameter on the predicted quality measures.

In this context, it is critical to highlight that the purpose of performing such sensitivity analysis is not to study the relation between configuration parameters and quality. This is because these relations are known a priori and have been already used in designing the fuzzy inference system. Performing such sensitivity analysis is mainly targeting the testing of the model in more scenarios as well as verifying that the obtained output trends do not contradict the logic and the rules that have been used in developing the model.

5.8.1. THE EFFECT OF THE NUMBER OF FLOW PATHS

The effect of the number of flow paths on the Quality of Configuration Morphological Structure (QCMS) and on the Configuration Capability Indicator (CCI) is illustrated in Figure 5.47.

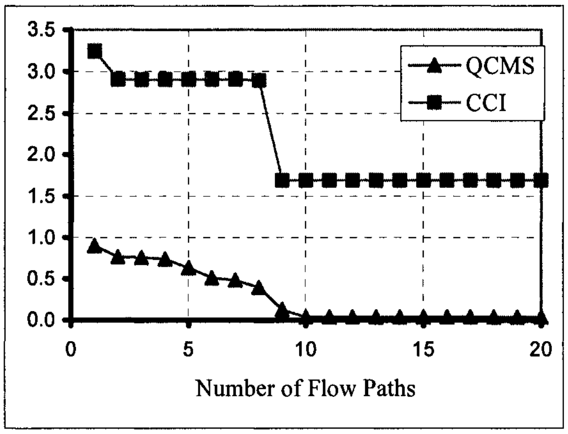


Figure 5.47 The effect of the Number of Flow Paths on the Quality of Configuration Morphological Structure (QCMS) and the Configuration Capability Indicator (CCI)

Figure 5.47 indicates that the increase in the number of flow paths adversely affects the Quality of Configuration Morphological Structure (QCMS), which in turn adversely affects the Configuration Capability Indicator. For instance, fixing other configuration parameters and increasing the number flow paths from 5 to 10, decreases the CCI from 2.9 Sigma to 1.7 Sigma. However, this observation cannot be used as a conclusion. This is because the values and the trend obtained for the effect of the number of flow paths on the QCMS as well as the CCI depends on the selected fixed values for the other configuration parameters.

5.8.2. THE EFFECT OF THE NUMBER OF SERIAL STATIONS

The effect of the number of serial stations on the QCMS and CCI is shown, by fixing the number of flow paths equals to three and the other parameters at their mean values, in Figure 5.48. This figure illustrates that as the increase in the number serial stations adversely affects the QCMS, which in turn adversely affects the CCI. In addition, the combined effect of changing both of the number of serial stations and the number of flow paths on the QCMS is shown in Figure 5.49. Also, it can be noticed that increasing the number of flow paths has a stronger negative effect on the QCMS, which intentionally considered while designing the rules according to insights from literature as explained in Section 5.3.1.1.

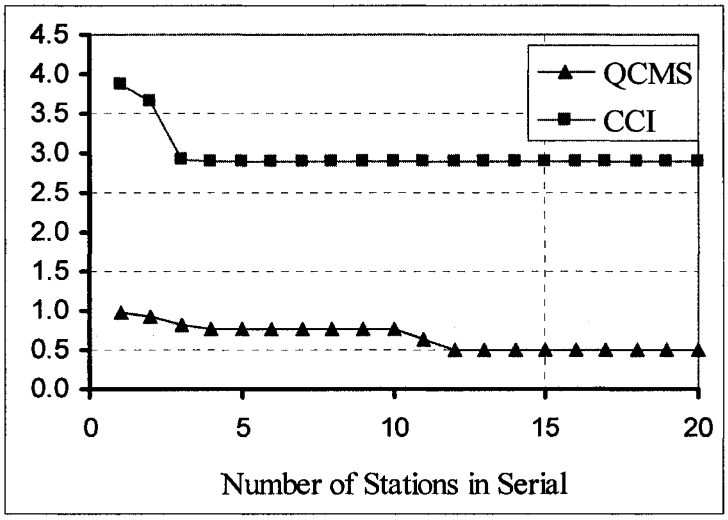


Figure 5.48. The effect of the Number of Flow Paths on Quality of Configuration Morphological Structure (QCMS) and the Configuration Capability Indicator (CCI)

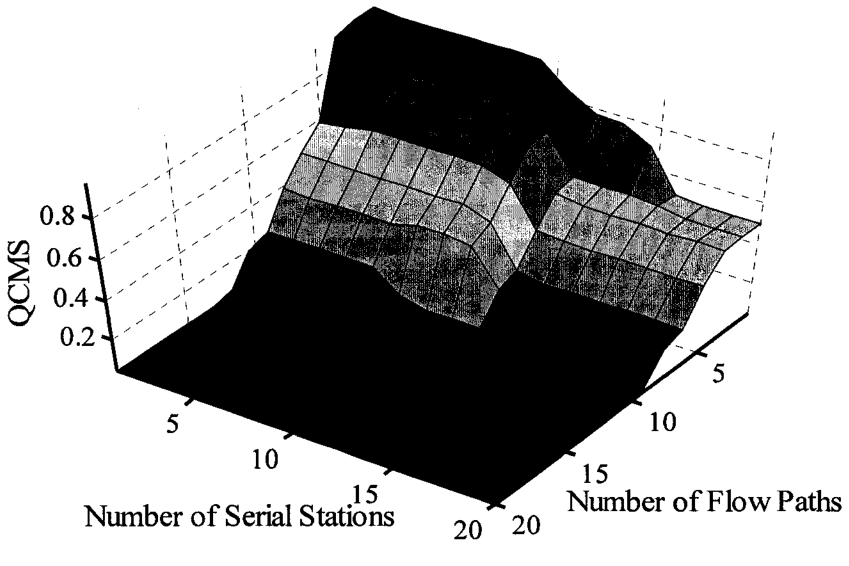


Figure 5.49. Quality of Configuration Morphological Structure (QCMS) as Affected by the Number of Flow Paths and the Number of Serial Stations

In all subsequent scenarios that necessitate fixing the number of serial stations and the number of flow paths while studying the effect of other parameters, their values will be assigned such that the resulting QCMS equals to its mean value (0.5). It has been arbitrarily assumed that the number of serial stations equals "10 , and the number of flow paths equals "6 ; as these values can result in a QCMS equals "0.5 . On the other hand, all the other parameters will be assigned their mean value.

5.8.3. The Effect of the Overall Capability of Processes and Mistake Proofing

The effect of the overall capability of processes on the Defect Prevention Capability (DPC) and the Configuration Capability Indicator (CCI) is shown in Figure 5.50.

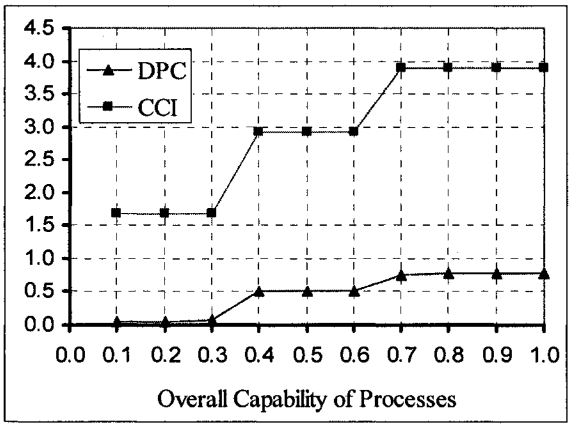


Figure 5.50 The Effect of the Overall Capability of Processes on the Defect Prevention Capability (DPC) and Configuration Capability Indicator (CCI)

Figure 5.50 indicates that increasing the overall capability of processes can significantly improve the Defect Prevention Capability (DPC) and subsequently the Configuration Capability Indicator (CCI). It should be pointed out that increasing the overall capability of processes can be achieved by not only by using highly capable individual processes, but also by minimizing the number of processes or steps required to manufacture the product. The later necessitates minimizing the product complexity.

Similarly, the effect of the implementation of mistake proofing is illustrated in Figure 5.51. It may be concluded from Figure 5.50 and Figure 5.51 that the increase in the overall capability processes and the increase in the mistake proofing implementation has almost the same positive impact on the improvement of the defect prevention capability, and hence the configuration capability indicator. However, this is applicable only for medium to high values for the overall capability of processes as shown in Figure 5.52. Through this figure, it can be verified that the rules have been designed such that the situations associated with low overall capability of processes will result in a low defect prevention capability and the configuration capability will be unacceptable regardless of the values of the other configuration parameters. As discussed earlier Case Study-2 (Cylinder Head Part Family), such a system has a high time-independent real complexity according to Suh [2005]. This is because the processes are incapable of performing their assigned operations. Therefore, in such a case, quality improvement targets cannot be achieved by improving other design parameters without improving the incapable the processes. The same discussion is valid for Figure 5.53, which illustrates the defect prevention capability as affected by the overall capability of processes and the quality of configuration morphological structure at the mean value of mistake proofing implementation. It also indicates that when the overall capability of processes is low, the defect prevention capability is low regardless of the value of the quality of configuration morphological structure.

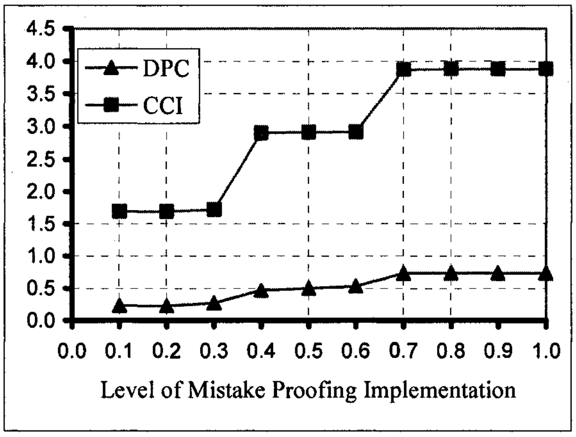


Figure 5.51 The Effect of the Level of Mistake Proofing Implementation on the Defect Prevention Capability (DPC) and Configuration Capability Indicator (CCI)

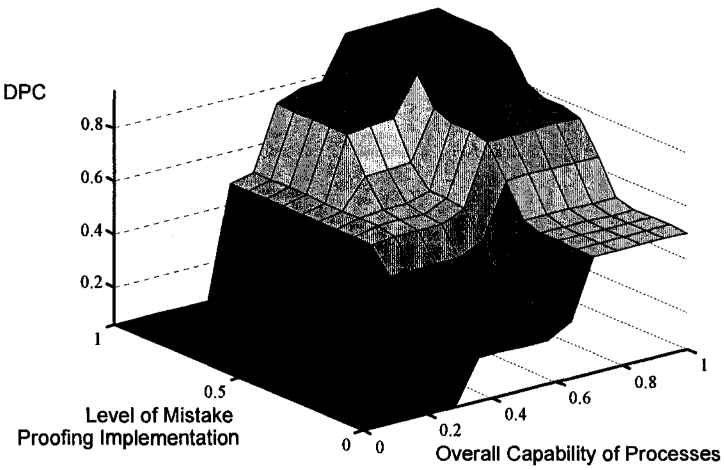


Figure 5.52 Defect Prevention Capability (DPC) as Affected by the Overall Capability of Processes and the level of Mistake Proofing Implementation (for QCMS =0.5)

In addition, Figure 5.54 illustrates the effect of the quality of configuration morphological structure and the level of mistake proofing implementation at fixed mean value for the overall capability of processes. Exploring Figure 5.52, Figure 5.53, and Figure 5.54, one can observe that the Defect prevention Capability (DPC) fuzzy inference system is designed such that the best value for the DPC can be obtained using a range of high overall capability of processes and mistake proofing implementation even at mean values for the QCMS. However, at mean values for mistake proofing implementation, the best values for the DPC can be obtained only at high values for the overall capability of processes associated with very high values for the QCMS as illustrated in Figure 5.53. On the other hand, the best values for the DPC can not be obtained at mean values for the overall capability of processes-the range represents that the process is capable or barely capable- even if it is associated with the best values for both the mistake proofing implementation and the QCMS as shown in Figure 5.54.

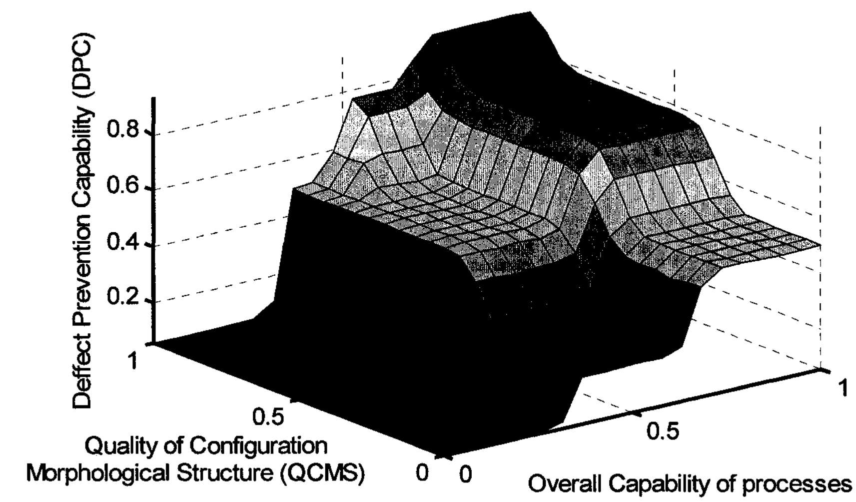


Figure 5.53 Defect Prevention Capability (DPC) as Affected by the Overall Capability of Processes and the QCMS (the level of Mistake Proofing Implementation =0.5)

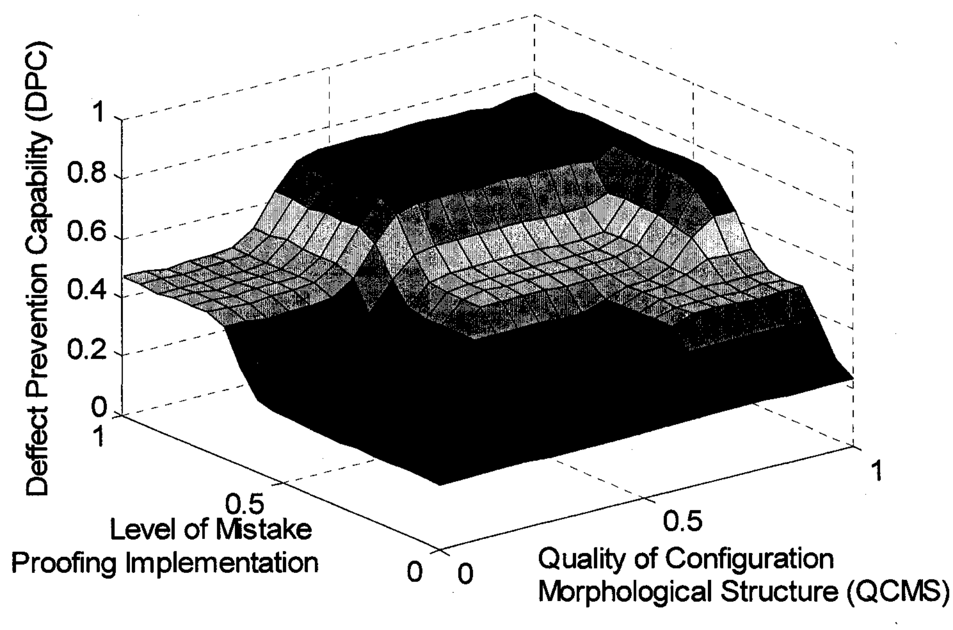


Figure 5.54 Defect Prevention Capability (DPC) as Affected by Mistake Proofing Implementation and the QCMS (for Overall Capability of Processes =0.5)

5.8.4. THE EFFECT OF THE ALLOCATION OF INSPECTION STATIONS

The effect of the allocation of inspection stations on the Error Detection Responsiveness (EDR), which in turn affects the Defect Detection Capability (DDC) and the Configuration Capability Indicator (CQI) is illustrated in Figure 5.55. This figure is obtained by fixing the configuration parameters at their mean values and varying the allocation of inspection stations from the best value "0 , which represents a case of inspection integrated with production stations to the worst value "1 representing end of line inspection. This figure indicates that error detection responsiveness can be significantly improved by using intensive in-process inspection, which is represented on Figure 5.55 by low values for the allocation of inspection stations measure. It is expected that the exact shape of the curve representing the relationship between the allocation of inspection station and the Error Detection Responsiveness (EDR) would vary by using different values of buffer size as illustrated in

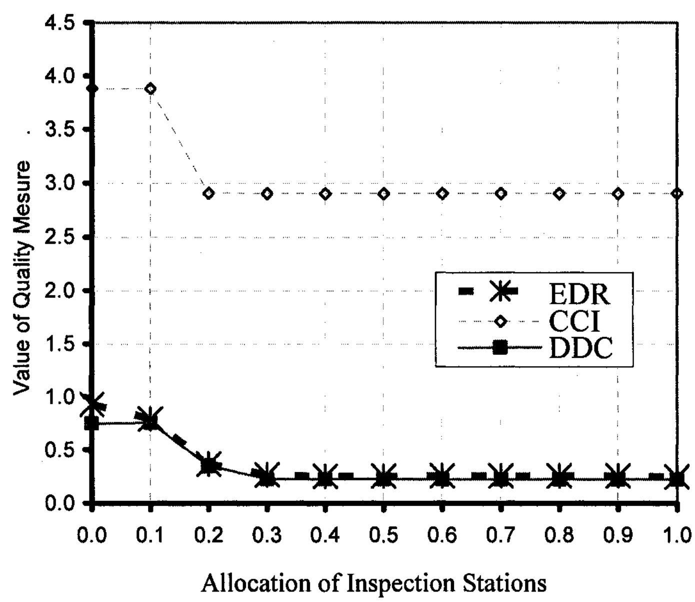


Figure 5.55 Effect of the Allocation of inspection Stations on Error Detection Responsiveness (EDR), Defect Detection Capability (DDC), and Configuration Capability Indicator (CCI)

5.8.5. THE EFFECT OF THE BUFFER SIZE

The effect of the buffer size has been addressed earlier using Figure 5.40 in the results of Case Study-3 (Gearbox Housing). In addition, Figure 5.56 demonstrates the effect of the buffer size and the allocation of inspection stations on the EDR at mean value for Jidoka implementation. Figure 5.56 also illustrates that the buffer size does not affect the EDR in scenarios associated with end of line inspection as well as in scenarios, in which the inspection stations are integrated with the production stations as explained earlier using Figure 5.40 in the results of Case Study-3 (Gearbox Housing).

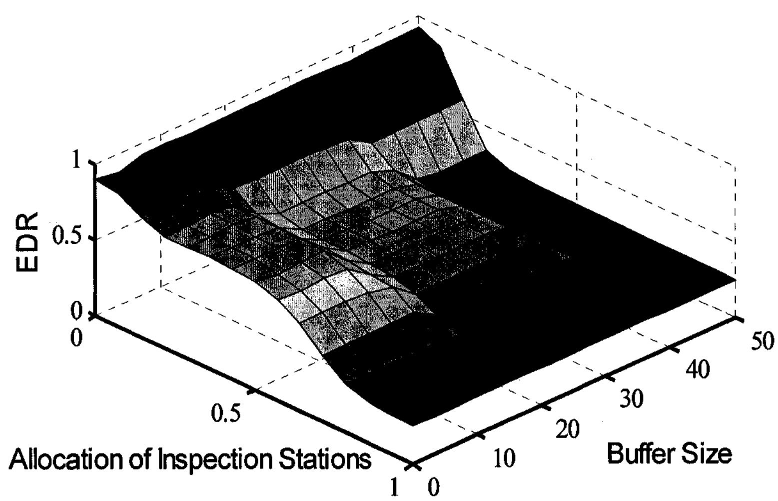


Figure 5.56 Error Detection Responsiveness (EDR) as Affected by the Allocation of Inspection Stations and Buffer Size at Mean Value for the Jidoka Implementation

5.8.6. THE EFFECT OF JIDOKA IMPLEMENTATION

The effect of Jidoka implementation on the Error Detection Responsiveness (EDR), which in turn affects the Defect Detection Capability (DDC) and the Configuration Capability Indicator (CQI) is illustrated in Figure 5.57, which is obtained at mean values for other configuration parameters. This figure demonstrates the implementation of Jidoka has a direct positive impact on the EDR, which is observed in Figure 5.57 by the proportional increase in the EDR as the level of Jidkoa increases.

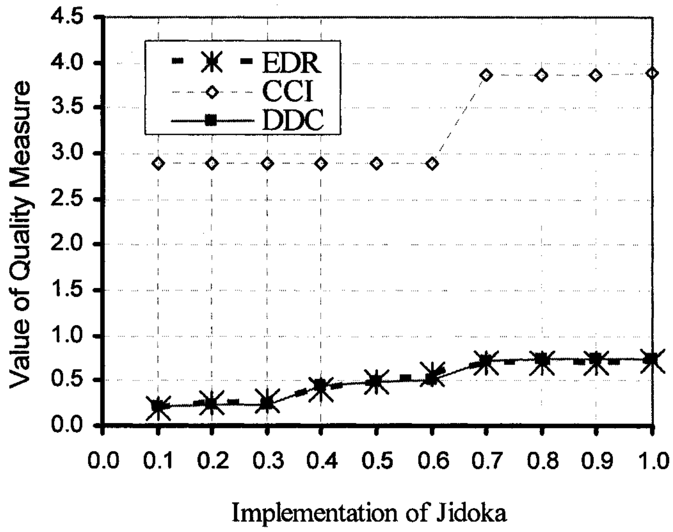


Figure 5.57 The Impact of the Level of Jidoka Implementation on Error Detection Responsiveness (EDR), Defect Detection Capability (DDC), and Configuration Capability Indicator (CCI)

5.8.7. The Effect of Inspection Error

The effect of inspection error on the Defect Detection Capability (DDC) and the Configuration Capability Indicator (CCI) is illustrated in Figure 5.58. The values for the measure considered for assessing the inspection error have been varied from the best value “6 to the worst value “0 as explained in the fuzzy variable design in Section 5.4.1.2. The impact of inspection error is investigated in two scenarios as shown in Figure 5.58. In one scenario, all the configuration parameters are fixed at their mean values. In the other scenario, results have been obtained at the best values for Error Detection Responsiveness (EDR) parameters. This is achieved by assigning value “0 for the allocation of inspection stations, “1 for Jidoka implementation, and “0 for buffer size. The Defect Detection Capability (DDC) is affected by both of the inspection error as well as the EDR. Therefore, in Figure 5.58 the trend of the decrease in the DDC as the inspection error increases is different for different values of the EDR. For high values for Error Detection Responsiveness (EDR), the DDC can continue to be relatively high for moderate values for the inspection error. This can be attributed to the effect of the high implementation of Jidoka, which helps in the instantaneous detection of errors in addition to the intensive in process inspection. The combined effect of the EDR as well as the inspection error on the defect detection capability is also illustrated in Figure 5.59.

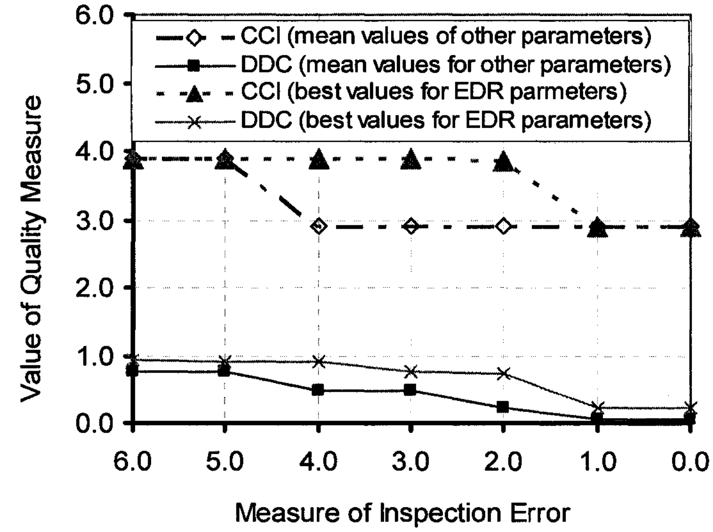


Figure 5.58 The Impact of Inspection Error on Defect Detection Capability (DDC), and Configuration Capability Indicator (CCI)

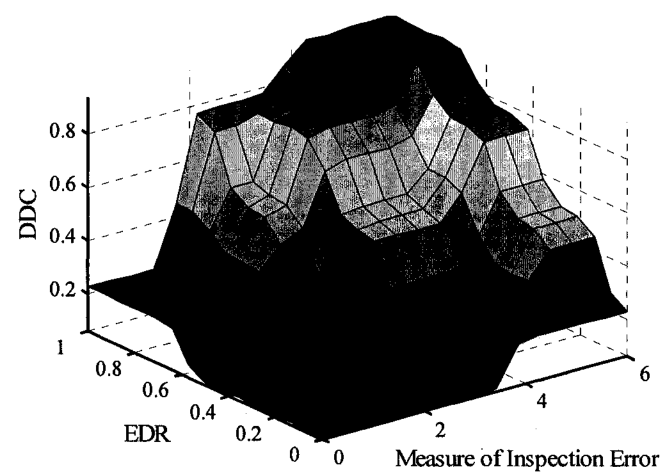


Figure 5.59 Defect Detection Capability (DDC) as Affected by the EDR and Inspection Error

The Configuration Capability Indicator as affected by the Defect Prevention Capability (DPC) and Defect Detection Capability (DDC) is illustrated in Figure 5.60. As mentioned earlier in 5.4.2, the fuzzy inference systems that assess the configuration capability based on the DPC and DDP have been designed such that the effect of the defect prevention capability is more dominant as opposed to the effect of the defect detection capability. This can be observed in Figure 5.60; where at very high values of DPC, the value of the configuration continues to be high even for moderate values for the DDC. However, at high values of the DDC, the CCI remains high as long as the DPC is high and then decreases with the decrease in the DPC. The system is designed in this way because there are several insights from literature and quality experts advising that preventing the occurrence of defects can significantly improve the obtained quality levels as opposed to allowing the defects to occur and then detecting them.

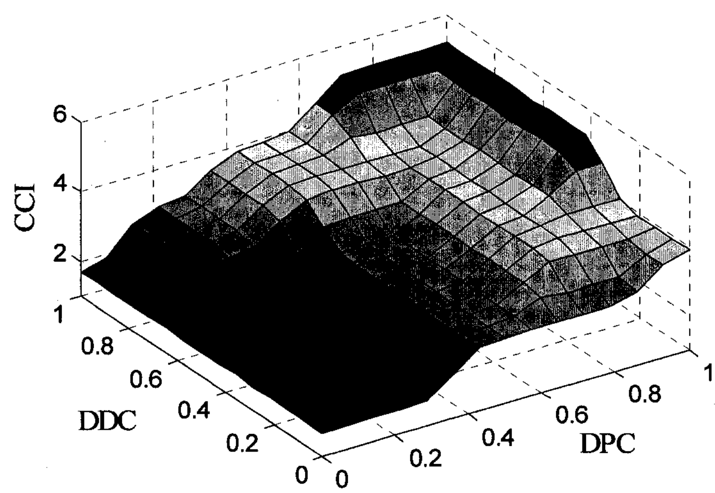


Figure 5.60 Configuration Capability Indicator (CCI) in terms of Defect Prevention Capability (DPC) and Defect Detection Capability (DDC)

From these discussions, it can be concluded that high quality levels can be achieved by investigating all the improvement opportunities. The improvement in only one parameter and ignoring the others will not achieve significant improvements in the overall obtained quality level. However, it is recommended that efforts should be directed first to designing the system such that it minimizes or prevents the occurrence of errors rather than let them occur and then detecting them. The prevention of errors will help in achieving higher quality levels without investing time and money in non-value added actives and this will significantly enhance the manufacturer competitiveness. Although the developed fuzzy inference system for quality prediction provides the system designer with the final assessment of the expected configuration capability in manufacturing a specific product, the hierarchal structure that has been used to build the model gives the advantage of having the intermediate quality measure available such as the defect detection capability and defect prevention capability. This will help the user of the model to identify the improvement opportunities easily and to investigate the sensitivity of the final measure with the change of the parameters considered for improvement.

The hierarchical structure also has the advantage of reducing the number of rules, as explained earlier in Section 5.2.2., from 187,500 rules (product of the number of fuzzy sets for all the input variables) to 250 rules (sum of rules for all the fuzzy inference systems). In addition, modifications in the design of the fuzzy variables or in the rules will be easier using the hierarchical structure as opposed to the conventional structure. This is a very critical issue because the developed model is expected to be updated and modified either to suite specific applications, to include other parameters, or to update it based on new gained knowledge.

Applying the model to several case studies with different scenarios as well as performing sensitivity analysis demonstrated the capability of the developed hierarchical fuzzy inference system in predicting the configuration capability level in terms of the considered configuration parameters. However, as any other fuzzy inference system, the accuracy of the output is highly dependent on the quality of the data used in developing the model. In this research, every possible effort has been made during the data acquisition from literature to have a good insight about the relation between quality and manufacturing system design.

The improvement opportunities for such a model can be related to two main aspects. One aspect is related to the quality of the data used in developing the model. Therefore, the model should be continuously updated and improved so that it expresses the most recent results associated with the progress in the field of manufacturing system design and quality. In addition, surveys from industry and quality experts can be obtained to enhance the quality of data used in the model. The other aspect is related to considering other configuration parameters that have not been included in this model. For instance, the model handled the system layout only from the point of view of the number of flow paths and the number of stations and the effect of the shape of the layout has not been considered. In addition, the model assumes that the inspection strategy is to perform 100% inspection and the sampling option has not been considered. Furthermore, the effect of the material handling equipment has not been considered.

Moreover, the use of sigma capability concept in assessing the overall capability of processes and in the developed configuration capability indicator is associated with the assumption that the outputs of the operations are normally distributed. Despite the wide applicability of the normal distribution, not all of the scenarios are expected to follow the normal distribution. In the meanwhile, this assumption can be accepted in this research because it is too challenging to predict the specifications of the actual distributions at the early stages of the manufacturing system development. In addition, the normal distribution assumption is in the first place made by the Six Sigma approach. Therefore, in order to obtain an output from the model that can be compared with benchmark targeted Six Sigma, this assumption has to be considered.

5.9. SUMMARY

In this chapter, A *Configuration Capability Indicator* (CCI) that is capable of mapping the manufacturing system configuration parameters into an expected product quality level has been developed. A hierarchical fuzzy inference system is used for modeling the ill-defined relation between manufacturing system design parameters and the resulting product quality. The proposed CCI predicts the system's output quality based on the manufacturing system's defect prevention capability as well as defect detection capability. The defect prevention capability is assessed based on the overall capability of processes, the quality of the system configuration morphological structure, as well as the implemented mistake proofing strategies. However, the defect detection capability is assessed based on the accuracy of error detection as well as the system responsiveness in error detection; which is assessed based on the allocation of inspection stations, implementation of Jidoka, and the buffer size.

The Matlab Fuzzy Logic Toolbox has been used to develop the individual fuzzy inference systems in the hierarchy. A simulink model has been developed to integrate the individual fuzzy system. For configuration produces more than one product, a configuration capability zone is proposed to graphically represent the manufacturing system configuration capability and compare it to the benchmark six sigma capability. The developed model has been applied to four case studies with different scenarios for illustration and verification. Results and discussions for the different scenarios are presented.

The Configuration Capability Indicator (CCI) presented in this chapter represents the first move toward the development of a comprehensive measure for the expected product quality as affected by manufacturing system design decisions. The CCI can assess the expected product quality at the early stages of system development and can significantly help in achieving higher quality levels at lower costs in a responsive manner. It can be also incorporated with other performance measures to the support the manufacturing system design decision-making.

6. PREDICTION OF ERRORS DUE TO HUMAN INVOLVEMENT IN MANUFACTURING TASKS

6.1. INTRODUCTION

It has been reported that errors due to human involvement in manufacturing tasks is one of the major causes of defects [Hinckly, 1993]. The evidence that human errors are a dominant source of quality problems can be found in published case studies. For instance, in the study of 23,000 production defects, Rook [1962] concluded that 82% originated from operators' mistakes. In the assembly process of a compact disc/mini disc dual deck player, Shibata [2002] reported that approximately 42% of the total defects are due to human involvement.

One might propose the use of robotics and automation to avoid human involvement in manufacturing, but it should be highlighted here that people will continue to be the most flexible and responsive resource a company may have [Bley, *et al.*, 2004]. In addition, it has been verified through empirical studies in the literature that automation has been implemented in many companies beyond economical value [Lay *et al.*, 2001]. Bley *et al.* [2004] reported that about one third of German companies that had invested in high automation have recognized that these solutions are not flexible enough to cope with the dynamic challenges of the current and future manufacturing environment. Based on that, they started to reduce the level of automation in their companies. Therefore, it seems to be a fact that people will continue to contribute significantly to the current and emerging manufacturing systems like Reconfigurable Manufacturing Systems (RMS).

As illustrated in the overall framework presented in Chapter 3, there is a need for assessing the yield of manual operations in order to calculate the overall capability of processes. In this research, it is assumed that the yield of a manual operation is equivalent to the probability that the operator successfully performed his job. In this chapter, a model for predicting the probability of errors due to human involvement in manufacturing tasks is presented.

Human Error Probability (HEP) is defined in the literature, for discrete tasks, as the number of errors divided by the number of opportunities for errors [Sträter, 2000]. Assessment of human error probabilities has been addressed in the literature as an integral part of Human Reliability Assessment (HRA) methodologies. In the field of HRA, several approaches have been developed since the early 1980s. For instance, Technique for Human Error Reliability Prediction (THERP), Human Cognitive Reliability (HCR), Absolute Probability Judgement (APJ), Human Error Assessment and Reduction Technique (HEART), Systematic Human Action Reliability (SHARP), Success Likelihood Index Method (SLIM), Socio-Technical Assessment of Human Reliability (STAHR), and (Tecnica Empirica Stima Errori Operatori - Empirical Technique for Estimating Operators' Errors (TESEO)) have all been annotated and summarized in critical reviews by Lee et al. [1988], Kirwan [1992 a, and b, 1998], Hollnagel [1998], and Spurgin and Lydell [2002].

For instance, one of the simplest methods is the Absolute Probability Judgement (APJ). This method requires either one expert or a group of experts with expert knowledge about the domain. The task of the expert(s) is to assess the HEP in the given context. The assessment can be done by experts either collaboratively or individually. Another example is the Human Error Assessment and Reduction Technique (HEART), which involves a classification of identified tasks into prescribed groups from a look-up table, which leads to a nominal human error probability (HEP). Error-producing conditions are applied to the task scenario under investigation in the form of multiplying value, and these values may be themselves factored according to the scenario. The combination of nominal HEP, error producing conditions and factoring ultimately leads to a final HEP value. Expert opinion is used to validate the selection of the task grouping and the error producing conditions. In addition, one of the most popular approaches is the Technique for Human Error Rate Prediction (THERP) [Swain and Guttmann, 1983], which was developed for application in nuclear power industry. This approach recognized the utility of a database, but focused on the ability to synthesize task-performance HEPs via event-tree, and the facility for modifying a "basic" or nominal HEP from the database by performance shaping factors (PSFs), to reflect the parameters in the situation being assessed. Recently, Bubb [2005] applied the THERP method to a manufacturing example in the electronic industry. He concluded that although the method was mainly developed for error prediction in high risk environments, it can be successfully applied to production processes.

Despite of the wide literature of HRA methods, the scope of application of these methods is mostly in the high risk systems such as nuclear power plants. Moreover, most of these methods, even when used in industrial applications, are originally developed and used for probabilistic safety assessment of accidents in industry. Reviewing the literature reveals that there is a lack in the research work that applies such methods in assessing the probability of errors for direct workers in a manufacturing context. In addition, these approaches are mainly dependent on empirical data or expert judgement. Most of these methods rely on the availability of human error probabilities for elemental tasks using databases for basic error probabilities, which is context independent. The model proposed in this chapter provides a manufacturing context specific model as it considers the error causes that are suitable for manufacturing environment as well as it developed a separate measure for task error proneness that can provide an indication for the necessity for the elimination of human involvement in cases associated with tasks that are highly error prone.

6.2. THE OVERALL PROCEDURE

The procedure considered in this research for assessing error probabilities due to human involvement in manufacturing tasks is illustrated in Figure 6.1. The initial step is concerned with the identification of the factors that affect the performance of the worker in a manufacturing context using cognitive mapping. Then, cause and effect analysis is used to classify those factors and to help in identifying the root causes of quality problems due to human involvement. The final step is concerned with the identification of the sets of attributes that contribute to the human error and using the multi-attribute utility theory [Keeney and Raiffa, 1993] to develop a measure for human errors based on those sets of attributes. Applying the multi-attribute theory involves two major steps.

First, developing utility functions to represent the utility of single attributes. A utility function is capable of translating the value of an attribute into "utility units". A utility function $u(x_i)$ serves to assess the effects of the magnitudes of the x_i attribute on the utility u(xi). In this research, information from previous literature will be used in the development of the individual utility functions. Engineering as Collaborative Negotiation (ECN) [Lu and Jin, 2005] approach as well as individual decision making are both used in the determination of the trend and the weight of the utility functions. The second step is concerned with developing a model for calculating the aggregated value of utility that represents human errors.

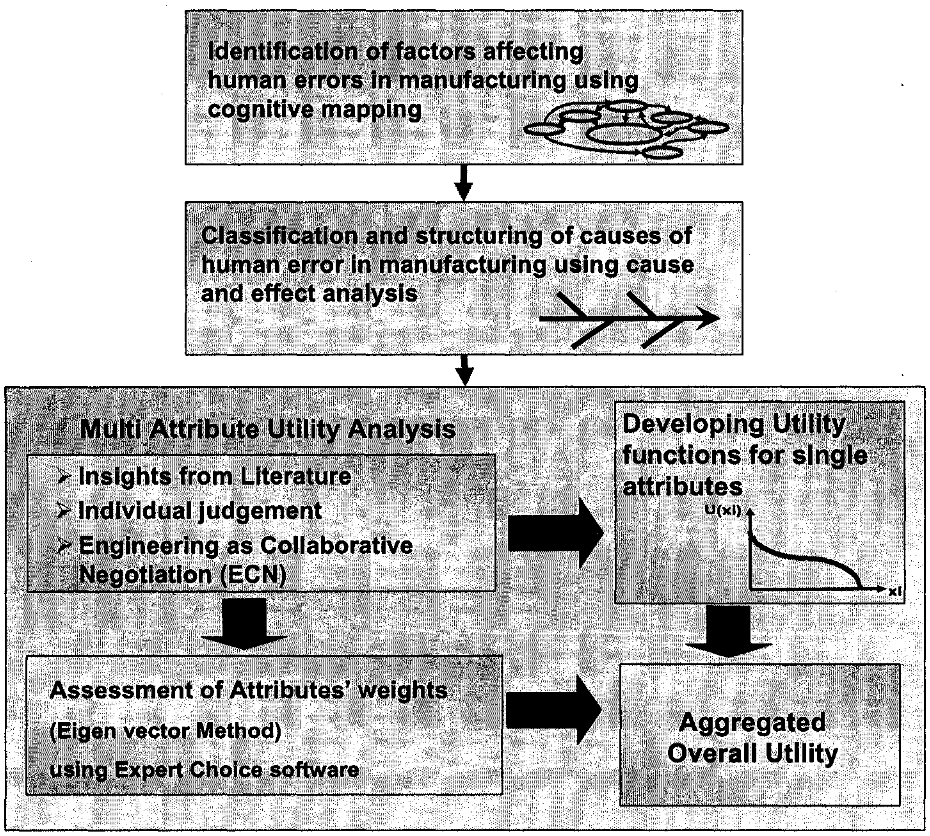


Figure 6.1 Overall Procedure for Assessing Errors due to Human Involvement

6.2.1. Root causes of Quality Problem Associated with Human Involvement

As quality can be highly affected by the variability and errors associated with human involvement in manufacturing, it is critical to assess and identify the root causes of variability and errors in the performance of manufacturing tasks. To do so, the different factors affecting worker performance in a reconfigurable manufacturing context have been identified using cognitive mapping as shown in Figure 6.2. The cognitive map illustrates the interrelationships between the different factors and indicates that there are many interrelated factors that contribute to variability and errors in worker performance. Using cause and effect analysis, those factors have been analyzed and classified as task related factors, worker related factors, system related factors, and management related factors as shown in Figure 6.3.

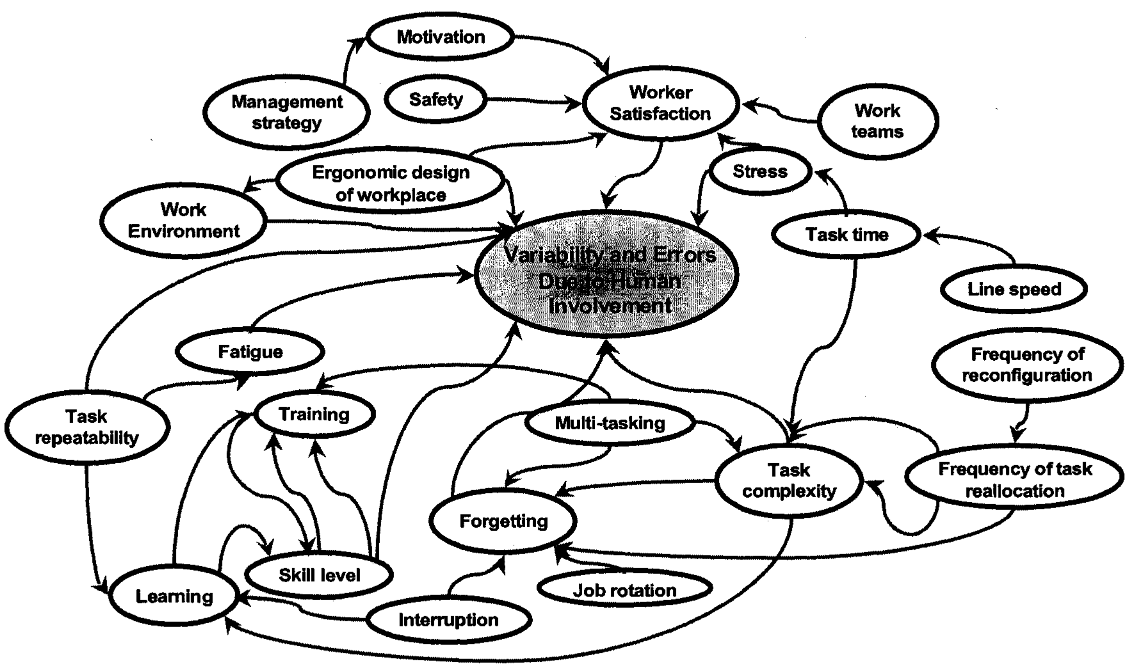


Figure 6.2 Cognitive mapping of the different factors affecting variability and error in human performance in a manufacturing context

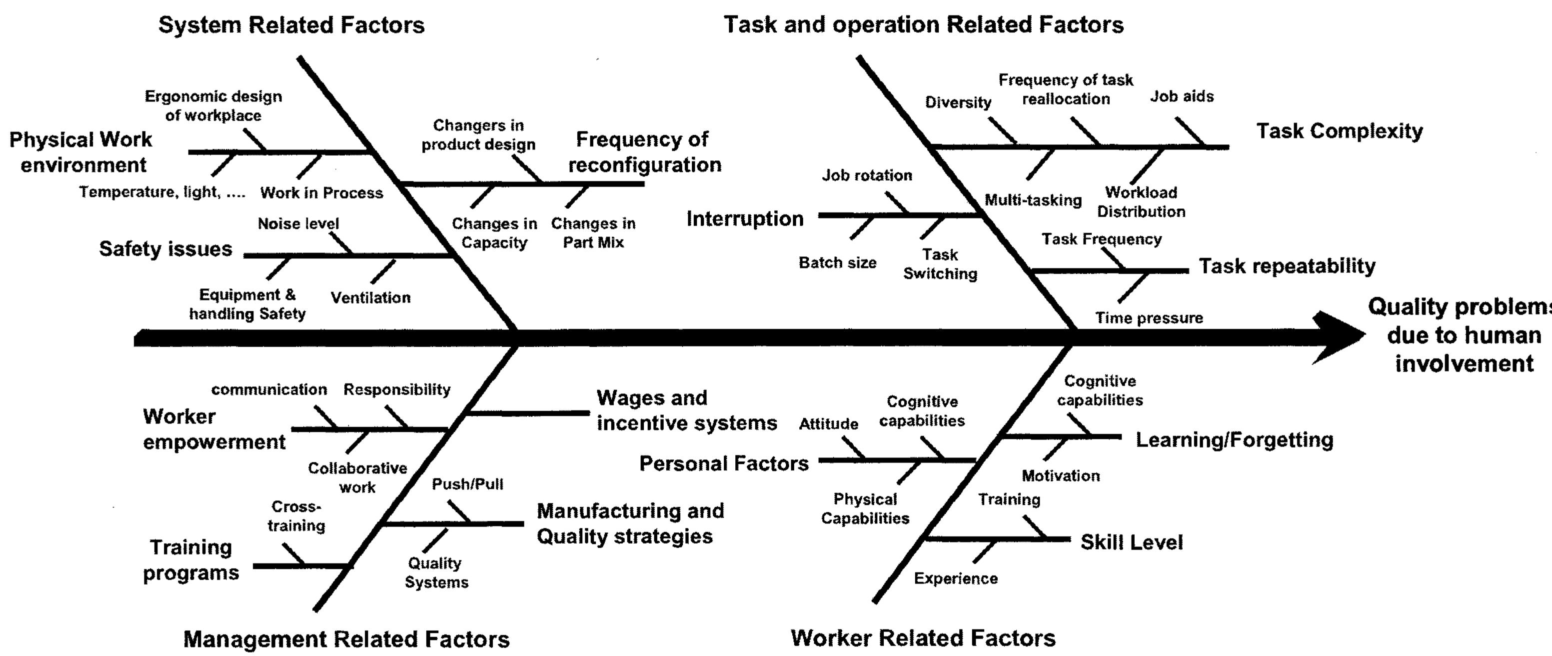


Figure 6.3 Overall Cause and Effect Diagram of The Quality Problems due to Human Involvement

6.3. MULTI-ATTRIBUTE UTILITY THEORY

Multi-attribute utility analysis is a powerful operational research tool that has been used in a wide range of applications by several researchers [Keeney, 1992; Barron and Barret, 1996; Kelly and Thorne, 2001; Bichler and Kalagnanam, 2005; and Downen, 2005]

6.3.1. THE ADDITIVE UTILITY FUNCTION

If it can either be proved, or reasonably assumed, that the criteria are mutually preferentially independent of each other and if uncertainty is not formally built into the multi-attribute model, then the simple linear additive evaluation model is applicable. The linear model shows how an option's values on the various attributes can be combined into one overall value. This is done by multiplying the value of each attribute by a weight, and then adding all those weighted scores together. However, this simple mathematical expression is only appropriate if the criteria are mutually preference independent, as shown by [Keeney and Raiffa, 1993]. A theorem by [Keeney and Raiffa, 1993] states that:

"Given attributes $X_1,......,X_n$, $n \geq 3$*, an additive utility function*

$$u(X_1, X_2, \cdots, X_n) = \sum_{i=1}^{n} u_i(X_i)$$

(where u_i *is a utility function over* X_i*) exists if and only if the attributes are mutually preferentially independent"*

Furthermore, Keeney and Raiffa [1976 and 1993] define preferential independence as:

"The set of attributes Y is preferentially independent of the complementary set Z if and only if the conditional preference structure in the y space given z' *does not depend on* z'*. More symbolically, Y is preferentially independent of Z if and only if for some* z'*,*

$$[(y', z') \succsim (y'', z')] \Rightarrow [(y', z) \succsim (y'', z)], \ \forall\, z, y', y'' \text{"}.$$

In other words, this definition means that an attribute y is preferentially independent of another attribute z, if preferences for values of the attribute y do not depend on the value of attribute z.

Where the preference relations between two attributes are written, according to [Keeney and Raiffa, 1993], as follows:

$y \sim z$; means y is indifferent to z

$y \succ z$; means y is preferred to z

$y \succsim z$; means "not $[y \prec z]$"

Figure 6.4 depicts an example of how a decision maker might structure his preferences for points in a two-dimensional evaluation space. This example assumes that the decision maker does not care whether (y', z') or (y'', z'') is achieved, and this is illustrated by having the both points on the same indifference curve. However, point (y''', z''') is preferred to (y', z'), therefore (y''', z''') lies on a more preferred indifference curve.

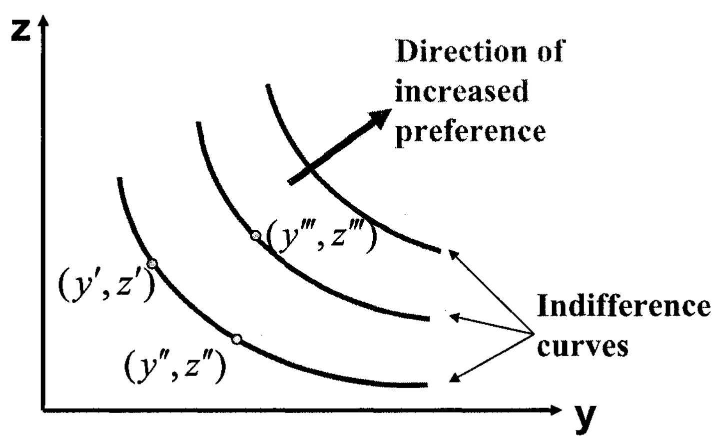


Figure 6.4 Indifference curves [Keeney and Raiffa, 1976]

6.4. MODEL DEVELOPMENT

In order to predict the human error in a reconfigurable manufacturing context, the interaction between task characteristics, worker capabilities as well as work environment should be considered as shown in Figure 6.5. It should be noted that these attributes are a subset of all the factors illustrates in Figure 6.3. It is assumed that these are the main sets of attributes affecting quality, and these are also reasonably assumed to be preferentially independent. The overall utility function will account for the probability of error for a task, with specific characteristics, that is being performed by an operator with specific capabilities in a certain manufacturing environment.

The multi-attribute utility theory will be used to assess the human error probability as a function of these different attributes. Therefore, the multi-attribute utility theory will be used to assess the human error probabilities as a function of these different attributes.

6.4.1. ATTRIBUTES REPRESENTING TASK ERROR PRONENESS

It has been reported in the literature that the human performance is strongly affected by the characteristics of the task being performed [Kvalseth, 1978], [Nembhard and Uzumeri, 2000], [Nembhard and Osothslip, 2002], and [Jiang *et al.*, 2003]. The concern here is the task attributes that affect the proneness to occurrence of errors. The considered task error-proneness attributes include: inherent difficulty of physical and cognitive task elements, diversity of task elements, coupling between task elements, as well as the level of implementation of job aids and mistake proofing techniques.

In order to analytically derive the contribution of each attribute to the task error proneness, we should first define:

X : Set of attributes representing the task error proneness; $X = \{x_1, x_2, x_3, x_4, x_5\}$

x_1 : An attribute representing the average inherent difficulty of cognitive task elements,

x_2 : An attribute representing the average inherent difficulty of physical task elements,

x_3 : An attribute representing the diversity between task elements

x_4 : An attribute representing the coupling between task elements

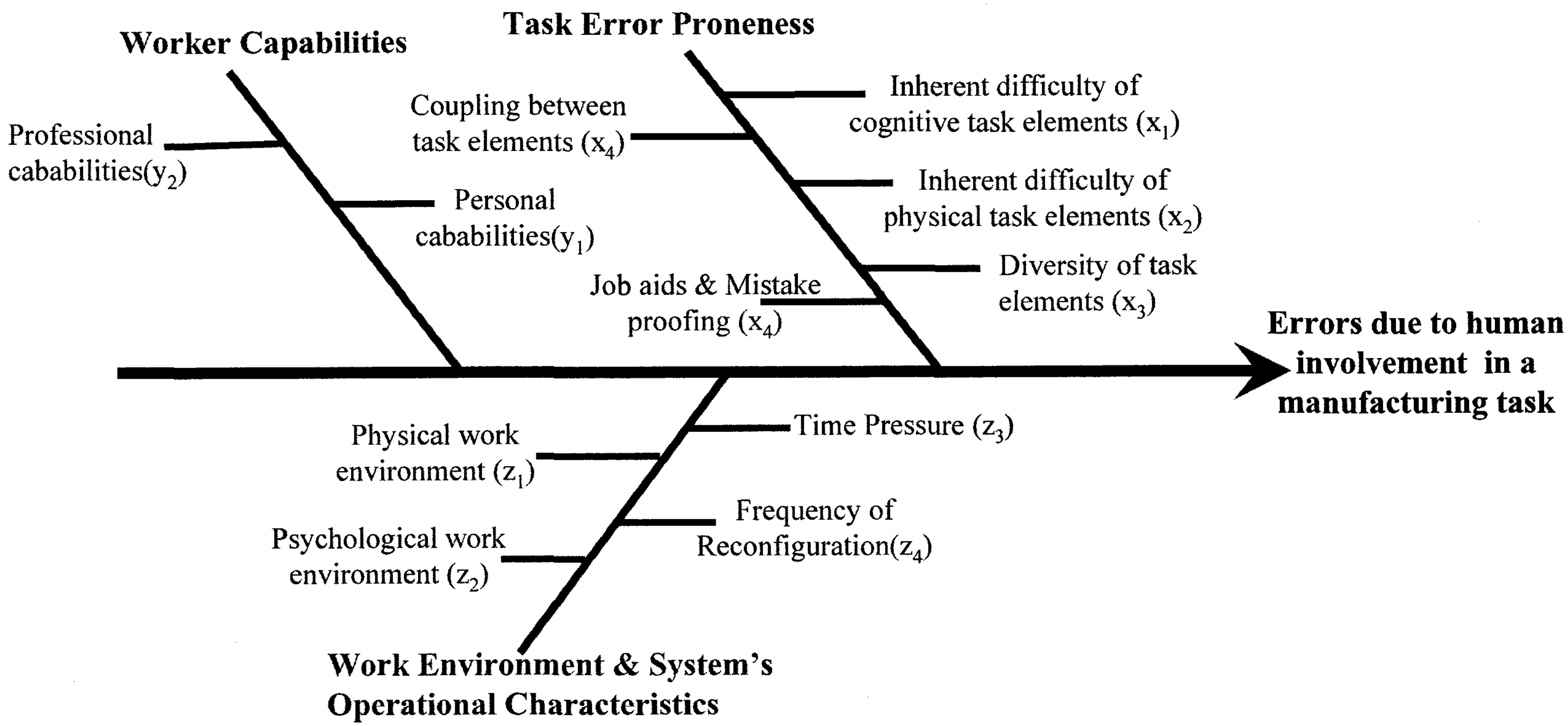


Figure 6.5 The Major Sets of Attributes Contributing to Human Error in Manufacturing

x_5 : An attribute representing the level of job aids and mistake proofing implementation

$u_x(x_i)$: Task error proneness utility for the attribute x_i , $i = 1, 2, \ldots, 5$

6.4.1.1. Inherent Difficulty of Task Elements

In this study, the task will be decomposed to its basic elements. These are classified as the cognitive and the physical task elements. This classification is based on the assessment of whether the task element is physically or cognitively demanding. Assessing the level of difficulty of physical or cognitive task elements will be based on a subjective score that ranges from 0 to 10; with the zero representing the easiest and 10 for the most difficult. Task error proneness utility functions for the inherent difficulty of cognitive and physical task elements are shown in Figure 6.6 and Figure 6.7, respectively. It should be noted that all the individual utility functions in this study have been assessed and constructed based on the procedure recommended by Keeney and Raiffa [1976] as indicated in Appendix C. As shown in Figure 6.6 and Figure 6.7

Figure 6.7, the utility functions for the difficulty of cognitive and physical task elements have been constructed to be monotonically increasing as the difficulty increases.

The difficulty of cognitive task elements, x_1, can be calculated as using Equation 6.1, and its utility can be expressed as in Equation 6.2.

$$x_1 = \frac{\sum_{j=1}^{M_c} D_{cj}}{M_c} \tag{6.1}$$

$$u_x(x_1) = 0.1735\, x_1^{0.7577} \tag{6.2}$$

where,

M_c : Number of cognitive task elements

D_{cj} : Inherent difficulty of cognitive task element j .

The average difficulty of physical task elements, x_2, can be calculated as using Equation 6.3, and its utility function can be expressed in Equation 6.4.

$$x_2 = \frac{\sum_{k=1}^{M_P} D_{pk}}{M_p} \tag{6.3}$$

$$u_x(x_2) = 0.0189\, x_1^{0.3972} \tag{6.4}$$

where,

M_P : Number of physical task elements

D_{pk} : Inherent difficulty of physical task element k

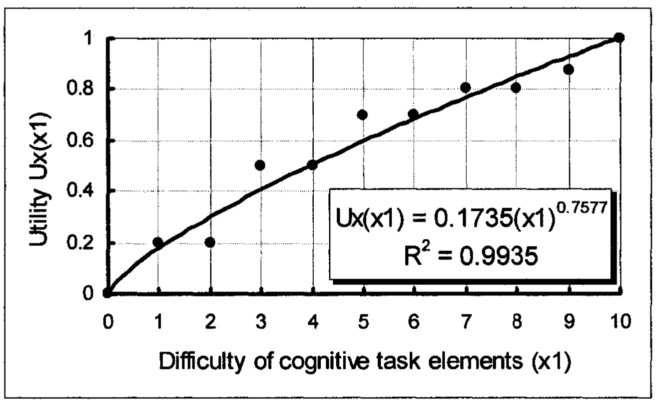


Figure 6.6 Utility Function for Difficulty of Cognitive Task Elements

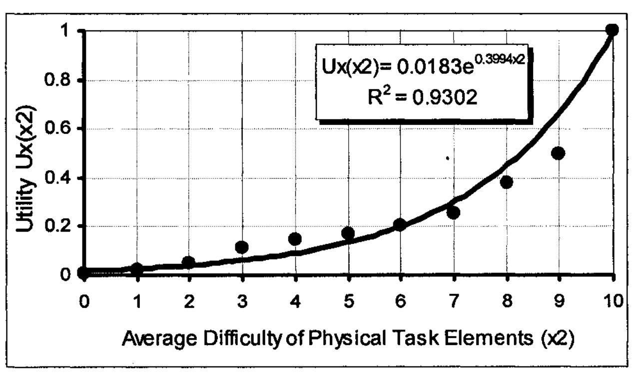


Figure 6.7 Utility Function for Difficulty of Physical Task Elements

6.4.1.2. Diversity of Task Elements

The information diversity measure that has been proposed by W. ElMaraghy and Urbanic [2004] has been adopted and implemented to assess the task diversity. The task diversity, T_D , will be expressed as a percentage ratio of the unique task elements to the total number of task elements as in Equation 6.5.

$$x_3 = T_D = (M_D / M)\% \ , \qquad (6.5)$$

where,

M : Total number of task elements, $M = M_C + M_P$

M_D : Number of unique task elements

T_D : Diversity of task elements

The task error proneness utility of the task diversity has been constructed to monotonically increase as the task diversity increases as shown in Figure 6.8. This utility function can be expressed as: $u_x(x_3) = x_3^2$.

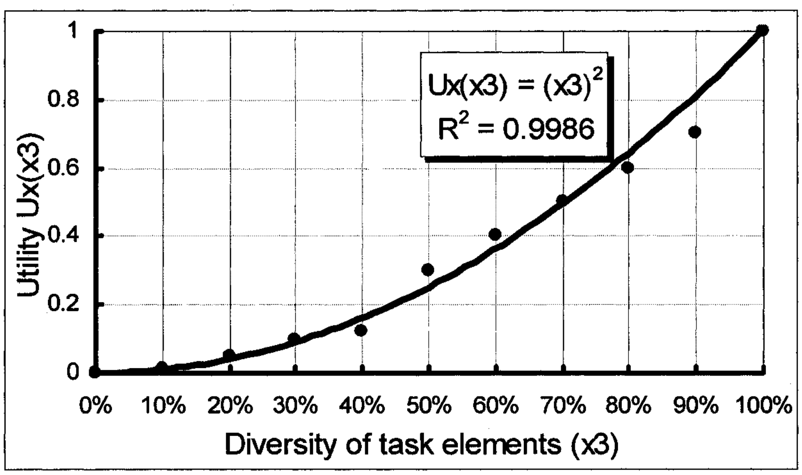


Figure 6.8 Utility Function for Diversity of Task Elements

6.4.1.3. Coupling between Task Elements

The attribute concerned with the coupling between task elements, x_4, will be considered to account for the dependencies between task elements and the propagation of errors. Two task elements are coupled if performing one in an inappropriate way could result in an inappropriate execution of the other element. To assess the coupling between task elements, a 0-1 matrix of task elements will be constructed and assessed through the ratio between the number of non-zero off diagonal elements and the total size of the matrix. The degree of coupling between task elements can be identified using the Equation 6.6

$$x_4 = T_{coupling} = N_{non-zero} /(M * (M - 1))/2 \tag{6.6}$$

where,

$T_{coupling}$: Coupling between task elements

$N_{non-zero}$: None-zero off diagonal entries in the task elements matrix

M : Total number of task elements, $M = M_C + M_P$

The task error proneness utility of the coupling between task elements has been constructed to linearly increase as the degree of coupling increases as shown in Figure 6.9. This utility function can be expressed as in Equation 6.7.

$$u_x(x_4) = x_4 \tag{6.7}$$

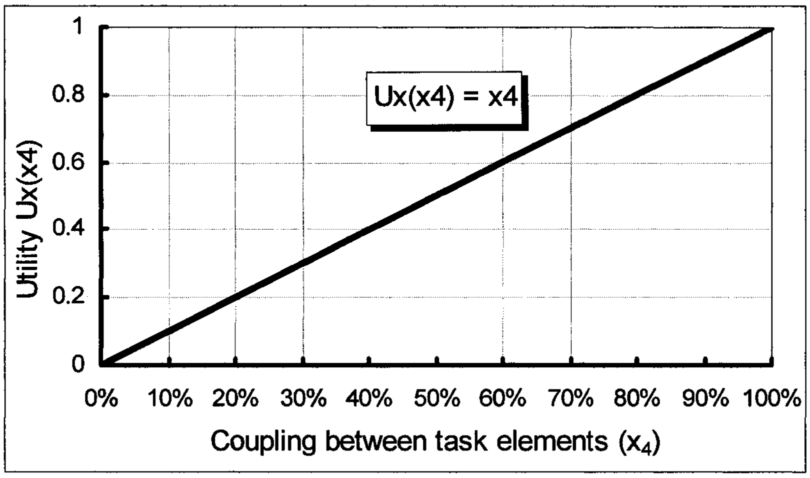


Figure 6.9 Utility Function for Coupling between Task Elements

6.4.1.4. The Level of Implementing Job Aids And Mistake Proofing Techniques

Job aids and mistake proofing techniques can decrease or eliminate the chances of committing errors. The attribute that will account for this, x_5, can assess the level of job aids and mistake proofing implementation. This can be calculated as a percentage ratio of the task elements where job aids and mistake proofing are implemented to the total number of task elements. The task error proneness utility of the job aids and mistake proofing implementation has been constructed to monotonically decrease as the level of implementation increases as shown in Figure 6.10. In this utility, with 100% implementation of mistake proofing, it is expected that the utility value will be zero. This represents the case where the mistake proofing implementation eliminates the chances of errors [Chao et al. 2001, and Cheldelin and Ishii, 2004]. This utility function can be expressed as in Equation 6.8

$$u_x(x_5) = 1 - x_5 \tag{6.8}$$

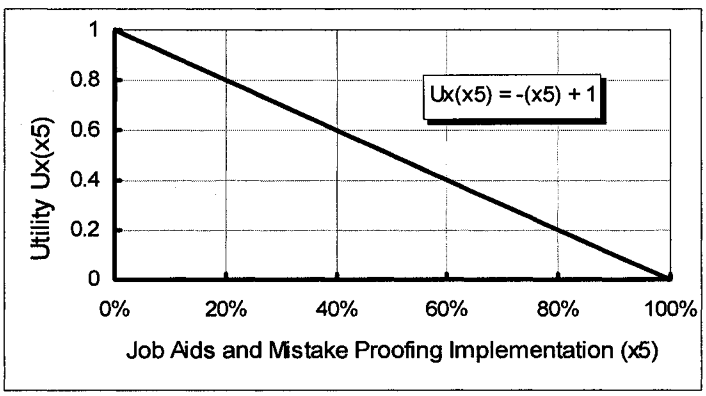


Figure 6.10 Utility Function for Job Aids and Mistake Proofing Implementation

6.4.1.5. Overall Task Error Proneness Utility Function

It has been verified that all the attributes contributing to the overall task error proneness, are mutually preferentially independent. To show this, we can, for instance, consider the inherent difficulty of cognitive task elements and the diversity between task elements and attempt to verify the preferential independence condition for these two attributes.

According to the definition of preferential independence that has been mentioned in Section 6.3.1, it will be found that it is preferable to have a task with low inherent difficulty of cognitive elements whatever the value of the diversity attribute. This means that the difficulty of cognitive elements is preferentially independent of task diversity. Also, it is preferable to have a task with low diversity regardless of the value of the difficulty of cognitive task elements. This means that task diversity is preferentially independent of difficulty of cognitive task elements attribute. Based on that, we can conclude that the difficulty of task elements attribute and the task diversity attribute are mutually preferentially independent. The same reasoning has been applied for all pairs of attributes and it has been verified that all the attributes are mutually preferentially independent. Therefore, according to the theorem stated in Section 6.3.1 [Keeney and Raiffa, 1976], the additive utility function can be used to assess their overall utility u_x.

$$u_x = \sum_{i=1}^{5} w_{xi}\, u_x(x_i), \tag{6.9}$$

where, w_{xi} is weight for attribute x_i, i =1,2,3,4,5,

and

$$\sum_{i=1}^{5} w_{xi} = 1. \tag{6.10}$$

It is worth mentioning here that the weight assessment can be performed based on the subjective judgment of the decision maker or based on collaborative assessment through the implementation of the ECN approach [Lu and Jin, 2005]. In this research, the eigenvector method [Saaty, 1980] has been used for the assessment of weights. This method involves comparisons between each pair of attributes and constructing a matrix known as pairwise comparison matrix (A). The entry w_{ij} represents how much more important attribute i is than attribute j in contributing to the overall utility. This relative importance is to be measured on an integer-valued 1-9 scale, with each number having the interpretation provided in Table 6.1.

Table 6.1 Interpretation of Entries in a Pairwise Comparison Matrix [Saaty, 1980]

Verbal Judgmen	Numerical value
Extreme	9
Very Strong to Extreme	8
Very Strong	7
Strong toVery Strong	6
Strong	5
Moderate to Strong	4
Moderate	3
Equal to Modirate	2
Equal	1

In general, the comparison matrix (A) is a square matrix with non-zero column vectors as shown in Equation (6.11). The comparison matrix is a reciprocal matrix; where $w_{ij} = w_{ji}$, and $w_{ii} = 1$ when attribute i is to be compared to itself.

$$A = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{bmatrix} = \begin{bmatrix} \frac{w_1}{w_1} & \frac{w_1}{w_2} & \cdots & \frac{w_1}{w_n} \\ \frac{w_2}{w_1} & \frac{w_2}{w_2} & \cdots & \frac{w_2}{w_n} \\ \vdots & \vdots & & \vdots \\ \frac{w_n}{w_1} & \frac{w_n}{w_2} & \cdots & \frac{w_n}{w_n} \end{bmatrix} \tag{6.11}$$

Using the concept of eigenvalue λ associated with the matrix A, the eigenvector W represents the vector of relative importance weights of the attributes.

$$
\begin{bmatrix}
\frac{w_1}{w_1} & \frac{w_1}{w_2} & \cdots & \frac{w_1}{w_n} \\
\frac{w_2}{w_1} & \frac{w_2}{w_2} & \cdots & \frac{w_2}{w_n} \\
\vdots & \vdots & & \vdots \\
\frac{w_n}{w_1} & \frac{w_n}{w_2} & \cdots & \frac{w_n}{w_n}
\end{bmatrix}
\times
\begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_n \end{bmatrix}
= \lambda \times
\begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_n \end{bmatrix}
= \lambda \times W \qquad (6.12)
$$

In this research, the Expert Choice Software has been used in assessing the weights for the attributes. For the task error proneness attributes, the comparison matrix is illustrated in Figure 6.11 Pairewise Comparison Matrix using Expert Choice for Task Error Proneness Attributes. The comparison expresses the relative contribution of each attribute to the task error proneness. For instance, the difficulty of cognitive task elements should be assigned a weight higher than the difficulty of physical task elements because it is expected that the cognitive load has a higher impact on the error occurrence that the physical load. The calculated weight values for the task error proneness attributes, using Expert Choice, are as follows:

$w_{x1} = 0.221$, $w_{x2} = 0.046$, $w_{x3} = 0.221$, $w_{x4} = 0.122$, and $w_{x5} = 0.390$.

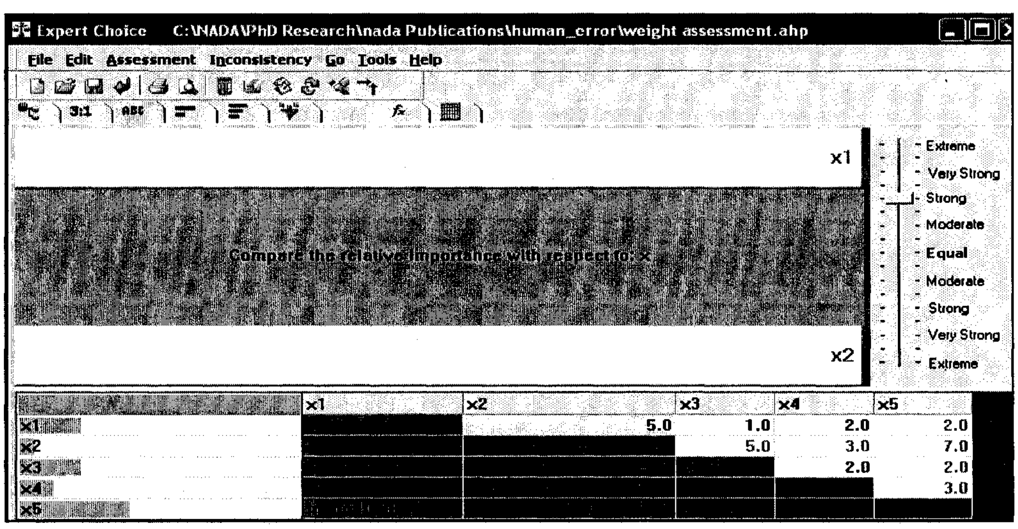


Figure 6.11 Pairewise Comparison Matrix using Expert Choice for Task Error Proneness Attributes

6.4.2. OPERATOR'S CAPABILITIES SET OF ATTRIBUTES

It has been demonstrated in literature that the personal and professional capabilities of the workers affect their performance and in turn affects the manufacturing system performance [McCreey and Krajewski, 1999], [Needy et al., 2000], [Govindaraju et al., 2001], [Buzacotte, 2002], and [Norman et al., 2002].

Let's define:

Y : Set of attributes representing the operator's capabilities, $Y = \{y_1, y_2\}$

y_1 : An attribute representing the operator's personal capabilities such as attitude, motivation, learning capabilities, age, and culture

y_2 : An attribute representing the operator's professional capabilities such as skill level, experience, and training level

$u_y(y_i)$: Operators characteristics utility for the attribute y_i, $i = 1,2$

The values of both of these attributes will be evaluated through a subjective ranking system in a range from 0 to 10; with 0 assigned for an operator with the worst capabilities and 10 for one with the best capabilities. Both the utility functions of these attributes are constructed to be monotonically decreasing as the worker capabilities increase as shown in Figure 6.12 Figure 6.13. The utility function concerned with operator's personal capabilities is designed to assign very high utility for operators with low personal capabilities level and to assign very low utility for operators with high personal capabilities level. In the mid level of personal capabilities, the utility decreases almost with constant rate as the personal capability level increases. However, the utility function concerned with operator's professional capabilities decreases linearly as the professional capabilities increase. These utility functions can be expressed as:

$$u_y(y_1) = 0.0025y_1^3 - 0.0367y_1^2 + 0.0175y_1 + 1 \tag{6.13}$$

$$u_y(y_2) = 1 - 0.1y_2 \tag{6.14}$$

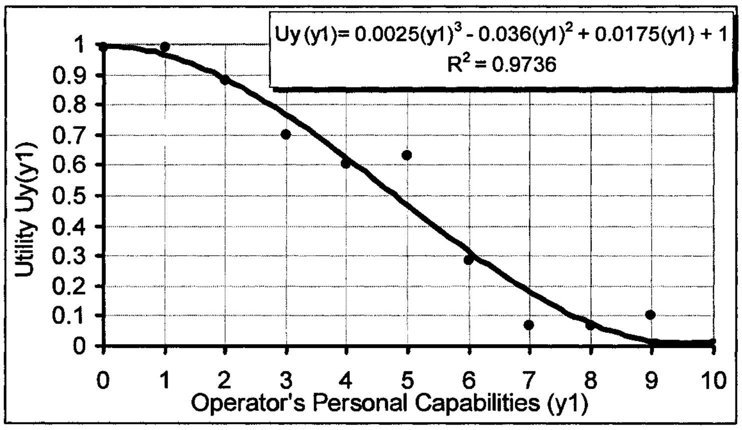


Figure 6.12 Utility Function for Operator's Personal Capabilities

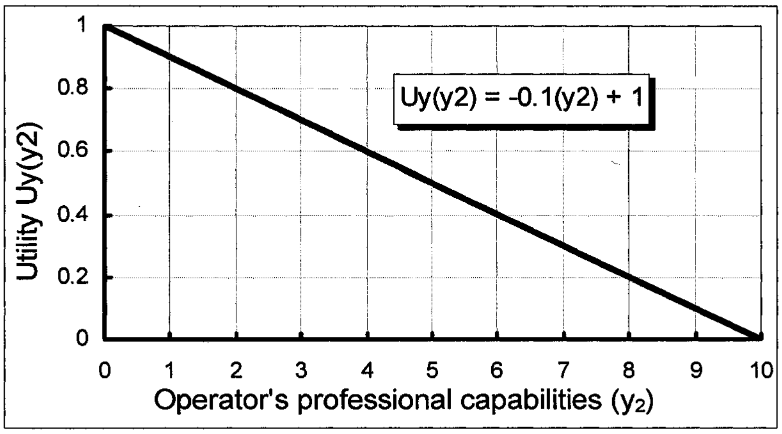


Figure 6.13 Utility Function for Operator's Professional Capabilities

6.4.2.1. Overall Operator's Capabilities Utility

It has been also verified that personal capabilities and professional capabilities are preferentially independent using the same reasoning explained in Section 6.4.1.5. Therefore, the additive utility function can be used to assess their overall utility u_y.

$$u_y = \sum_{i=1}^{2} w_{yi} \, u_y(y_i), \tag{6.15}$$

where, w_{yi} is weight for attribute y_i, i =1,2, and

$$\sum_{i=1}^{2} w_{yi} = 1 \tag{6.16}$$

The weight assessment has been accomplished using the same method as in the case of task error proneness. The comparison matrix the operator's attributes is illustrated in Figure 6.14. In which, the operator's professional capabilities demonstrated to have moderate to equal importance in contributing to the occurrence of error. The calculated weight values for the task error proneness attributes, using Expert Choice, are as follows: $w_{y1} = 0.333$, and $w_{y2} = 0.667$.

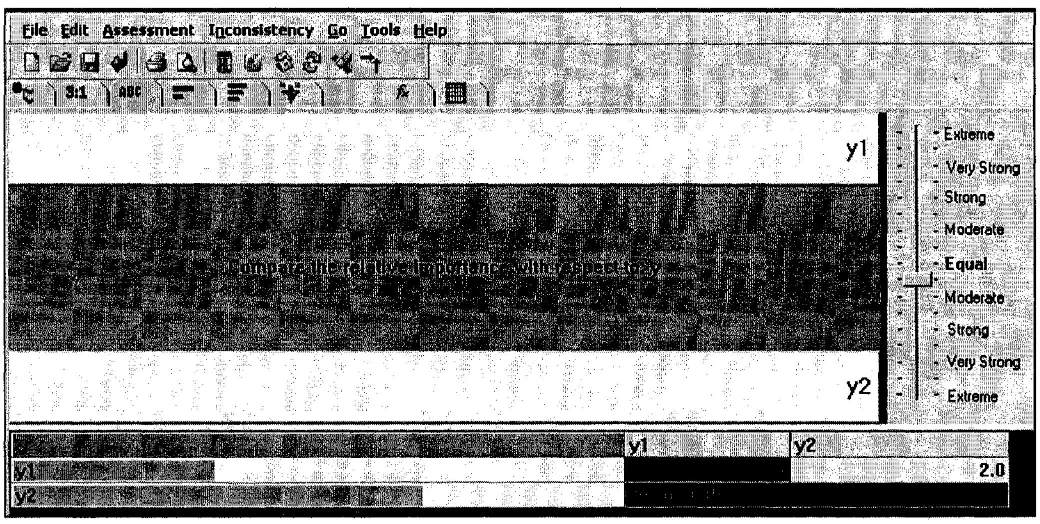


Figure 6.14 Pairewise Comparison Matrix for Operator's Attributes

6.4.3. WORK ENVIRONMENT AND SYSTEM OPERATIONAL CHARACTERISTICS

Work environment characteristics as well as system's operating characteristics that could affect the human error will be captured through the set of attributes Z. Let us define:

Z : Set of attributes representing the work environment as well as system's operational characteristics, $Z = \{z_1, z_2, z_3, z_4\}$

z_1 : An attribute representing the physical work environment such as ergonomic design of workplace, temperature, and noise.

z_2 : An attribute representing the psychological work environment such as worker empowerment, collaborative work, wages, and incentives.

z_3 : An attribute representing the time pressure

z_4 : An attribute representing the frequency of reconfiguration

$u_z(z_i)$: Work environment utility for the attribute z_i , $i = 1, 2, \ldots, 4$

6.4.3.1. Work Environment

Two attributes have been considered to account for the work environment. One represents the physical work environment and the other represents the psychological work environment. It is well established in the literature that the physical work environment can highly affect the worker performance in terms of the quality of the output. For instance, empirical verification of the existence of a positive relationship between the ergonomic design of workplaces and achieved product quality levels has been addressed in several publications [Helander and Burri, 1994], [Eklund, 1995], [Schwind, 1996], [Gonzlalez et al., 2003], and [Shikdar and Das, 2003]. In this study, the attribute Z_1 will account for assessing "how good is the physical work environment". To do so, a ranking system that considers the ergonomic design of workplace, the safety, as well as other factors that might contribute to the quality of the physical work environment. This ranking system ranges from 0 to 10; with zero assigned to the worst physical work environment and 10 for the best. Similarly, the attribute, Z_2, will be considered to assess the psychological work environment through a ranking system similar to the used with Z_1. The psychological work environment ranking system should include the criteria that affects the worker satisfaction and hence affects his performance. These criteria could include supervision, wages and incentive, as well as collaborative work teams and worker empowerment.

The utility functions for physical and psychological work environment have been constructed to be monotonically decreasing as the measure of their work environment increases. These two utilities have been construct the way shown in Figure 6.15 and Figure 6.16 to reflect that at moderate levels of work environment, the utility resulting from the psychological work environment is still much higher than the one resulting from the physical work environment. This supports the argument that the psychological work environment has greater effects on the occurrence of errors. Also, it indicates that achieving low error probabilities requires more effort to be directed toward achieving excellent physical work environment. These utilities are calculated as:

$$u_z(z_1) = e^{-0.4z_1} \tag{6.17}$$

$$u_z(z_2) = -0.009z_2^2 - 0.01z_2 + 1 \tag{6.18}$$

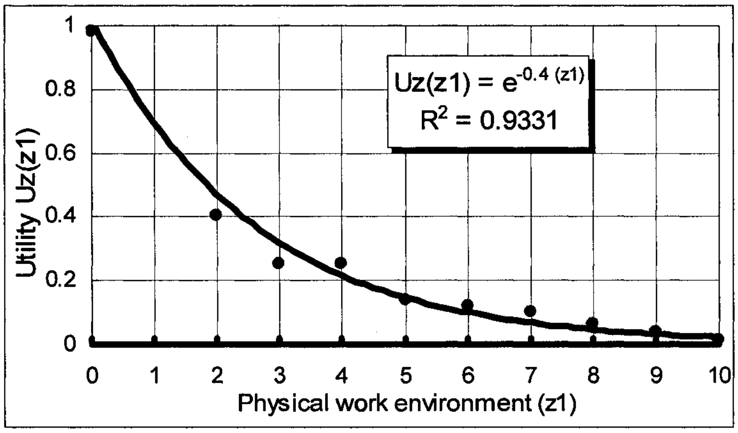


Figure 6.15 Utility Function for Physical Work Environment

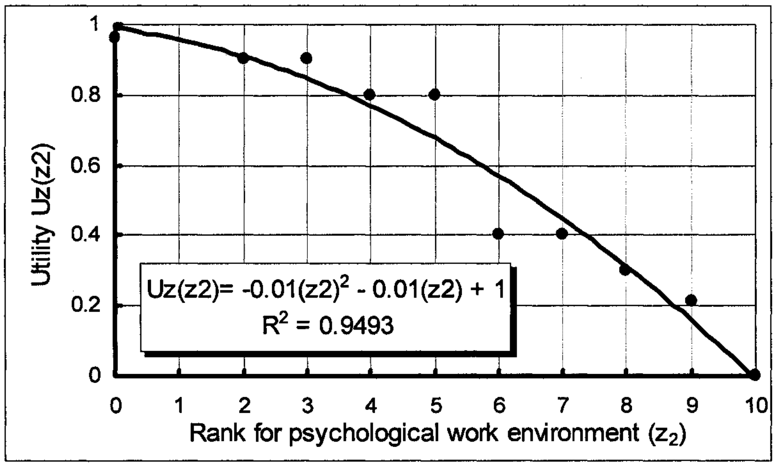


Figure 6.16 Utility Function for Psychological Work Environment

6.4.3.2. Time Pressure

The time pressure as an attribute contributing to human error probabilities will account for measuring how the task that is being performed is stressful in terms of the available time for its completion. Therefore, the time pressure will be assessed as percentage ratio between operator's task time and the planned cycle time

$$z_3 = T_{tp} = T_S / CT, \tag{6.19}$$

where

T_S : The operator's task time

CT : The planned cycle time

The previous expression for z_3 is valid only when there is no sharing or collaboration in performing the task. In case of task sharing,

$$z_3(sharing) = \frac{Task\,time\ per\ operator * no.\ of\ operators}{CT} \tag{6.20}$$

Some researchers have considered the relation between human error and the time available for performing the task. For example, Boring and Gertman [2004] have assigned values for the human error probabilities for different levels for the available time. In their assignment of probability values, they assumed that the probability of error will continue to decrease with increase of time available. This could be true in situations that deal with safety issues and the response to emergency situations. However, in dealing with repetitive manufacturing tasks the assignment of values should be different.

In our model, for the construction of the time pressure utility function that is shown in Figure 6.17 considers: When the operator's task time exactly equals to the planned cycle time, this will represent the most stressful situation with time pressure 100%. At this highly stressful point, the probability of committing errors due to time pressure is at its maximum value. Therefore, the utility function reaches to 1 at 100% time pressure. As the time pressure decreases the utility decreases until it reach to zero; where there is no effect for the time pressure. In other words, there is enough time to perform the task with no time stresses. However, too much decrease in the time pressure below 30% could result in a task that is not repetitive. It means that some effects of forgetting will start to affect the probability of committing errors. Therefore, the utility starts to slightly increase again. This type of utility function is called nonmonotonic utility functions. The time pressure utility can be assessed using the following relation:

$$u_z(z_3) = -105.7 z_3^6 + 312 z_3^5 - 346.39 z_3^4 + 181.34 z_3^3 - 43.434 z_3^2 + 2.8781 z_3 + 0.3 \qquad (6.21)$$

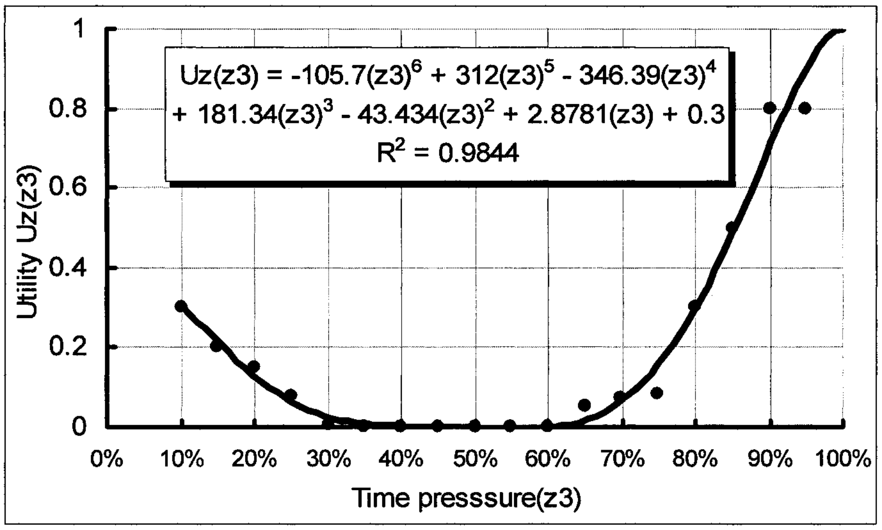


Figure 6.17 Utility Function for Time Pressure

6.4.3.3. Frequency of Reconfiguration

The attribute z_4 accounts for the frequency of the facility reconfiguration that is associated with task reallocation. Frequent system reconfiguration is expected to have negative impacts on the learning process [Askin and Huang, 1997], and [Jaber and Bonny, 2003]. Hence, the frequency of reconfiguration can be considered as a factor that directly affects the probability of human error. This attribute can be measured in terms of the number of reconfigurations during the system's life cycle. In the context of reconfigurable manufacturing system, it can be assumed that the expected life cycle for the system is about 10 years. In order to construct the utility function for that attribute, the highest expected frequency of reconfiguration can be assumed to be associated with reconfiguring the system every shift. On the other hand, the lowest frequency of reconfiguration could be associated with no reconfigurations during the life cycle; i.e. only the initial configuration of the system.

The utility is assigned the value zero for no reconfigurations and the value 1 for reconfiguring the system every shift. The expected utility values for different reconfiguration frequencies are shown in Table 6.2. These values have been estimated by discussing the effect of system reconfiguration on the worker performance when the system is to be reconfigured every year, every month, etc. The classical utility theory has been developed to deal with individual decision making or at most it is highly dependent on discussions and interactions between the problem's analyst and the decision maker. However, in this research the ECN (Engineering as Collaborative Negotiation) approach has been applied and a group of researchers at the Intelligent Manufacturing Systems Centre, University of Windsor, has brain stormed and made a joint collaborative decision regarding the relation between the frequency of system reconfiguration and human error. A consensual agreement has been obtained with respect to the trend of the utility curve. This trend along with the values shown in Table 6.2 has been used to perform curve fitting to achieve the reconfiguration frequency utility illustrated in Figure 6.18.

Table 6.2 The expected utility values for different reconfiguration frequencies

Frequency of Reconfiguration (Number of reconfigurations during the life cycle) Assuming the life cycle = 10 years		**Expected utility**
1	(No reconfigurations; just the initial configuration)	0.00
10	(Reconfiguring the system every year)	0.01
20	(Reconfiguring the system every 6 months)	0.05
120	(Reconfiguring the system every month)	0.50
520	(Reconfiguring the system every week)	0.90
3650	(Reconfiguring the system every day)	1.00
10950	(Reconfiguring the system every shift; assume 3 sifts/day)	1.00

6.4.3.4. Overall Work Environment and System Operational Characteristics Utility

The four attributes considered in assessing the impact of work environment and operational characteristics are mutually preferentially independent. Therefore, the additive utility function can be used to assess their overall utility u_z.

$$u_z = \sum_{i=1}^{4} w_{zi}\, u_z(z_i), \tag{6.22}$$

where, w_{zi} is weight for attribute z_i, i =1,2,3,4, and

$$\sum_{i=1}^{4} w_{zi} = 1 \tag{6.23}$$

In order to assess these weights, the pairwise comparison matrix has been developed as shown in Figure 6.18. The calculated weight values for the work environment and system's operating characteristics attributes, using Expert Choice, are as follows: $w_{z1} = 0.109$, $w_{z2} = 0.189$, $w_{z3} = 0.351$, and $w_{z4} = 0.351$.

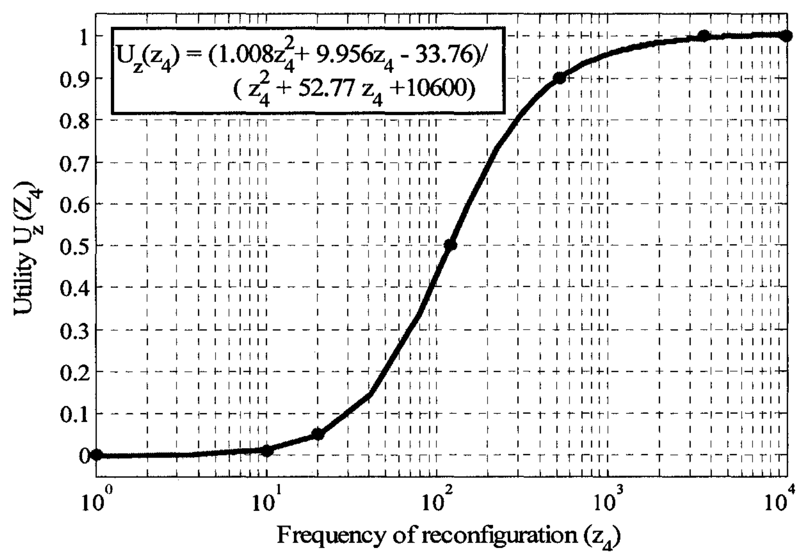


Figure 6.18 Utility Function for Frequency of Reconfiguration

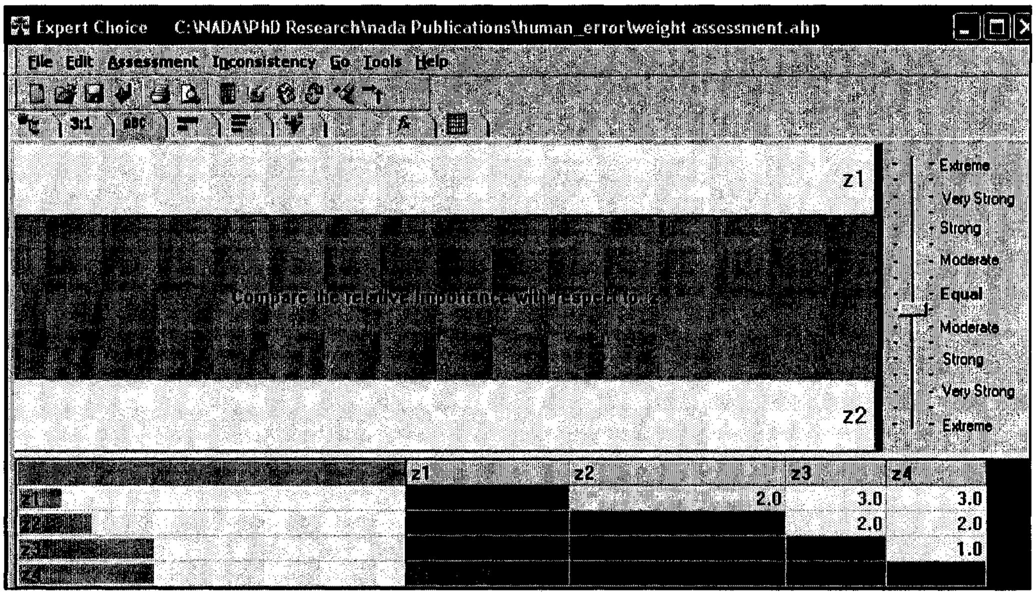


Figure 6.19 Pairewise Comparison Matrix for Work Environment and System's Operational Characteristics Attributes

6.4.4. Overall Utility

The overall utility that will represent the effect of different sets of attributes on the human error can be assessed in terms of the sub overall utilities u_x , u_y, and u_z using the following equation:

$$u(X,Y,Z) = w_x u_x + w_y u_y + w_z u_z \, , \tag{6.24}$$

where w_x, w_y, and w_z are weights for u_x , u_y, and u_z, respectively, and

$$w_x + w_y + w_z = 1 \tag{6.25}$$

In order to assess these weights, X and Z will be assumed of equal importance and they have moderate importance over Y in contributing to the occurrence of errors. The values for their weights, using Expert Choice, are as follows:

$w_x = w_z = 0.429$, and $w_y = 0.143$.

The overall utility function in Equation 6.24 does not represent the probability of human error. Instead, a mapping should exist between the overall utility values and the human error probability. Human error probabilities in assembly and inspection tasks may lie in the range shown in Table 6.3 according to an empirical studies made by Rook [1962] and annotated by Hinckley [1993].

The range of error rates in Table 6.3 may vary; increase or decrease according to a specific task environment. Thus, we will consider a range that is believed to cover a wide range of industrial tasks involving humans. That range is mathematically reflected by the following calibration equation:

$$\log_{10}(HEP) = 6 * \log_{10}(u(X,Y,Z)) \tag{6.26}$$

This logarithmic mapping is schematically illustrated in Figure 6.20.

Table 6.3 Errors rates in assembly and inspection tasks [Hinckely, 1993]

Example	
Errors in assembly	**Error Rate**
Insufficient solder	0.002
Component wired backwards	0.001
Transposition of 2 wires	0.0006
Component (small) Omitted	0.0003
Wrong value component used	0.0002
Solder joint omitted	0.000005
Operation omitted	0.000003
Errors in inspection	**Error Rate**
Center line location	0.0417
Algebraic sign	0.025
Measurement reading	0.0083
Copy error	0.0043

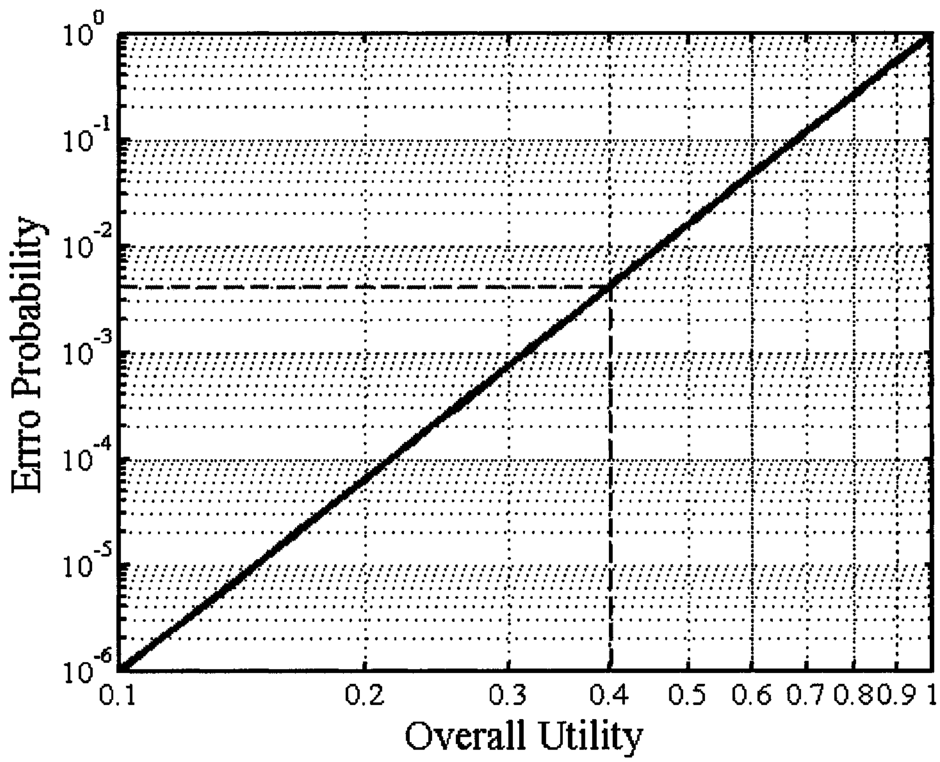


Figure 6.20 Mapping Overall Utility to Error Probability

6.5. EXAMPLE: JEEP INTAKE MANIFOLD ASSEMBLY

The developed model has been applied on one of the workers' tasks used in the assembly of the Jeep intake manifold, shown in Figure 20, at Siemens VDO [Sobh and Guler, 2004]. The considered task is one of the tasks to be done by a single operator as a part of the assembly process. The considered task is the assembly of the captive fastener and MAP (Manifold Absolute Pressure) sensors as shown in Figure 6.21. The task includes unloading the assembled part from station and visually inspecting the part for proper installation of all components (8 captive fasteners), then placing the good part to transfer, and then getting an MAP sensor and placing it to lower shell, and finally placing the part on transfer chute.

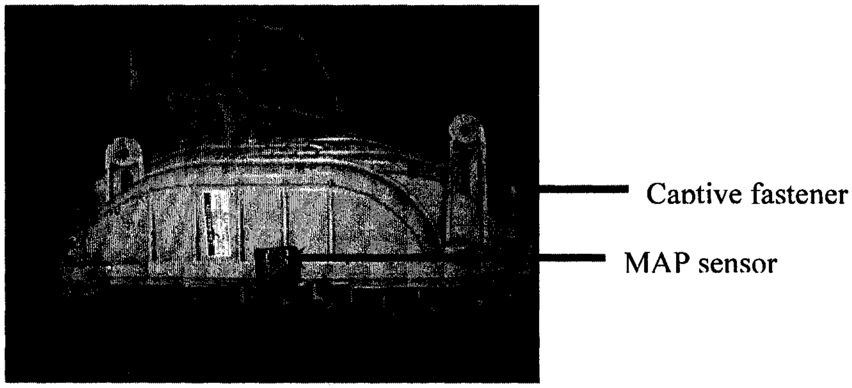


Figure 6.21 Siemens Jeep Intake Manifold [Sobh and Guler, 2004]

The task was analyzed and decomposed to its basic elements as shown in Table 4. The subjective assessment of the inherent difficulty of physical and cognitive task elements and their average values is shown in Table 5.

Table 6.4 Task Decomposition to Its Basic Elements

Task element	Task element Description
m_{p1}	Unload assembled part from station
m_{p2}	Look at the part to visually inspect it
m_{c1}	Decide whether the part is defective or not
m_{p3}	Place the good part to transfer table
m_{p4}	Get an MAP sensor
m_{c2}	Decide the right orientation of the sensor
m_{p5}	Place the MAP sensor to the lower shell
m_{p6}	Place part on transfer chute

Table 6.5 The Inherent Difficulty of Physical and Cognitive Task Elements

Task element	m_{p1}	m_{p2}	m_{c1}	m_{p3}	m_{p4}	m_{c2}	m_{p5}	m_{p6}	Average
D_{pj}	4	3	-	2	2	-	4	2	2.83
D_{cj}	-	-	3	-	-	2	-	-	2.5

To assess the coupling between task elements, a matrix for the task elements will be constructed as explained in Section 6.4.1. The coupling matrix for this example is as follows:

	m_{p1}	m_{p2}	m_{p3}	m_{p4}	m_{p5}	m_{p6}	m_{c1}	m_{c2}
m_{p1}	1	0	0	0	0	0	0	0
m_{p2}	0	1	1	0	0	0	1	0
m_{p3}	0	1	1	0	0	0	1	0
m_{p4}	0	0	0	1	0	0	0	0
m_{p5}	0	0	0	0	1	0	0	1
m_{p6}	0	0	0	0	0	1	0	0
m_{c1}	0	1	1	0	0	0	1	0
m_{c2}	0	0	0	0	1	0	0	1

In this example, the following sets of task elements are coupled:

$\{m_{p2}, m_{c1}\}, \{m_{c1}, m_{p3}\}, \{m_{p2}, m_{p3}\}, \{m_{c2}, m_{p5}\}$

In this context, coupling between two task elements implies that if one of the task elements is not performed properly, the other task element expected to be affected by that. For instance, if the operator did not look carefully at the part under inspection or has vision troubles or performing the task in an inadequate work environment, it is expected that he might not take the correct decision regarding whether the part is defective or not. The degree of coupling in the task under consideration can be calculated using Equation 6.6.

$x_4 =$ 4/28= 0.1428

From Equation 6.5, the diversity ratio can be calculated as:

$x_3 = T_D = 6/8 = 0.75$

In this example, there is no job aids or mistake proofing used in the task under consideration, therefore, $x_5 = 0$

6.6. RESULTS AND DISCUSSION

In the considered implementation example, the values for task error proneness attributes provided in Section 6.6 will be used to assess the overall utility. In addition, the manufacturing company experience major changes in the product design every 5 years and also minor changes in the design every year. Therefore, in this example, it will be reasonably assumed that the system is reconfigured every year. The other values for attributes concerning the operator capabilities, work environment and other operational characteristics will be assigned their mean values. The sub-criteria utilities can be calculated using Equations 6.9, 6.15, and 6.22. The resulting sub-crireria utilities are as follows:

$u_x = 0.6184$,

$u_y = 0.4942$, and

$u_z = 0.156$.

The overall utility is $u(X,Y,Z) = 0.4029$ according to Equation 6.24. For this example, the probability of error equals to 0.0043 as shown in Figure 6.20 according to the mapping relation in Equation 6.26. The estimated value for the error probability seems very reasonable for such a task compared with the set of tasks listed in Table 6.3.

In order to investigate the effect of different attributes on the overall utility, different scenarios were considered. Consider a case where the system is to be reconfigured every month; $z_4 = 120$ and considering all the other attributes are assigned their mean values. Figure 6.22 illustrates the effect of varying the task diversity as well as the time pressure vs. the overall utility. This figure depicts the combined effect of the utility curves of the two attributes. Such a curve can be useful when the system designer is faced with a scenario in which changes in the product design will result in an increase in the task diversity. Assuming that the designer is satisfied with the current level of error occurrence, in this case the designer can use such a figure to compensate for the diversity increase through the adjustment of the time pressure to achieve the same level for the overall utility. This can also be achieved through assigning the job to another worker with better capabilities or enhancing the capabilities of the current worker through training programs. Similar three dimensional plots can be used to demonstrate the impact of varying two different attributes on the overall utility. For instance, Figure 6.23 illustrates the relation between task diversity as well as operator's personal capabilities on the overall utility. This figure indicates lowest error probability is achieved at the highest value for the operator's personal capabilities and lowest value for the task diversity. Figure 6.24 illustrates that the overall utility increases with increase of the inherent difficulty of cognitive and physical task elements.

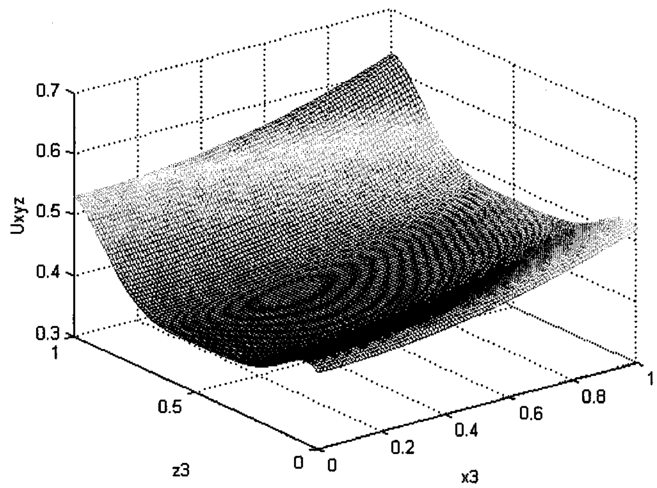


Figure 6.22 The Impact of Task Diversity (x_3) and Time Pressure (z_3) on the Overall Utility (Uxyz)

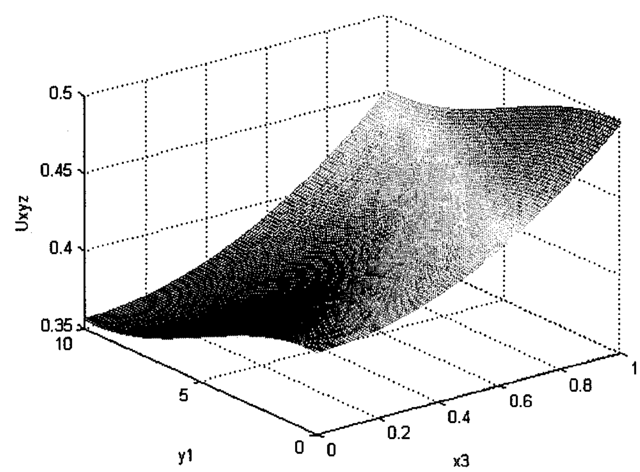


Figure 6.23 The Impact of Task Diversity (x_3) and Operator's Personal Capabilities (y_1) on the Overall Utility

The impact of the frequency of reconfiguration and the level of mistake proofing implementation on the overall utility is shown in Figure 6.25. This figure illustrates that increasing the level of mistake proofing implementation can significantly decrease the bad effects due to increased frequencies of reconfiguration. Moreover, the impact of the frequency of reconfiguration and time pressure on the overall utility is illustrated in Figure 6.26. In this figure, the possibility of error occurrence is relatively high at high frequency of reconfiguration and high time pressure; which represents a stressful turbulent working conditions.

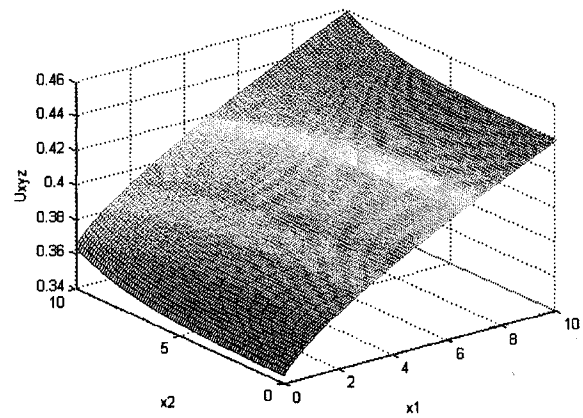


Figure 6.24 The Impact of the Difficulty of Cognitive Task Elements (x_1) and the Difficulty of Physical Task Elements (x_2) on the Overall Utility

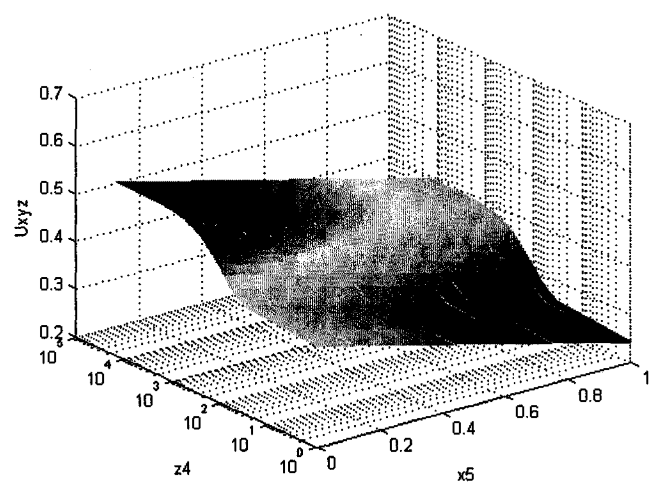


Figure 6.25 The Impact of Mistake Proofing and Job Aids (x_5) and Frequency of Reconfiguration (z_4) on the Overall Utility

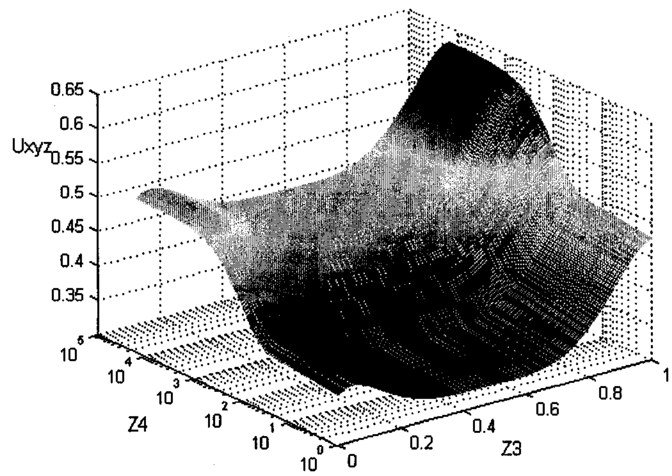


Figure 6.26 The Impact of Frequency of Reconfiguration (z_4) and Time Pressure (z_3) on the Overall Utility

The obtained results indicate that the developed model is capable of capturing the different attributes contributing to human error and can be used by the designer for assessing the probability of errors due to human involvement in manufacturing. The model can help the designer in investigating different scenarios and assessing different alternatives for minimizing the human error. These alternatives may include changing the task design to minimize its proneness to error, increasing the operator's capabilities, and enhancing the work environment. The use of such proactive assessment tool is more critical in the context of reconfigurable manufacturing systems because frequent operators' task reallocation is expected to cope with the system reconfiguration. The model can also be used in the early design stages to assess whether the targeted error levels are achievable or not. For instance, in case where the task is highly prone to error and the errors due to human involvement will not be acceptable, the degree of human involvement in performing the task should be reconsidered. In such a case, a balance should be made between the high flexibility offered by a human and the errors caused by him. The ability to investigate these opportunities in the early stages of manufacturing system configuration or reconfiguration can significantly help in achieving better results and save time and money.

6.7. SUMMARY

In this chapter, a model for assessing the errors due to human involvement in manufacturing tasks has been developed. The root causes of human errors have been identified through performing a cause and effect analysis. A measure for assessing the task error proneness has been developed. The multi-attribute utility theory has been implemented to assess human errors based on the task error proneness, the operator capabilities, the work environment as well as the system's operating characteristics. Individual decision making as well as collaborative decision making, through the implementation of the ECN approach, have been used in the multi-attribute utility analysis. The model has been applied to an industrial case study and the results for human error probabilities lie in a reasonable range compared with errors probabilities obtained from empirical case studies. In addition, the model can be used by the system designer to assess the errors due to human involvement in the early stages of system development; which is critical to investigate different improvement opportunities to achieve lower levels of errors due to human involvement.

7. SUMMARY AND CONCLUSIONS

7.1. CONTRIBUTIONS

This research has made the first move toward the development of a comprehensive measure for the expected product quality level as affected by manufacturing system design decisions. In summary, this study has achieved the following main contributions:

1. A conceptual framework, which identifies the configuration parameters that affect the resulting product quality, has been developed. This framework proposed two main approaches for quality assessment. One is through the direct impact of manufacturing system configuration parameters on quality and the other through assessing quality in terms of product complexity, task complexity, and system complexity.
2. A model that is capable of comparing different system configurations based on the expected product quality has been developed using the Analytic Hierarchy Process (AHP) [Nada et al., 2006a, and 2006b].
3. A hierarchical fuzzy inference system has been developed to model the ill-defined relation between manufacturing system design parameters and the resulting product quality. This model is capable of mapping the considered configuration parameters into a Configuration Capability Indicator (CCI), expressed in terms of sigma capability level, which can be compared to the benchmark Six Sigma capability [Nada et al. 2006c].
4. For a system configuration that produces more than one product, a configuration capability zone is proposed to graphically represent the manufacturing system configuration capability and compare it to the benchmark Six Sigma capability zone.
5. A context specific model for assessing errors due to human involvement in manufacturing tasks has been developed using multi-attribute utility analysis. The

assessed human error probability can be used to give an estimate for the yield of manual operations, which can be used in assessing the overall capability of processes [Nada et al. 2006d, and 2006e].

7.2. CONCLUSIONS

Application of the developed AHP model to the gearbox housing case study demonstrates the capability of the model in providing the system designer with a relative quality based comparison between the considered set of configuration alternatives.

The developed hierarchical fuzzy inference model has been applied to several case studies (Test Parts ANC-90 and ANC-101, Cylinder Head Part Family, Gearbox Housing, Rack Bar Machining) with different configuration scenarios for verification and validation. The results demonstrate the capability of the model in predicting the configuration capability level in terms of the considered configuration parameters. These parameters include defect prevention parameters as well as defect detection related parameters. The defect prevention related parameters include the overall capability of processes, the level of mistake proofing implementation, the number of flow paths, as well as the number of serial stations. The defect detection related parameters include the allocation of inspection station, the inspection error, the level of Jidoka implementation, as well as the buffer size.

The results of applying the AHP model and the fuzzy inference model to the Gearbox housing case study indicate that the two models reached the same conclusion regarding the ranking of alternatives.

The application of the developed Configuration Capability Indicator (CCI) emphasized that high quality levels can be achieved by investigating all the improvement opportunities and the improvement in only one parameter and ignoring the others will not achieve significant improvements in the overall obtained quality level. However, it is recommended that efforts should be directed first to design the system such that it minimizes or prevents the occurrence of errors rather than let them occur and then detecting them. The prevention of errors will help in achieving higher quality levels without investing time and money in non-value added actives and this will significantly enhance the manufacturer competitiveness.

Although the developed models provide the system designer with the final assessment of the expected configuration capability in manufacturing a specific product, the hierarchical structure that has been used in building the model has the advantage of providing the intermediate quality measures, such as the defect detection capability and defect prevention capability. This will help the user of the model to identify the improvement opportunities easily and to investigate the sensitivity of the final measure with the change of the parameters considered for improvement.

Besides, using the hierarchical structure in developing the fuzzy inference model significantly reduced the number of rules. In addition, modifications in the design of the fuzzy variables or in the rules will be easier using the hierarchical structure as opposed to the conventional structure. This is a very critical issue because the developed model is expected to be updated and modified either to include other parameters, or to update it based on new gained knowledge.

Moreover, the application of the developed fuzzy model reveals that highly capable configuration scenarios represent low complexity scenarios. In addition, the configuration parameters considered for predicting the Configuration Capability Indicator (CCI) are not function of time, even the overall capability of processes represents the short term behaviour of the system. Therefore, according to Suh's [2005] classes of complexity, the predicted CCI represents the time-independent real complexity of the system configuration. When the system is in the operating mode, quality could be affected by other parameters that are functions of time such as the deterioration of equipment through lifetime, or the gradual deterioration of quality due tool wear. In such cases, the system tends to have a time-dependent combinatorial complexity.

Based on the discussions provided in Chapter 5, it has been concluded that higher quality levels can be achieved by following two main approaches. The first is reducing the time-independent real complexity, which can be achieved by designing the system with high capability level. The models developed in this research will help the system designer in assessing the expected capability level at the early stages of system development. The second approach is to transform time-dependent combinatorial complexity into periodic complexity by the appropriate use of on-line quality control tools.

Furthermore, it has been demonstrated that product complexity, in terms of the number of steps or operations needed to produce it, adversely affects the resulting product quality level. Therefore, it is recommended that high product quality levels can be achieved not only by using highly capable processes, but also by minimizing the product complexity during the design stage.

7.3. RECOMMENDATIONS FOR FUTURE RESEARCH

Recommendations for future research can be summarized as follows:

1. Considering the assessment of the expected product quality level in terms of product complexity, task complexity, and system complexity as proposed in the overall framework (Chapter 3)
2. More research work is needed to develop analytical models for exploring and quantifying the effect of manufacturing system design parameters on the achieved quality level.
3. Improving the developed fuzzy inference system through the incorporation of the system design parameters that have not been considered such as the material handling, batch size, rework loops, number and ratio of the products to be simultaneously manufactured.
4. Incorporating the neural networks with the developed fuzzy inference system in order to improve the performance of the fuzzy system by tuning the rules or their membership functions through learning from data. This necessitates the availability of sets of data to train the neural network and adjust the rules.

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APPENDIX A

FUZZY RULES FOR QUALITY PREDICTION INFERENCE SYSTEMS

Table A-1. Fuzzy Rules for FIS_QCMS

1. If (No._of_Flow_Paths is Low) and (No._of_Serial-Stations is Low) then (Quality_of_Configuration_Morphological_Structure is High)
2. If (No._of_Flow_Paths is Low) and (No._of_ Serial-Stations is Low-Med) then (Quality_of_Configuration_Morphological_Structure is High)
3. If (No._of_Flow_Paths is Low) and (No._of_ Serial-Stations is Med) then (Quality_of_Configuration_Morphological_Structure is High)
4. If (No._of_Flow_Paths is Low) and (No._of_ Serial-Stations l is Med-High) then (Quality_of_Configuration_Morphological_Structure is Med-High)
5. If (No._of_Flow_Paths is Low) and (No._of_ Serial-Stations is High) then (Quality_of_Configuration_Morphological_Structure is Med)
6. If (No._of_Flow_Paths is Low-Med) and (No._of_ Serial-Stations l is Low) then (Quality_of_Configuration_Morphological_Structure is High)
7. If (No._of_Flow_Paths is Low-Med) and (No._of_ Serial-Stations l is Low-Med) then (Quality_of_Configuration_Morphological_Structure is Med-High)
8. If (No._of_Flow_Paths is Low-Med) and (No._of_ Serial-Stations is Med) then (Quality_of_Configuration_Morphological_Structure is Med-High)
9. If (No._of_Flow_Paths is Low-Med) and (No._of_ Serial-Stations is Med-High) then (Quality_of_Configuration_Morphological_Structure is Med)
10. If (No._of_Flow_Paths is Low-Med) and (No._of_ Serial-Stations is High) then (Quality_of_Configuration_Morphological_Structure is Med)
11. If (No._of_Flow_Paths is Med) and (No._of_ Serial-Stations is Low) then (Quality_of_Configuration_Morphological_Structure is Med)
12. If (No._of_Flow_Paths is Med) and (No._of_ Serial-Stations is Low-Med) then (Quality_of_Configuration_Morphological_Structure is Med)
13. If (No._of_Flow_Paths is Med) and (No._of_ Serial-Stations is Med) then (Quality_of_Configuration_Morphological_Structure is Med)
14. If (No._of_Flow_Paths is Med) and (No._of_ Serial-Stations is Med-High) then (Quality_of_Configuration_Morphological_Structure is Low-Med)
15. If (No._of_Flow_Paths is Med) and (No._of_ Serial-Stations is High) then (Quality_of_Configuration_Morphological_Structure is Low-Med)
16. If (No._of_Flow_Paths is Med-High) and (No._of_ Serial-Stations is Low) then (Quality_of_Configuration_Morphological_Structure is Low-Med)
17. If (No._of_Flow_Paths is Med-High) and (No._of_ Serial-Stations is Low-Med) then (Quality_of_Configuration_Morphological_Structure is Low-Med)
18. If (No._of_Flow_Paths is Med-High) and (No._of_ Serial-Stations l is Med) then (Quality_of_Configuration_Morphological_Structure is Low)
19. If (No._of_Flow_Paths is Med-High) and (No._of_ Serial-Stations is Med-High) then (Quality_of_Configuration_Morphological_Structure is Low)
20. If (No._of_Flow_Paths is Med-High) and (No._of_ Serial-Stations is High) then (Quality_of_Configuration_Morphological_Structure is Low)
21. If (No._of_Flow_Paths is High) and (No._of_ Serial-Stations is Low) then (Quality_of_Configuration_Morphological_Structure is Low)
22. If (No._of_Flow_Paths is High) and (No._of_ Serial-Stations is Low-Med) then (Quality_of_Configuration_Morphological_Structure is Low)
23. If (No._of_Flow_Paths is High) and (No._of_ Serial-Stations is Med) then (Quality_of_Configuration_Morphological_Structure is Low)
24. If (No._of_Flow_Paths is High) and (No._of_ Serial-Stations is Med-High) then (Quality_of_Configuration_Morphological_Structure is Low)
25. If (No._of_Flow_Paths is High) and (No._of_ Serial-Stations is High) then (Quality_of_Configuration_Morphological_Structure is Low)

Table A-2. Fuzzy Rules for FIS_EDR

1. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is High) and (Buffer_Size is Low) then (Error_Detection_Responsiveness is High)
2. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is High) and (Buffer_Size is Low-Med) then (Error_Detection_Responsiveness is High)
3. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is High) and (Buffer_Size is Med) then (Error_Detection_Responsiveness is High)
4. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is High) and (Buffer_Size is Med-High) then (Error_Detection_Responsiveness is High)
5. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is High) and (Buffer_Size is High) then (Error_Detection_Responsiveness is High)
6. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Med-High) and (Buffer_Size is Low) then (Error_Detection_Responsiveness is High)
7. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Med-High) and (Buffer_Size is Low-Med) then (Error_Detection_Responsiveness is High)
8. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Med-High) and (Buffer_Size is Med) then (Error_Detection_Responsiveness is High)
9. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Med-High) and (Buffer_Size is Med-High) then (Error_Detection_Responsiveness is High)
10. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Med-High) and (Buffer_Size is High) then (Error_Detection_Responsiveness is High)
11. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Med) and (Buffer_Size is Low) then (Error_Detection_Responsiveness is High)
12. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Med) and (Buffer_Size is Low-Med) then (Error_Detection_Responsiveness is High)
13. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Med) and (Buffer_Size is Med) then (Error_Detection_Responsiveness is High)
14. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Med) and (Buffer_Size is Med-High) then (Error_Detection_Responsiveness is High)
15. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Med) and (Buffer_Size is High) then (Error_Detection_Responsiveness is High)
16. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Low-Med) and (Buffer_Size is Low) then (Error_Detection_Responsiveness is Med-High)
17. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Low-Med) and (Buffer_Size is Low-Med) then (Error_Detection_Responsiveness is Med-High)
18. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Low-Med) and (Buffer_Size is Med) then (Error_Detection_Responsiveness is Med-High)
19. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Low-Med) and (Buffer_Size is Med-High) then (Error_Detection_Responsiveness is Med-High)
20. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Low-Med) and (Buffer_Size is High) then (Error_Detection_Responsiveness is Med-High)
21. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Low) and (Buffer_Size is Low) then (Error_Detection_Responsiveness is Med)
22. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Low) and (Buffer_Size is Low-Med) then (Error_Detection_Responsiveness is Med)
23. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Low) and (Buffer_Size is Med) then (Error_Detection_Responsiveness is Med)
24. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Low) and (Buffer_Size is Med-High) then (Error_Detection_Responsiveness is Med)
25. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Low) and (Buffer_Size is High) then (Error_Detection_Responsiveness is Med)

Table A-2 (Cont'd). Fuzzy Rules for FIS_EDR

26. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is High) and (Buffer_Size is Low) then (Error_Detection_Responsiveness is High)
27. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is High) and (Buffer_Size is Low-Med) then (Error_Detection_Responsiveness is High)
28. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is High) and (Buffer_Size is Med) then (Error_Detection_Responsiveness is Med-High)
29. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is High) and (Buffer_Size is Med-High) then (Error_Detection_Responsiveness is Med-High)
30. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is High) and (Buffer_Size is High) then (Error_Detection_Responsiveness is Med)
31. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is Med-High) and (Buffer_Size is Low) then (Error_Detection_Responsiveness is High)
32. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is Med-High) and (Buffer_Size is Low-Med) then (Error_Detection_Responsiveness is High)
33. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is Med-High) and (Buffer_Size is Med) then (Error_Detection_Responsiveness is Med-High)
34. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is Med-High) and (Buffer_Size is Med-High) then (Error_Detection_Responsiveness is Med-High)
35. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is Med-High) and (Buffer_Size is High) then (Error_Detection_Responsiveness is Med)
36. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is Med) and (Buffer_Size is Low) then (Error_Detection_Responsiveness is Med-High)
37. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is Med) and (Buffer_Size is Low-Med) then (Error_Detection_Responsiveness is Med-High)
38. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is Med) and (Buffer_Size is Med) then (Error_Detection_Responsiveness is Med)
39. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is Med) and (Buffer_Size is Med-High) then (Error_Detection_Responsiveness is Med)
40. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is Med) and (Buffer_Size is High) then (Error_Detection_Responsiveness is Low-Med)
41. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is Low-Med) and (Buffer_Size is Low) then (Error_Detection_Responsiveness is Med)
42. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is Low-Med) and (Buffer_Size is Low-Med) then (Error_Detection_Responsiveness is Med)
43. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is Low-Med) and (Buffer_Size is Med) then (Error_Detection_Responsiveness is Low-Med)
44. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is Low-Med) and (Buffer_Size is Med-High) then (Error_Detection_Responsiveness is Low-Med)
45. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is Low-Med) and (Buffer_Size is High) then (Error_Detection_Responsiveness is Low)
46. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is Low) and (Buffer_Size is Low) then (Error_Detection_Responsiveness is Med)
47. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is Low) and (Buffer_Size is Low-Med) then (Error_Detection_Responsiveness is Med)
48. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is Low) and (Buffer_Size is Med) then (Error_Detection_Responsiveness is Low-Med)
49. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is Low) and (Buffer_Size is Med-High) then (Error_Detection_Responsiveness is Low)
50. If (Allocation_of_Inspection_Stations is In-process) and (Level_of_Jidoka_Implementation is Low) and (Buffer_Size is High) then (Error_Detection_Responsiveness is Low)

Table A-2 (Cont'd). Fuzzy Rules for FIS_EDR

51. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is High) and (Buffer_Size is Low) then (Error_Detection_Responsiveness is Med)
52. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is High) and (Buffer_Size is Low-Med) then (Error_Detection_Responsiveness is Med)
53. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is High) and (Buffer_Size is Med) then (Error_Detection_Responsiveness is Med)
54. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is High) and (Buffer_Size is Med-High) then (Error_Detection_Responsiveness is Med)
55. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is High) and (Buffer_Size is High) then (Error_Detection_Responsiveness is Med)
56. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is Med-High) and (Buffer_Size is Low) then (Error_Detection_Responsiveness is Low-Med)
57. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is Med-High) and (Buffer_Size is Low-Med) then (Error_Detection_Responsiveness is Low-Med)
58. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is Med-High) and (Buffer_Size is Med) then (Error_Detection_Responsiveness is Low-Med)
59. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is Med-High) and (Buffer_Size is Med-High) then (Error_Detection_Responsiveness is Low-Med)
60. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is Med-High) and (Buffer_Size is High) then (Error_Detection_Responsiveness is Low-Med)
61. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is Med) and (Buffer_Size is Low) then (Error_Detection_Responsiveness is Low-Med)
62. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is Med) and (Buffer_Size is Low-Med) then (Error_Detection_Responsiveness is Low-Med)
63. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is Med) and (Buffer_Size is Med) then (Error_Detection_Responsiveness is Low-Med)
64. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is Med) and (Buffer_Size is Med-High) then (Error_Detection_Responsiveness is Low-Med)
65. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is Med) and (Buffer_Size is High) then (Error_Detection_Responsiveness is Low-Med)
66. If (Allocation_of_Inspection_Stations is Intensive_in-process) and (Level_of_Jidoka_Implementation is Low-Med) and (Buffer_Size is Low) then (Error_Detection_Responsiveness is Low)
67. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is Low-Med) and (Buffer_Size is Low-Med) then (Error_Detection_Responsiveness is Low)
68. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is Low-Med) and (Buffer_Size is Med) then (Error_Detection_Responsiveness is Low)
69. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is Low-Med) and (Buffer_Size is Med-High) then (Error_Detection_Responsiveness is Low)
70. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is Low-Med) and (Buffer_Size is High) then (Error_Detection_Responsiveness is Low)
71. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is Low) and (Buffer_Size is Low) then (Error_Detection_Responsiveness is Low)
72. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is Low) and (Buffer_Size is Low-Med) then (Error_Detection_Responsiveness is Low)
73. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is Low) and (Buffer_Size is Med) then (Error_Detection_Responsiveness is Low)
74. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is Low) and (Buffer_Size is Med-High) then (Error_Detection_Responsiveness is Low)
75. If (Allocation_of_Inspection_Stations is End-of-Line) and (Level_of_Jidoka_Implementation is Low) and (Buffer_Size is High) then (Error_Detection_Responsiveness is Low)

Table A-3 Fuzzy Rules used in FIS_DPC

1. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is High) and (Level_of_Mistake_Proofing_Implementation is High) then (DPC is High)
2. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is High) and (Level_of_Mistake_Proofing_Implementation is Med-High) then (DPC is High)
3. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is High) and (Level_of_Mistake_Proofing_Implementation is Med) then (DPC is High)
4. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is High) and (Level_of_Mistake_Proofing_Implementation is Low-Med) then (DPC is Med-High)
5. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is High) and (Level_of_Mistake_Proofing_Implementation is Low) then (DPC is Med)
6. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is Med-High) and (Level_of_Mistake_Proofing_Implementation is High) then (DPC is High)
7. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is Med-High) and (Level_of_Mistake_Proofing_Implementation is Med-High) then (DPC is High)
8. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is Med-High) and (Level_of_Mistake_Proofing_Implementation is Med) then (DPC is Med-High)
9. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is Med-High) and (Level_of_Mistake_Proofing_Implementation is Low-Med) then (DPC is Med-High)
10. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is Med-High) and (Level_of_Mistake_Proofing_Implementation is Low) then (DPC is Med)
11. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is Med) and (Level_of_Mistake_Proofing_Implementation is High) then (DPC is High)
12. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is Med) and (Level_of_Mistake_Proofing_Implementation is Med-High) then (DPC is High)
13. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is Med) and (Level_of_Mistake_Proofing_Implementation is Med) then (DPC is Med-High)
14. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is Med) and (Level_of_Mistake_Proofing_Implementation is Low-Med) then (DPC is Med)
15. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is Med) and (Level_of_Mistake_Proofing_Implementation is Low) then (DPC is Med)
16. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is Low-Med) and (Level_of_Mistake_Proofing_Implementation is High) then (DPC is Med-High)
17. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is Low-Med) and (Level_of_Mistake_Proofing_Implementation is Med-High) then (DPC is Med-High)
18. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is Low-Med) and (Level_of_Mistake_Proofing_Implementation is Med) then (DPC is Med)
19. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is Low-Med) and (Level_of_Mistake_Proofing_Implementation is Low-Med) then (DPC is Med)
20. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is Low-Med) and (Level_of_Mistake_Proofing_Implementation is Low) then (DPC is Med)
21. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is Low) and (Level_of_Mistake_Proofing_Implementation is High) then (DPC is Med-High)
22. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is Low) and (Level_of_Mistake_Proofing_Implementation is Med-High) then (DPC is Med-High)
23. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is Low) and (Level_of_Mistake_Proofing_Implementation is Med) then (DPC is Med)
24. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is Low) and (Level_of_Mistake_Proofing_Implementation is Low-Med) then (DPC is Med)
25. If (Overall_Capability_of_Processes is Highly-Capable) and (QCMS is Low) and (Level_of_Mistake_Proofing_Implementation is Low) then (DPC is Med)

Table A-3 (Cont'd). Fuzzy Rules used in FIS_DPC

26. If (Overall_Capability_of_Processes is Capable) and (QCMS is High) and (Level_of_Mistake_Proofing_Implementation is High) then (DPC is Med-High)
27. If (Overall_Capability_of_Processes is Capable) and (QCMS is High) and (Level_of_Mistake_Proofing_Implementation is Med-High) then (DPC is Med-High)
28. If (Overall_Capability_of_Processes is Capable) and (QCMS is High) and (Level_of_Mistake_Proofing_Implementation is Med) then (DPC is Med-High)
29. If (Overall_Capability_of_Processes is Capable) and (QCMS is High) and (Level_of_Mistake_Proofing_Implementation is Low-Med) then (DPC is Med)
30. If (Overall_Capability_of_Processes is Capable) and (QCMS is High) and (Level_of_Mistake_Proofing_Implementation is Low) then (DPC is Low-Med)
31. If (Overall_Capability_of_Processes is Capable) and (QCMS is Med-High) and (Level_of_Mistake_Proofing_Implementation is High) then (DPC is Med-High)
32. If (Overall_Capability_of_Processes is Capable) and (QCMS is Med-High) and (Level_of_Mistake_Proofing_Implementation is Med-High) then (DPC is Med-High)
33. If (Overall_Capability_of_Processes is Capable) and (QCMS is Med-High) and (Level_of_Mistake_Proofing_Implementation is Med) then (DPC is Med)
34. If (Overall_Capability_of_Processes is Capable) and (QCMS is Med-High) and (Level_of_Mistake_Proofing_Implementation is Low-Med) then (DPC is Med)
35. If (Overall_Capability_of_Processes is Capable) and (QCMS is Med-High) and (Level_of_Mistake_Proofing_Implementation is Low) then (DPC is Low-Med)
36. If (Overall_Capability_of_Processes is Capable) and (QCMS is Med) and (Level_of_Mistake_Proofing_Implementation is High) then (DPC is Med-High)
37. If (Overall_Capability_of_Processes is Capable) and (QCMS is Med) and (Level_of_Mistake_Proofing_Implementation is Med-High) then (DPC is Med-High)
38. If (Overall_Capability_of_Processes is Capable) and (QCMS is Med) and (Level_of_Mistake_Proofing_Implementation is Med) then (DPC is Med)
39. If (Overall_Capability_of_Processes is Capable) and (QCMS is Med) and (Level_of_Mistake_Proofing_Implementation is Low-Med) then (DPC is Low-Med)
40. If (Overall_Capability_of_Processes is Capable) and (QCMS is Med) and (Level_of_Mistake_Proofing_Implementation is Low) then (DPC is Low-Med)
41. If (Overall_Capability_of_Processes is Capable) and (QCMS is Low-Med) and (Level_of_Mistake_Proofing_Implementation is High) then (DPC is Med)
42. If (Overall_Capability_of_Processes is Capable) and (QCMS is Low-Med) and (Level_of_Mistake_Proofing_Implementation is Med-High) then (DPC is Med)
43. If (Overall_Capability_of_Processes is Capable) and (QCMS is Low-Med) and (Level_of_Mistake_Proofing_Implementation is Med) then (DPC is Low-Med)
44. If (Overall_Capability_of_Processes is Capable) and (QCMS is Low-Med) and (Level_of_Mistake_Proofing_Implementation is Low-Med) then (DPC is Low-Med)
45. If (Overall_Capability_of_Processes is Capable) and (QCMS is Low-Med) and (Level_of_Mistake_Proofing_Implementation is Low) then (DPC is Low-Med)
46. If (Overall_Capability_of_Processes is Capable) and (QCMS is Low) and (Level_of_Mistake_Proofing_Implementation is High) then (DPC is Med)
47. If (Overall_Capability_of_Processes is Capable) and (QCMS is Low) and (Level_of_Mistake_Proofing_Implementation is Med-High) then (DPC is Med)
48. If (Overall_Capability_of_Processes is Capable) and (QCMS is Low) and (Level_of_Mistake_Proofing_Implementation is Med) then (DPC is Low-Med)
49. If (Overall_Capability_of_Processes is Capable) and (QCMS is Low) and (Level_of_Mistake_Proofing_Implementation is Low-Med) then (DPC is Low-Med)
50. If (Overall_Capability_of_Processes is Capable) and (QCMS is Low) and (Level_of_Mistake_Proofing_Implementation is Low) then (DPC is Low-Med)

Table A-3 (Cont'd). Fuzzy Rules used in FIS_DPC

51. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is High) and (Level_of_Mistake_Proofing_Implementation is High) then (DPC is Med)
52. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is High) and (Level_of_Mistake_Proofing_Implementation is Med-High) then (DPC is Med)
53. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is High) and (Level_of_Mistake_Proofing_Implementation is Med) then (DPC is Med)
54. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is High) and (Level_of_Mistake_Proofing_Implementation is Low-Med) then (DPC is Low-Med)
55. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is High) and (Level_of_Mistake_Proofing_Implementation is Low) then (DPC is Low-Med)
56. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is Med-High) and (Level_of_Mistake_Proofing_Implementation is High) then (DPC is Med)
57. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is Med-High) and (Level_of_Mistake_Proofing_Implementation is Med-High) then (DPC is Med)
58. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is Med-High) and (Level_of_Mistake_Proofing_Implementation is Med) then (DPC is Med)
59. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is Med-High) and (Level_of_Mistake_Proofing_Implementation is Low-Med) then (DPC is Low-Med)
60. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is Med-High) and (Level_of_Mistake_Proofing_Implementation is Low) then (DPC is Low-Med)
61. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is Med) and (Level_of_Mistake_Proofing_Implementation is High) then (DPC is Med)
62. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is Med) and (Level_of_Mistake_Proofing_Implementation is Med-High) then (DPC is Med)
63. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is Med) and (Level_of_Mistake_Proofing_Implementation is Med) then (DPC is Med)
64. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is Med) and (Level_of_Mistake_Proofing_Implementation is Low-Med) then (DPC is Low-Med)
65. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is Med) and (Level_of_Mistake_Proofing_Implementation is Low) then (DPC is Low-Med)
66. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is Low-Med) and (Level_of_Mistake_Proofing_Implementation is High) then (DPC is Low-Med)
67. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is Low-Med) and (Level_of_Mistake_Proofing_Implementation is Med-High) then (DPC is Low-Med)
68. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is Low-Med) and (Level_of_Mistake_Proofing_Implementation is Med) then (DPC is Low-Med)
69. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is Low-Med) and (Level_of_Mistake_Proofing_Implementation is Low-Med) then (DPC is Low)
70. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is Low-Med) and (Level_of_Mistake_Proofing_Implementation is Low) then (DPC is Low)
71. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is Low) and (Level_of_Mistake_Proofing_Implementation is High) then (DPC is Low-Med)
72. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is Low) and (Level_of_Mistake_Proofing_Implementation is Med-High) then (DPC is Low-Med)
73. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is Low) and (Level_of_Mistake_Proofing_Implementation is Med) then (DPC is Low-Med)
74. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is Low) and (Level_of_Mistake_Proofing_Implementation is Low-Med) then (DPC is Low)
75. If (Overall_Capability_of_Processes is Barely-Capable) and (QCMS is Low) and (Level_of_Mistake_Proofing_Implementation is Low) then (DPC is Low)

Table A-3 (Cont'd). Fuzzy Rules used in FIS_DPC

76. If (Overall_Capability_of_Processes is Incapable) and (QCMS is High) and (Level_of_Mistake_Proofing_Implementation is High) then (DPC is Low-Med)
77. If (Overall_Capability_of_Processes is Incapable) and (QCMS is High) and (Level_of_Mistake_Proofing_Implementation is Med-High) then (DPC is Low-Med)
78. If (Overall_Capability_of_Processes is Incapable) and (QCMS is High) and (Level_of_Mistake_Proofing_Implementation is Med) then (DPC is Low)
79. If (Overall_Capability_of_Processes is Incapable) and (QCMS is High) and (Level_of_Mistake_Proofing_Implementation is Low-Med) then (DPC is Low)
80. If (Overall_Capability_of_Processes is Incapable) and (QCMS is High) and (Level_of_Mistake_Proofing_Implementation is Low) then (DPC is Low)
81. If (Overall_Capability_of_Processes is Incapable) and (QCMS is Med-High) and (Level_of_Mistake_Proofing_Implementation is High) then (DPC is Low-Med)
82. If (Overall_Capability_of_Processes is Incapable) and (QCMS is Med-High) and (Level_of_Mistake_Proofing_Implementation is Med-High) then (DPC is Low-Med)
83. If (Overall_Capability_of_Processes is Incapable) and (QCMS is Med-High) and (Level_of_Mistake_Proofing_Implementation is Med) then (DPC is Low)
84. If (Overall_Capability_of_Processes is Incapable) and (QCMS is Med-High) and (Level_of_Mistake_Proofing_Implementation is Low-Med) then (DPC is Low)
85. If (Overall_Capability_of_Processes is Incapable) and (QCMS is Med-High) and (Level_of_Mistake_Proofing_Implementation is Low) then (DPC is Low)
86. If (Overall_Capability_of_Processes is Incapable) and (QCMS is Med) and (Level_of_Mistake_Proofing_Implementation is High) then (DPC is Low)
87. If (Overall_Capability_of_Processes is Incapable) and (QCMS is Med) and (Level_of_Mistake_Proofing_Implementation is Med-High) then (DPC is Low)
88. If (Overall_Capability_of_Processes is Incapable) and (QCMS is Med) and (Level_of_Mistake_Proofing_Implementation is Med) then (DPC is Low)
89. If (Overall_Capability_of_Processes is Incapable) and (QCMS is Med) and (Level_of_Mistake_Proofing_Implementation is Low-Med) then (DPC is Low)
90. If (Overall_Capability_of_Processes is Incapable) and (QCMS is Med) and (Level_of_Mistake_Proofing_Implementation is Low) then (DPC is Low)
91. If (Overall_Capability_of_Processes is Incapable) and (QCMS is Low-Med) and (Level_of_Mistake_Proofing_Implementation is Low) then (DPC is Low)
92. If (Overall_Capability_of_Processes is Incapable) and (QCMS is Low-Med) and (Level_of_Mistake_Proofing_Implementation is High) then (DPC is Low)
93. If (Overall_Capability_of_Processes is Incapable) and (QCMS is Low-Med) and (Level_of_Mistake_Proofing_Implementation is Med-High) then (DPC is Low)
94. If (Overall_Capability_of_Processes is Incapable) and (QCMS is Low-Med) and (Level_of_Mistake_Proofing_Implementation is Med) then (DPC is Low)
95. If (Overall_Capability_of_Processes is Incapable) and (QCMS is Low-Med) and (Level_of_Mistake_Proofing_Implementation is Low-Med) then (DPC is Low)
96. If (Overall_Capability_of_Processes is Incapable) and (QCMS is Low) and (Level_of_Mistake_Proofing_Implementation is High) then (DPC is Low)
97. If (Overall_Capability_of_Processes is Incapable) and (QCMS is Low) and (Level_of_Mistake_Proofing_Implementation is Med-High) then (DPC is Low)
98. If (Overall_Capability_of_Processes is Incapable) and (QCMS is Low) and (Level_of_Mistake_Proofing_Implementation is Med) then (DPC is Low)
99. If (Overall_Capability_of_Processes is Incapable) and (QCMS is Low) and (Level_of_Mistake_Proofing_Implementation is Low-Med) then (DPC is Low)
100. If (Overall_Capability_of_Processes is Incapable) and (QCMS is Low) and (Level_of_Mistake_Proofing_Implementation is Low) then (DPC is Low)

Table A-4. Fuzzy Rules used in FIS_DDC

1. If (Inspection_Error is Low) and (EDR is High) then (DDC is High)
2. If (Inspection_Error is Low) and (EDR is Med-High) then (DDC is High)
3. If (Inspection_Error is Low) and (EDR is Med) then (DDC is Med-High)
4. If (Inspection_Error is Low) and (EDR is Low-Med) then (DDC is Med)
5. If (Inspection_Error is Low) and (EDR is Low) then (DDC is Low-Med)
6. If (Inspection_Error is Low-Med) and (EDR is High) then (DDC is High)
7. If (Inspection_Error is Low-Med) and (EDR is Med-High) then (DDC is Med-High)
8. If (Inspection_Error is Low-Med) and (EDR is Med) then (DDC is Med)
9. If (Inspection_Error is Low-Med) and (EDR is Low-Med) then (DDC is Low-Med)
10. If (Inspection_Error is Low-Med) and (EDR is Low) then (DDC is Low-Med)
11. If (Inspection_Error is Med) and (EDR is High) then (DDC is Med-High)
12. If (Inspection_Error is Med) and (EDR is Med-High) then (DDC is Med-High)
13. If (Inspection_Error is Med) and (EDR is Med) then (DDC is Med)
14. If (Inspection_Error is Med) and (EDR is Low-Med) then (DDC is Low-Med)
15. If (Inspection_Error is Med) and (EDR is Low) then (DDC is Low) (1)
16. If (Inspection_Error is Med-High) and (EDR is High) then (DDC is Med-High)
17. If (Inspection_Error is Med-High) and (EDR is Med-High) then (DDC is Med)
18. If (Inspection_Error is Med-High) and (EDR is Med) then (DDC is Low-Med)
19. If (Inspection_Error is Med-High) and (EDR is Low-Med) then (DDC is Low)
20. If (Inspection_Error is Med-High) and (EDR is Low) then (DDC is Low)
21. If (Inspection_Error is High) and (EDR is High) then (DDC is Low-Med)
22. If (Inspection_Error is High) and (EDR is Med-High) then (DDC is Low-Med)
23. If (Inspection_Error is High) and (EDR is Med) then (DDC is Low)
24. If (Inspection_Error is High) and (EDR is Low-Med) then (DDC is Low)
25. If (Inspection_Error is High) and (EDR is Low) then (DDC is Low)

Table A-5. Fuzzy Rules used in FIS_CCI

1. If (DPC is High) and (DDC is High) then (Configuration_Capability is Excellent)
2. If (DPC is High) and (DDC is Med-High) then (Configuration_Capability is Excellent)
3. If (DPC is High) and (DDC is Med) then (Configuration_Capability is Excellent)
4. If (DPC is High) and (DDC is Low-Med) then (Configuration_Capability is Good)
5. If (DPC is High) and (DDC is Low) then (Configuration_Capability is Good)
6. If (DPC is Med-High) and (DDC is High) then (Configuration_Capability is Excellent)
7. If (DPC is Med-High) and (DDC is Med-High) then (Configuration_Capability is Good)
8. If (DPC is Med-High) and (DDC is Med) then (Configuration_Capability is Good)
9. If (DPC is Med-High) and (DDC is Low-Med) then (Configuration_Capability is Good)
10. If (DPC is Med-High) and (DDC is Low) then (Configuration_Capability is Acceptable)
11. If (DPC is Med) and (DDC is High) then (Configuration_Capability is Good)
12. If (DPC is Med) and (DDC is Med-High) then (Configuration_Capability is Good)
13. If (DPC is Med) and (DDC is Med) then (Configuration_Capability is Acceptable)
14. If (DPC is Med) and (DDC is Low-Med) then (Configuration_Capability is Acceptable)
15. If (DPC is Med) and (DDC is Low) then (Configuration_Capability is Acceptable)
16. If (DPC is Low-Med) and (DDC is High) then (Configuration_Capability is Acceptable)
17. If (DPC is Low-Med) and (DDC is Med-High) then (Configuration_Capability is Acceptable)
18. If (DPC is Low-Med) and (DDC is Med) then (Configuration_Capability is Unacceptable)
19. If (DPC is Low-Med) and (DDC is Low-Med) then (Configuration_Capability is Unacceptable)
20. If (DPC is Low-Med) and (DDC is Low) then (Configuration_Capability is Unacceptable)
21. If (DPC is Low) and (DDC is High) then (Configuration_Capability is Unacceptable)
22. If (DPC is Low) and (DDC is Med-High) then (Configuration_Capability is Unacceptable)
23. If (DPC is Low) and (DDC is Med) then (Configuration_Capability is Unacceptable)
24. If (DPC is Low) and (DDC is Low-Med) then (Configuration_Capability is Unacceptable)
25. If (DPC is Low) and (DDC is Low) then (Configuration_Capability is Unacceptable)

APPENDIX B

PROCEDURE FOR DEVELOPING THE FUZZY MODEL AND A SAMPLE OF THE MATLAB OUTPUT REPORT

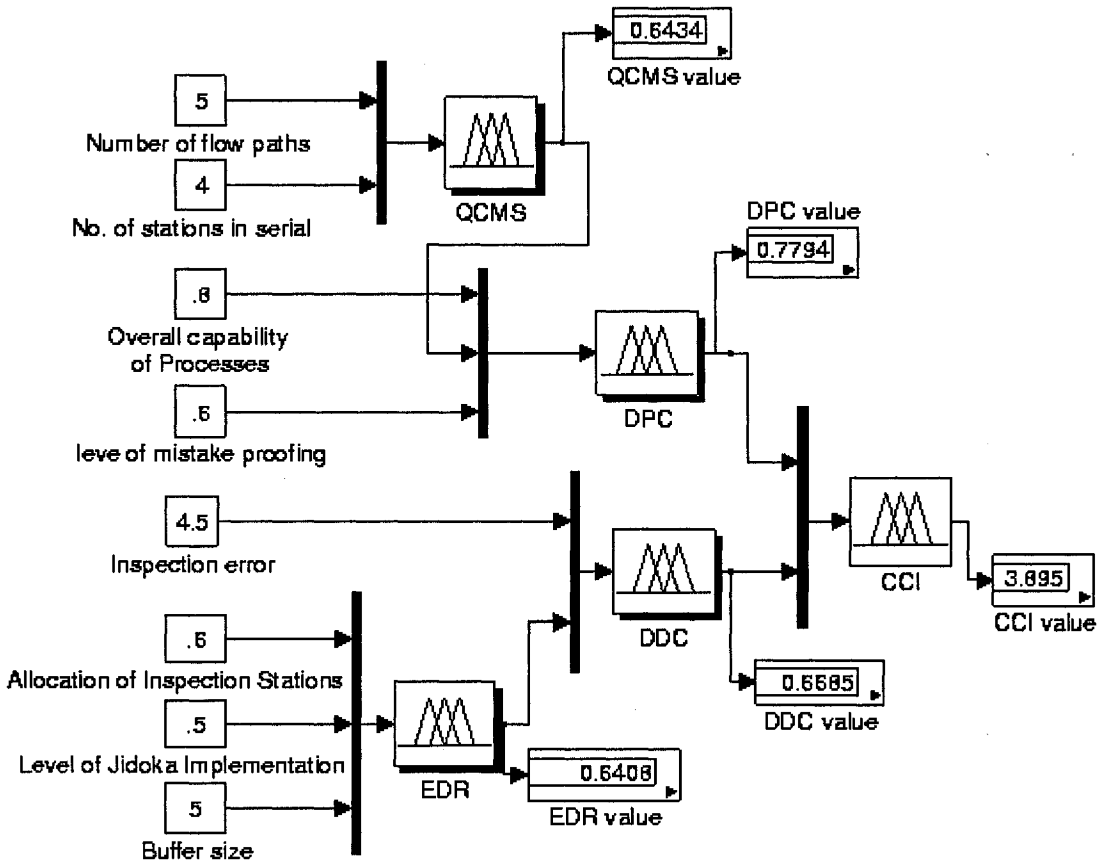
B1. PROCEDURE FOR DEVELOPING THE HIERARCHAL FUZZY INFERENCE SYSTEM

The hierarchal fuzzy inference presented in Chapter 5 has been developed using the following steps:

- Structuring the hierarchy that consists of the individual fuzzy inference systems
- Designing the fuzzy variables for inputs and outputs
- Designing the sets of fuzzy rules for each individual fuzzy inference system. In this research, every possible effort has been made during the data acquisition from literature to have a good insight about the relation between quality and manufacturing system design. It should be pointed out that the data used in building the model can be easily updated by including new research outcomes, surveys, as well as inputs from quality experts as these become available.
- The design of the fuzzy variables and rules can also be made to suite specific applications by introducing new rules or changing emphases on some rules.
- Using Matlab Fuzzy Logic Toolbox [The Math Works, 2002] to develop each individual fuzzy inference system
- Using Matlab Simulink [The Math Works, 2002] to integrate the individual fuzzy inference systems by using fuzzy logic controllers to represent the individual fuzzy inference systems and connecting these fuzzy logic controllers in the Simulink environment

B2. A SAMPLE OF MATLAB GENERATED OUTPUT REPORT FOR TEST PART ANC-90 CASE STUDY (PART A USING CONFIGURATION SCENARIO 1)

simulink_fuzzy_model
Details for simulink_fuzzy_model
nada
19-Apr-2006 15:32:15



Model - simulink_fuzzy_model
Full Model Hierarchy

1. simulink_fuzzy_model

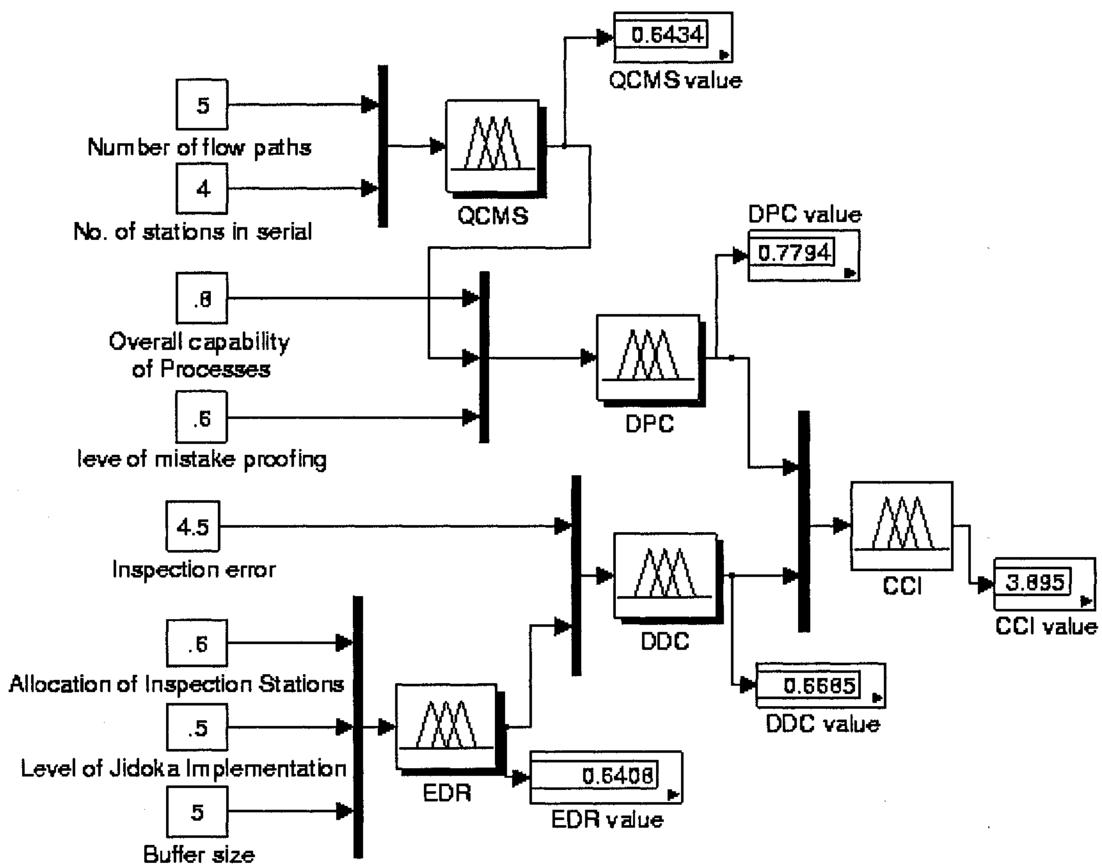
Simulation Parameter	Value
Solver	FixedStepDiscrete
RelTol	1e-3
Refine	1

Simulation Parameter	Value
MaxOrder	5
ZeroCross	on

[more info]

System - simulink_fuzzy_model

Description. sim



Constant Block Properties

Name	Value	VectorParams1D	OutDataTypeMode	ConRadixGroup
Allocation of Inspection Stations	.6	on	Inherit from 'Constant value'	Use specified scaling
Buffer size	5	on	Inherit from 'Constant value'	Use specified scaling
Inspection error	4.5	on	Inherit from 'Constant value'	Use specified scaling
leve of mistake proofing	.6	on	Inherit from 'Constant value'	Use specified scaling
Level of Jidoka	.5	on	Inherit from 'Constant	Use specified

Name	Value	VectorParams1D	OutDataTypeMode	ConRadixGroup
Implementation			value'	scaling
No. of serial stations	4	on	Inherit from 'Constant value'	Use specified scaling
Number of flow paths	5	on	Inherit from 'Constant value'	Use specified scaling
Overall capability of Processes	.8	on	Inherit from 'Constant value'	Use specified scaling

Display Block Properties

Name	Format	Decimation	Floating	SampleTime
CCI value	short	1	off	-1
DDC value	short	1	off	-1
DPC value	short	1	off	-1
EDR value	short	1	off	-1
QCMS value	short	1	off	-1

FIS Block Properties

Name	fis
CCI	CCI
DDC	DDC
DPC	DPC
EDR	EDR
QCMS	QCMS

Mux Block Properties

Name	Inputs	DisplayOption
Mux	3	bar
Mux1	2	bar
Mux2	2	bar
Mux3	2	bar
Mux4	3	bar

Block Type Count

BlockType	Count	Block Names
Constant	8	Allocation of Inspection Stations , Buffer size , Inspection error, Level of Jidoka Implementation , No. of serial stations , Number of flow paths , Overall capability of Processes, leve of mistake proofing
Mux	5	Mux, Mux1, Mux2, Mux3, Mux4
FIS (m)	5	CCI, DDC, DPC, EDR, QCMS
Display	5	CCI value, DDC value, DPC value, EDR value, QCMS value

Model Variables

Variable Name	Parent Blocks	Calling string	Value
CCI	CCI	CCI	name: 'CCI' type: 'mamdani' andMethod: 'min' orMethod: 'max' defuzzMethod: 'centroid' impMethod: 'min' aggMethod: 'max' input: [1x2 struct] output: [1x1 struct] rule: [1x25 struct]
DDC	DDC	DDC	name: 'DDC' type: 'mamdani' andMethod: 'min' orMethod: 'max' defuzzMethod: 'centroid' impMethod: 'min' aggMethod: 'max' input: [1x2 struct] output: [1x1 struct] rule: [1x25 struct]
DPC	DPC	DPC	name: 'DPC' type: 'mamdani' andMethod: 'min' orMethod: 'max' defuzzMethod: 'centroid' impMethod: 'min' aggMethod: 'max' input: [1x3 struct] output: [1x1 struct] rule: [1x100 struct]
EDR	EDR	EDR	name: 'EDR' type: 'mamdani' andMethod: 'min' orMethod: 'max' defuzzMethod: 'centroid' impMethod: 'min' aggMethod: 'max' input: [1x3 struct] output: [1x1 struct] rule: [1x75 struct]
QCMS	QCMS	QCMS	name: 'QCMS' type: 'mamdani' andMethod: 'min' orMethod: 'max' defuzzMethod: 'centroid' impMethod: 'min' aggMethod: 'max' input: [1x2 struct] output: [1x1 struct] rule: [1x25 struct]

APPENDIX C

PROCEDURE FOR UTILITY FUNCTIONS ASSESSMENT

C1. PROCEDURE FOR UTILITY FUNCTIONS ASSESSMENT

A utility function is a mathematical representation of the human judgements translates the values of the attribute into a utility score. The procedure used in this research to construct the utility functions for individual attributes considered in the developed model for human error assessment is illustrated in this appendix. According to Keeny and Riffa [1976], a utility function for individual attribute can be constructed through carrying out the following steps:

1. **Description and selection of the attribute score range.**

   In this step, the minimum and maximum values for the attribute should be determined. For attributes that are difficult to measure, subjective scores for theses utilities are to be designed at this stage. After that, the attribute worst-case and best-case values should be assigned to the utility function minimum and maximum values depending on the physical meaning of the utility function. The next steps will be concerned with how to determine the function joining these two assigned points.

2. **Identification of the relevant qualitative characteristics of the utility function**

   At this stage of utility assessment, it can be determined whether the function is monotonically increasing or decreasing with the change of the attribute value or not. In addition, the general trend of the shape of the curve can be identified through discussing the concavity or convexity characteristics of the curve.

3. **Quantitative assessment for a set of points**

   Once the qualitative features of the utility function are stated, the assessment usually proceeds with specifying quantitative utility values for a few points of the attribute scores. This depends on numerical estimations that assign utility judgement for a given utility score, which is known as direct value rating.

4. **Interpolation and consistency checks**

   This involves the use of curve fitting to specify the utility function based on the estimated points. The most widely used functions are exponential, logarithmic, and polynomial. The selection of which one to use depends on the qualitative and quantitative characteristics of the curve which have been already specified in the previous steps. It should be pointed out that using curve fitting might result in inconsistency between the obtained curve and the predefined qualitative and quantitative curve characteristics. For example, in situations where the minimum value for the utility function is determined to be zero, using curve fitting one may obtain a fitted utility function that result in negative values. In such cases, some adjustments should be done until a suitable utility function is obtained.

It is worth mentioning that this procedure proposed by Keeny and Riffa [1976] is mainly based on interactive process between the analyst and decision maker. In this research, insights from literature as well as inputs from researchers and Professors at the Intelligent Manufacturing Centre (IMS), during brain storming sessions, University of Windsor have been used to help in constructing the utility functions.

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