

**ANALYZING QUALITY FUNCTION DEPLOYMENT (QFD)  
BASED ON VOICE OF CUSTOMER (VoC)**

A thesis submitted to the Faculty of Information Technology  
in partial fulfillment of the requirements for the degree  
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University Utara Malaysia

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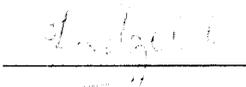
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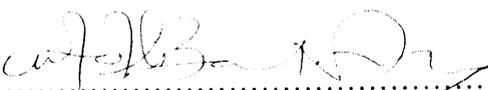
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## ABSTRACT

*Analyzing Quality Function Deployment (QFD) based on voice of customer aims to provide an advanced machine planning methodology based on QFD principles, for identifying and minimize the risks of project failures due to failure in complying with the voice of the customers. The methodology was developed by reviewing current design product definition and QFD tools that have been applied to a number of industry-based machine design projects in academic institution as well as an in-depth study at selected industry organization. This study focuses on the development of general QFD for machine specification selection where it later can be used for any kind of machine evaluation before buying is made. NN models were generated and statistical methods were used to explain the relationship between attributes used in this study. A set of questionnaires was used as an instrument comprises of two main sections; a **Customer Profile** and **Possible Customer Requirements**. For **Customer Profile**, there are three parameters used namely, **Name of Company or Institution**, **Type of Customer** and **Type of Work piece Material Used**. For **Possible Customer Requirements**, there are six (6) sections according to **Machine Standard Specification**, **Machine Control**, **Machine Safety**, **Machine Performance**, **Machine Maintenance** and **Machine after Sales Services**. The important subject to focus is the customer voices selected to model QFD for industry; including **Professional**, **Management level**, **Maintenance** and **Operator**. In summary, the findings from the experiments conducted indicate that the significant correlations of QFD with customer voices help to explain the relationship between attributes used in the study. The study also indicates that NN forecasting model has been established with 87.696% accuracy in determining the customer voices based on QFD. The study indicates that the approach has potential in explaining the relationship between QFD and the customers, as well as predicting the type of customer if QFD information is provided. Hence, the study reveals the type of machine and type of operation that are favourable to customer prior to acquiring the machines for their industrial usage.*

## ABSTRAK

*Analisis Quality Function Deployment (QFD) berdasarkan kehendak pelanggan bertujuan untuk menyediakan satu metodologi perancangan untuk mesin termaju berasaskan prinsip QFD bagi mengenalpasti dan meminimumkan risiko kegagalan projek disebabkan kesilapan dalam memenuhi kehendak pelanggan. Metodologi dibangunkan berdasarkan penilaian semula definisi rekabentuk produk semasa dan alat bantu QFD yang telah diaplikasikan kepada industri yang berasaskan penggunaan mesin dalam penghasilan produk merangkumi institusi pengajian tinggi dan beberapa organisasi industri terpilih. Kajian ini memfokus kepada pembangunan QFD umum untuk pemilihan spesifikasi mesin dimana ia akan digunakan untuk sebarang penilaian spesifikasi mesin sebelum pembelian dibuat. Model Rangkaian Neural (NN) telah dibangunkan dan kaedah statistik digunakan untuk menerangkan perkaitan antara atribut yang digunakan dalam kajian. Pendekatan soal selidik digunakan sebagai kaedah pengumpulan data dimana soal selidik terbahagi kepada dua bahagian iaitu **Customer Profile** dan **Possible Customer Requirements**. Bagi **Customer Profile**, tiga parameter yang digunakan iaitu **Name of Company or Institution**, **Type of Customer** dan **Type of Work piece Material Used**. Manakala bagi **Possible Customer Requirements**, terdapat enam (6) sub-bahagian dimulai dengan **Machine Standard Specification**, **Machine Control**, **Machine Safety**, **Machine Performance**, **Machine Maintenance** dan **Machine After Sales Services**. Suara pengguna yang dipilih untuk memodelkan QFD bagi industri termasuklah **Professional**, **Management**, **Maintenance** dan **Operator**. Sebagai kesimpulan, dapatan kajian menunjukkan wujud kolerasi signifikan QFD dengan suara pelanggan dapat menerangkan hubungan di antara atribut kajian. Dapatan kajian juga menunjukkan bahawa model ramalan Rangkaian Neural (NN) menghasilkan pengukuhan ketepatan 87.696% dalam menentukan kehendak pelanggan menggunakan QFD. Kajian menunjukkan bahawa pendekatan QFD mempunyai potensi dalam menerangkan hubungan antara QFD dengan pelanggan. Oleh itu, dapatan kajian menunjukkan jenis mesin dan jenis operasi yang dipilih oleh pelanggan dan meramal jenis pelanggan yang terlibat sebelum memilih mesin terbaik untuk kegunaan industri.*

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## DEDICATION

To my beloved husband and children,

Ruslizam bin Daud

Afifah An-Nur binti Ruslizam

Afif Al-Ikhlās bin Ruslizam

To my parents,

Haji Nordin bin Haji Ismail

Hajjah Che Esah binti Haji Nor

To my mother in-law and the whole families

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## LIST OF ABBREVIATION

QFD.....	Quality Function Deployment
VoC.....	Voice of Customer
NN.....	Neural Network
SPSS.....	Statistical Package for the Social Science
DFSS.....	Design for Six Sigma
PTRs.....	Product Technical Requirements
HoQ.....	House of Quality
EC.....	Engineering Characteristics
CA.....	Customer Attributes
QFD DSS.....	Quality Function Deployment Decision Support System
FL-QFD.....	Fuzzy Logic-Quality Function Deployment
AI.....	Artificial Intelligence
BP.....	Back propagation

# CHAPTER 1

## INTRODUCTION

This chapter presents an overview of the project which includes the background of the project, the problem statement, objectives of the project, and the scope of the project and the significance of the project.

### 1.1 Background

To succeed in developing new products or improve an existing one is not easy. Studies indicate that as much as somewhere between 35 percent and 44 percent of all products launched is considered failures (Urban, 1980). It is one thing to actually discover and measure the customers' needs and wants but, to achieve results, these findings need to be implemented, i.e translated into company language. Many companies depend on their warranty programs, customer complaints, and inputs from their sales staff to keep them in touch with their customers (Akao, 1990). The result focuses on what is wrong with the existing product or service, with little or no attention on what is right or what the customer really wants.

One process oriented design method constructed to carry out the translation process and make sure that the findings are implemented is quality function deployment (QFD). QFD is one of the techniques that aim to fulfill the customers' satisfaction at the very beginning, namely the product design phase. It enables the companies to become

proactive to quality problems rather than taking a reactive position by acting on customer complaints. QFD is used to plan and design new or improved products or services.

According to Wikipedia (2006), Quality function deployment of QFD is a flexible and comprehensive group decision making technique used in product or service development, brand marketing, and product management. QFD can strongly help an organization focuses on the critical characteristics of a new or existing product or service from the separate viewpoints of the customer market segments, company, or technology development needs. The results of the technique yields transparent and visible graphs and matrices that can be reused for future product/service development.

This project presents alternative ways to identify the relationship between type of customer and QFD. It also aims to build QFD forecasting model with respect to different types of customers. The combination of effort in QFD and the utilizing of neural network as a tool for IT in manufacturing and product development will torch the light towards the creation of the QFD forecasting model. Some statistical techniques may be utilized to support the findings in this project.

## **1.2 Problem Statement**

Method of gathering data from customers for QFD analysis still consume much time, much works involved using papers, more people involved, coverage responds is limited and many more disadvantages. In other aspects, it only can be understood by those who are really in that technical area or those who experience in product development.

In practice however, existing QFD implementations have limitations which must be addressed before the technique can effectively be used in engineering design. The main problems which must be addressed are summarized as follows:

- (1) As systems become larger, analysis of the data becomes more difficult because of the magnitude of the resulting QFD matrix (Daetz, 1989).
- (2) For large QFD matrices, it becomes almost impossible to record the QFD matrix manually in a paper form, and modify the matrix in light of subsequent changes (Wolfe, 1994).
- (3) There is a lack of intelligent software tools which can provide useful, consistent, reasoned analysis of QFD information (Syan and Menon, 1994).
- (4) Conventional QFD procedures have embedded in itself a tendency for subjective valuation of the weight in the relational matrix of House of Quality (HOQ). This might cause bias in the outcome and vary the actual result.

Based on the problems stated above, and since statistical has been claimed to produce low accuracy (Yu & Fu, 2004), therefore this study attempts to propose an alternative way of analyzing QFD such as using Neural Network (NN).

### **1.3 Objective**

The main objectives of the study can be specifically stated as:

- To identify the relationship between type of customer and QFD based on survey results.
- To build QFD and evaluate forecasting model with respect to type of customer.

## **1.4 Scope of the project**

This project focuses on the development of general QFD for machine selection where it later can be used for any kind of machine evaluation. There will be no customization on certain product brand name or specific services. NN models were generated and statistical methods were used to explain the relationship between attributes used in this study. For customer voices, four types of customers have been used throughout the study as suggested by Abd.Rahman & Mohd. Shariff (2003).

## **1.5 Significance of the project**

There are few reasons why we need to build QFD forecasting model and identification of relationship between type of customer and QFD:

- QFD forecasting model is to help the manufacturer determines the best machine specifications.
- QFD forecasting model allows the customers to provide responses on a product/service with no limit in computerized form.
- Help the designer to concentrate much more on identifying customer satisfaction towards the design specification of the product. The data gathering from customers would be easier to understand and analyze.

Upon the completion of this project, it will be expected to benefits all purpose of measurement related to customer satisfaction and needs. The future application may be applied into new product development, product liability, ISO9000 series, process assurance, services, part suppliers, material and processing equipment manufacturers, reliability and technology deployment.

## **1.6 Overview of Project**

This chapter presents the overview of the study. Chapter 2 discusses the literature related to QFD, followed by the methodology, which is discussed in Chapter 3. Chapter 4 discusses the analysis of the survey result. Chapter 5 is the final chapter that concludes the findings and the significance of the study.

## **CHAPTER 2**

### **LITERATURE REVIEW**

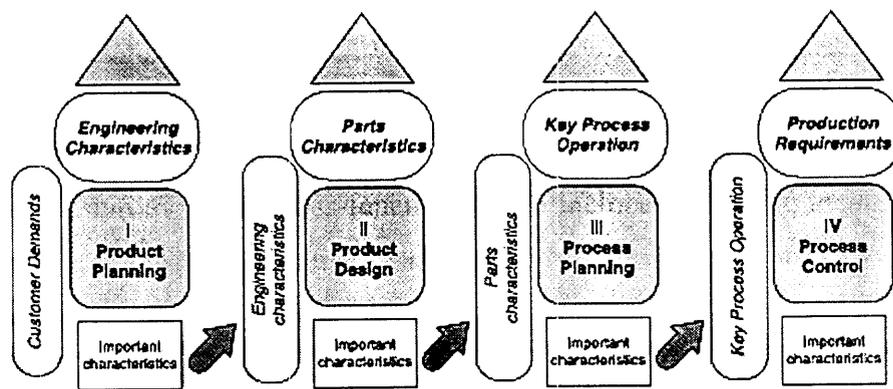
This chapter briefly presents the review of the relevant information that is related to the project. This section describes the literature on related areas in the study including data mining, neural networks and statistical techniques. It also includes the discussion on Neural Network (NN) application in Quality Function Deployment (QFD).

#### **2.1 Introduction to QFD**

Global competitiveness has recently become the biggest concern of both manufacturing and service companies, which seek for higher levels of quality for their products and services and continuous improvement to keep up with the rapid pace of development and change throughout the world. Quality function deployment (QFD), which offers a vast selection of techniques to ensure the improvement of quality and productivity has been a topic on the research agenda for the last four decades.

QFD was introduced in 1972 to help design supertankers in Mitsubishi's shipyards in Kobe, Japan. Ford and Xerox brought it to the United States in 1986. Since 1972, it has been adopted by Japanese, American, and European firms. QFD is a systematic method for transforming customer requirements to design and process parameters. It is also considered as a key practice of Design for Six Sigma (DFSS) (Yunus, 1994).

Cohen, L. (1995) perceives that QFD is becoming a widely used customer-oriented approach and tool in product design. According to Ertugul *et al.* (2003), QFD is a customer-oriented design tool with cross-functional team members reaching a consensus in developing a new or improved product to increase customer satisfaction. QFD starts with the house of quality (HOQ) that translates the customer needs into a planning matrix. It translates the customer needs into measurable product technical requirements (PTRs). A robust evaluation method should consider the interrelationships among customer needs and PTRs while determining the importance levels of PTRs in the HOQ.



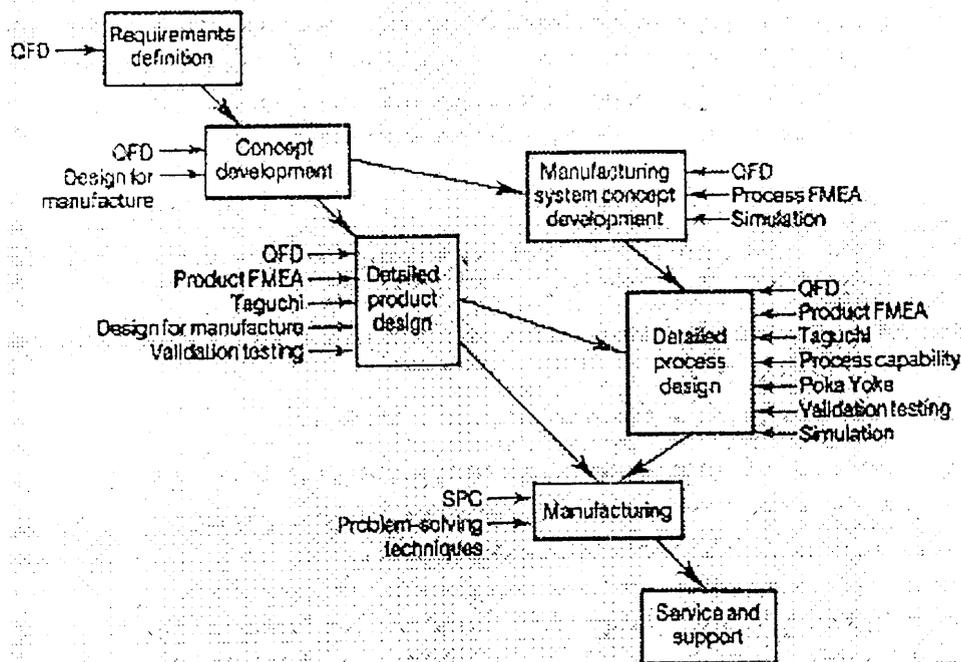
**Figure 2.1:** The Four Phases of QFD

*Source:* Vivianne & Hefin (2000)

Moskowitz (1997) defines that QFD is a customer-oriented design tool for developing new or improved products to increase customer satisfaction by integrating marketing, design engineering, manufacturing, and other related functions of an organization. QFD aims to maximize customer satisfaction; however, considerations such as cost budget, technical difficulty, limit the number and the extent of the possible design requirements that can be incorporated into a product.

QFD has been heralded as an important part of the product development process. It is an investment in people and information. It uses cross-functional teams to determine customer requirements and to translate them into product designs and specifications through highly structured and well-documented methods. It enables an organization to

measure customer “wants” and map them against the engineering “how” in a way that highlights trade-offs and drives the product’s design towards customer requirements. The importance of QFD in the product introduction process can be seen in Fig. 2.2.

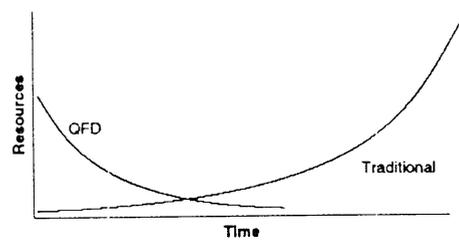


**Figure 2.2:** Quality Technique In The Product Introduction Process

*Source:* A.D. Brown *et al.* (1989).

QFD helps the companies to maintain their competitiveness using three strategies: decreasing costs, increasing revenues, and reducing the time to produce new products or services (cycle time reduction). QFD allows for the company to allocate resources and to coordinate skills and functions based on customer needs, and thus, may result in lower production costs by ignoring aspects meaning little or nothing to the customer. Its systematic nature also evaluates the necessary decisions for change and development at the beginning of the design process, reducing and even avoiding the mid-project changes and corrections. Enabling to develop the right product or service for the customers with the lowest possible cost, QFD attracts the customers, which results in higher selling rates, leading to higher revenues. In this way, QFD facilitates the entire development process,

minimizing the corrections and waste during this phase, and as a matter of fact, optimizing the time required for introducing a new or improved product or service to the market.



**Figure 2.3:** Allocation of Time against Resources.

*Source:* Adapted from L.P.Sullivan, “Quality Function Deployment,” *Quality Progress* (June 1996).

In traditional design and implementation projects, the allocation of resources increases as a function of time right up to implementation. In QFD, in contrast, there is an allocation of more resources up front and less is needed at the time of producing a product or delivering a service.

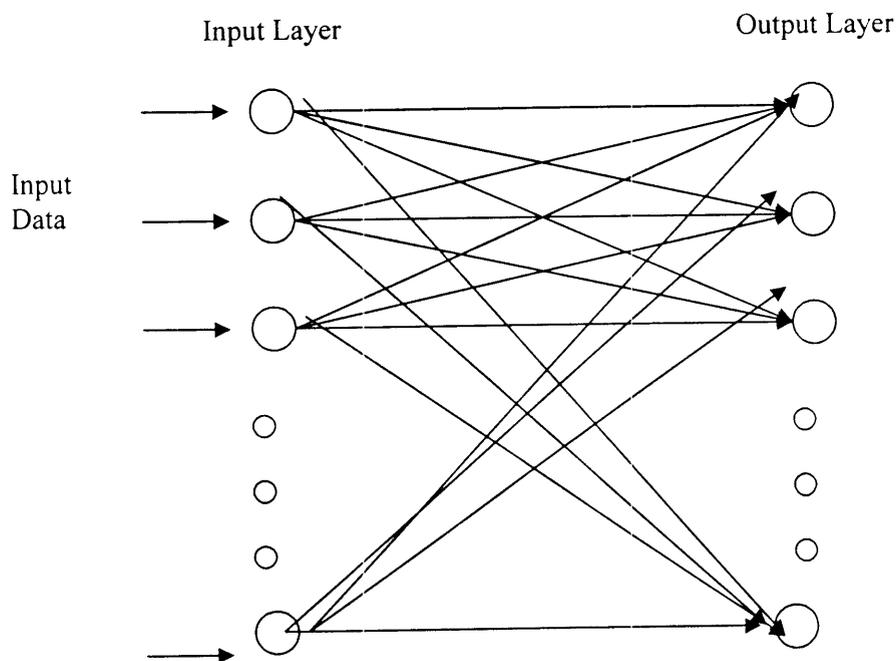
In addition, QFD is the only comprehensive quality system aimed specifically at satisfying the customer. It concentrates on maximizing customer satisfaction (positive quality)-measured by metrics, such as repeat business. QFD focuses on delivering value by seeking out both spoken and unspoken needs, translating these into actions and designs, and communicating this throughout the organization. Further, QFD allows customers to prioritize their requirements, tell the organization how they are doing compared to other competitors, and then directs response to optimize those aspects for the organization that will bring the greatest competitive advantage (Glenn, 1994).

QFD takes the voice of the customer from the beginning of product development and deploys it throughout the firm. Through QFD, the voice of the customer aligns the company’s resources to focus on maximizing customer satisfaction. Customer satisfaction is influenced by product development outcomes which, in turn, are influenced by the technical and organizational dimensions of QFD as well as the project’s

profile. As identified by practitioners, consultant, and academics, the primary product development outcomes are better product designs, less time-to-market, and lower product costs. Organizations, unfortunately, cannot set these outcomes directly; they must manipulate the technical and organizational dimensions as well as the project's profile.

## 2.2 Definition of Neural Network

In general, a neural network (NN) model consists of neurons or processing elements, each of which is connected to other elements according to some schema by connection weights. The connection weights between processing elements contain the knowledge stored in the artificial neural network model. Usually, the processing elements are classified as input units, output units, or hidden units. Model input is supplied through the input units, and model output is shown on the output units. The hidden elements are necessary to enable the system to learn relationships which are not linearly separable. Fig. 2.4 illustrates a typical neural network model. The model learns by adjusting its connection weights in response to the input-output pairs presented to it during training. NNs are trained by example; they are not usually programmed with a priori knowledge.



**Figure 2.4:** Neural Network Model Example

Though much of the motivation driving neural computing research has been geared towards development of specialized hardware, the mathematical models have been coded into software and proven to be valuable tools in the areas of signal processing, system modeling, pattern recognition, and classification.

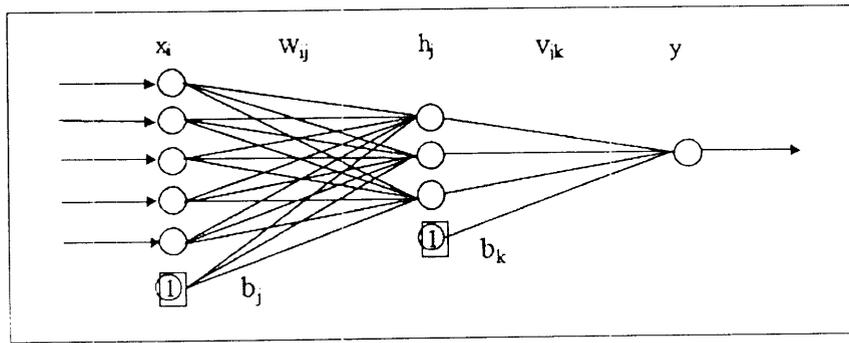
In NN models for prediction, inputs and their associated outputs are presented to the network's input and output processing elements, respectively. The connection weights are adjusted after the input - output pair of vectors is presented to the network until the network is able to produce the desired output within some pre-determined error bounds. The algorithm for adjusting the weights depends upon the type of network model used. In this application, the backward error propagation model was used. Backward error propagation is described in detail in nearly all neural network text books (NeuralWare 1991, Hertz, Krough, & Palmer 1991, Rumelhart & McClelland 1986, and Aleksander & Morton 1991).

NN, originally derived from neurobiological models, are massively parallel, computer intensive, and data driven algorithmic systems composed of a multitude of highly interconnected nodes, known as neurons as well. Mimicking human neurobiological information processing activities, each elementary node of a neural network is enabled to receive an input signal from external sources or other nodes and the algorithmic procedure equipped in each node is sequentially activated to locally transforming the corresponding input signal into an output signal to other nodes or environment (Yu Chao, 2004).

Neural Network (NN) can be considered as simplified mathematical models of the human brain which function as computing network (Hammerstrom, 1993). They consist of simple processing elements called "neuron" that exchange signals along "weighted" connection. NN makes use of the way that the human brain learns and functions and represents this information in mathematical algorithms incorporated in computers. They possess the ability to learn from examples and thus have the ability to manage systems from their observed behaviors rather than from theoretical understanding. This ability to learn from experience is very useful in the real world.

Many different NN models have been proposed since 1980s and they basically can be divided into two categories, namely feed forward and feedback network. The feedback networks consist of the nodes that connect to them, rendering a node able to influence other nodes and even it. Two typical examples of this category known as Kohonen self-organization networks and Hopfield networks.

NNs share their origins with the infancy of machine-based information processing, when McCulloch and Pitts first showed that a network of interconnecting threshold units can replicate any Boolean function. These units are modeled on the response of neural cells in biological nervous systems, hence the evocative name given to this field. Later, Rosenblatt carried out his investigations with analogue electro-mechanical systems for visual pattern recognition, developing the seminal concept of the perceptron as an embodiment of the McCulloch-Pitts already idealized model of the neuron. This work demonstrated a key property of neural network systems, namely their distributed associative memory function. This means to say that the new information is stored in the weighted links between the threshold units rather than at specified memory addresses. An immediate consequence of this is that the component elements of the stored memories, for instance on bits in a binary image, do not have a one-to-one correspondence with any network parameters. Instead, the overall recall accuracy degrades slowly as weight-links are disturbed, rather like seeing through frosted glass. A physical example of this phenomenon is holography, where the resolution of the reconstructed 3-D image increases with the size of the film used to capture the interference pattern that makes up the hologram. Architecture of Multilayer Perceptron (MLP) whose key feature is the representation created by an intermediate or hidden layer of processing units with non-linear transfer functions. This schematic represents the feed-forward path for the MLP:  $x$ ,  $h$  and  $y$  are the layers of neurons,  $w$  and  $b$  is the weights and a bias term is shown in Fig. 2.5.



**Figure 2.5:** Architecture of Multilayer Perceptron (MLP).

### 2.3 Introduction to Neural Network Application In Quality Function Deployment

QFD takes the voice of the customer from the beginning of product development and deploys it throughout the firm. Through QFD, the voice of the customer aligns the company's resources to focus on maximizing customer satisfaction. Customer satisfaction is influenced by product development outcomes which, in turn, are influenced by the technical and organizational dimensions. Basically, QFD is aimed to fulfill the customer's expectation of the product or service. San Myint (2003) describes a framework of an intelligent quality function deployment (IQFD) for discrete assembly environment of QFD as well as the project's profile. They used Taguchi experimental design for manufacturing process optimization using historical data and a neural network process model (Wimalin & James, 2005). QFD with applied statistics techniques are employed to facilitate the translation of prioritized set of customer requirements into a set of system level requirements during conceptual design (Yu & Fu, 2004).

QFD is a proven tool for process and product development, which translates the voice of customer (VoC) into engineering characteristics (EC), and prioritizes the ECs based on the customer's requirements. Conventional QFD evaluates these targets for crisp weights of the customer attributes (CA), identified from the VoCs. Fuzzy logic approach to prioritize engineering characteristics in QFD (FL-QFD) addresses the issue of defining non-crisp customer attributes in the QFD. It is an innovative method of determining

optimum rating of engineering characteristics (EC) by simulating the QFD matrix for randomized customer attributes (CA) in the fuzzier range (Rajam & Selladurai, 2004).

Engineering systems have become increasingly complex to design and build while the demand for quality and effective development at lower cost and shorter time continues. The study is to present neural networks based approach in QFD process to prescribe a new methodology to generate a conceptual design baseline. A generalized neural networks oriented conceptual design process is introduced and a hybrid intelligent system combining neural networks and expert systems for conceptual design. Statistical regression methods adopted in the past is computationally inexpensive but with poor accuracy (Yu & Fu, 2004). Hence, NN has potential to be used with QFD.

## 2.4 Overview of Neural Network Application In Process Analyzing and Modeling

Neural Network (NN) are an important technology of Artificial Intelligence (AI), which have been widely used, in recent years, for manufacturing process monitoring using output pattern recognition (Guh & Tannock, 1999). They have also been used, less frequently, for process modeling (Heider *et al.*, 2002; Jimenez-Marquez *et al.*, 2003), the approach which has been adopted for this study. A number of successful implementations of neural networks process modeling have been reported in Table 2.1.

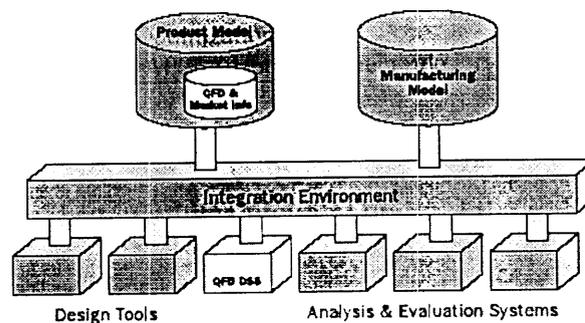
**Table 2.1:** Summarization of the Application of Neural Networks in Process Modeling and Analyzing

Author (Year)	Process / Production	Training Data	Architecture / learning algorithm
Wimalin & James (2005)	Production of hollow wide cord fan blades for aircraft engines (Rolls Royce)	EX	MLP
Yu & Fu (2004)	Ship design principle	AC	BP
Rajam & Selladurai (2004)	Flexible manufacturing process (FMS)	EX & SIM	BP
Jimenez-Marquez <i>et al</i> (2003)	Cheese manufacturing	AC	MLP/QN
Heider <i>et al</i> (2002)	Thermoplastic tow placement process	SIM	MLP/BP
Benardos & Vosniakos (2002)	CNC face milling	EX	MLP/LM

Hsieh & Tong (2001)	IC manufacturing	EX	MLP/BP
Cook <i>et al</i> (2000)	Particleboard manufacturing	AC	AP
Nascimento <i>et al</i> (2000)	Chemical process	AC & SIM	MLP/BP
Raj <i>et al</i> (2000)	Metal forming and machining	SIM	MLP/LM
Edwards <i>et al</i> (1999)	Paper making industry	AC	MLP
Ko <i>et al</i> (1999)	Metal forming process	EX & SIM	MLP/BP
Yarlagadda & Chiang (1999)	Pressure die casting	AC & SIM	MLP/LM
<b>Notes:</b> AC = actual process data, EX = experimental data, SIM = simulated data, MLP = Multilayer Perceptron, BP = Back propagation algorithm, QN = Quasi-Newton Optimization algorithm, LM = Levenberg-Marquardt algorithm, AP = Adaptive gradient rule			

## 2.5 Existing Method in Analyzing and Modeling Quality Function Deployment

Harding & Popplewell (1996) developed architecture for future computer-aided engineering systems in QFD DSS tools. It is based on the use of two information models, a product model and a manufacturing model. Fig.2.6 shows about the application programs include any of the wide range of design, analysis and support tools which members of the concurrent engineering team may wish to use during the project lifecycle.

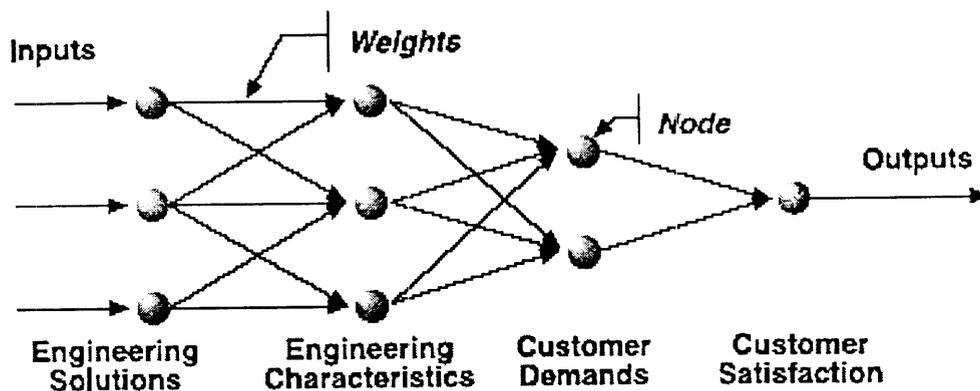


**Figure 2.6:** Architecture for Future Computer-Aided Engineering Systems

Source: Harding & Popplewell (1996)

Zhang *et al.* (1996) have proposed a machine learning approach to QFD, in which a neural network automatically evaluates the data by learning from examples. Customer demands, engineering characteristics and engineering solutions are interconnected as shown in Fig. 2.7 and represented in a neural network format. Engineering solutions are considered as the input, and customer satisfaction rating as the output. Each neuron represents a node (e.g engineering solution is a node) and each link between neurons

represents a relationship (e.g there are relationship between engineering characteristics and customer demands).



**Figure 2.7:** Neural Network: Design Theory and Their Interrelationship

*Source:* Zhang *et al.* (1996).

Vivianne & Hefin (2000) reviews methods and techniques to help QFD by integrating fuzzy logic with QFD. The techniques such as fuzzy logic, NN, and the Taguchi method can be combined with QFD. A fuzzy logic exhibits some useful features for exploitation in QFD. However, only NN is considered in this study as it is the first attempt to employ such technique in analyzing real data.

NNs have found to be a good alternative to traditional analytical techniques, for the modeling of complex manufacturing process. This is because of the number of process variables involved, and the non-linear nature of problems. One major application with NN is forecasting since they can provide a valid alternative to such conventional approaches as time series and regressions. Compared to the traditional statistical methods, NNs are apparently bare of priori assumptions supposedly underlying the models, more capable of addressing problems in the nonlinear domain where the dependent and independent variables are not realized with linear relationship, and rather more general and flexible to approximate any desired accuracy (Zhang *et al.*, 1998).

## 2.6 Statistical Approach In Analyzing and Modeling QFD

For optimization to be effective, it needs a source of accurate and easily computed data. Statistical regression methods adopted in the past is computationally inexpensive but with poor accuracy (Yu & Fu, 2004). The statistical approach used in this study is Descriptive Statistics and Multinomial Logistic Regression (LR) for building models based on the respondents results.

## 2.7 The House of Quality (HOQ) or QFD Chart for QFD

The first chart is normally known as the "house of quality", owing to its shape (Fig. 2.8(a)). Fig. 2.8(b) shows an example of the house of quality for 9 Room. The QFD charts help the team to set targets on issues, which are most important to the customer and how these can be achieved technically. The ranking of the competitors' products can also be performed by technical and customer benchmarking. The QFD chart is a multifunctional tool that can be used throughout the organization. For engineers, it is a way to summarise basic data in a usable form. For marketing, it represents the customer's voice and general managers use it to discover new opportunities (Clausing & Pugh, 1991).

The HOQ falls into two shapes, for 8 Room and 9 Room as shown in Fig. 2.8(a) and Fig. 2.8(b).

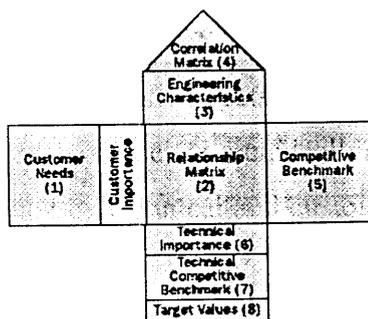


Figure 2.8(a): House of Quality (HOQ) for 8 Room

Source: Hauser & Clausing (1988)

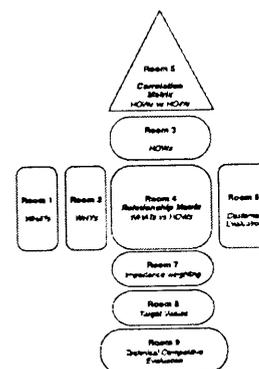


Figure 2.8(b): House of Quality (HOQ) for 9 Room

Source: Vivianne & Hefin (2000)

## 2.8 The Importance of Enhancing QFD

While the structure provided by QFD can be significantly beneficial, it is not a simple method to use. This study addresses the issues of QFD modeling and has presented the potential techniques for building such a model. Modeling QFD by using NNs and statistical tools are proposed and compared to identify QFD specification based on customer voices.

**Table 2.2:** QFD's Beneficial and Drawbacks.

Benefits	Drawbacks
Customer oriented	Ambiguity in the VOC
Brings together large amounts of verbal data	Need to input and analyze large amounts of subjective data
Brings together multi functional teams	QFD development records are rarely kept
Reduces development time by 50 percent and reduces start-up and engineering cost by 30 percent	Manual input of customer survey into the house of quality (HOQ) is time consuming and difficult
Helps design quality into the products at the design stage	QFD analyses often stop after the first HOQ, so links between the four QFD phases are broken
Organizes data in a logical way	The HOQ can become very large and complex
QFD is used not only for products, but for processes and services as well	Setting target values in the HOQ method is imprecise
Strengthens good relationship between customer and company	Strength of relationship is ill-defined
Improves customer satisfaction	QFD is a qualitative method

*Source:* Vivianne & Hefin (2000).

## 2.9 Conclusion

From the literature review, it can be said that neural network approach is the best solution to be as a tool to built QFD model. The findings of this study should be useful to professionals, managers, engineers, researchers and academicians, and this study will offer several contributions to the QFD implementation and performance literature in Malaysian machine planning design. The next chapter will explain the methodologies used for the study.

## CHAPTER 3

### METHODOLOGY

This chapter describes the procedures used to conduct the study, including the project design, selection of the survey sample, survey study result, profile of participants, design of the instruments that was used to collect data, the data collection process, the procedures for analyzing the data, and architecture for modeling of QFD, and steps for building such a forecasting model.

#### 3.1 The Development of The Survey Instrument

The instrument has been used in facilitating the study is questionnaire. A questionnaire was constructed based on the study by Abd Rahman & Mohd Shariff (2003) regarding the application of QFD method for pultrusion machine design planning. It has also been adopted from Khodabocus (2003). Khodabocus study indicates that the most important for QFD questionnaire design for the service is the subject matter under investigation and the statistical analysis employed in the study. This questionnaire is also based on the success factors of QFD projects by Herzwurm *et al.* (1997). The performed questionnaire is mainly divided into 2 main sections as follows:

**Table 3.1: Questionnaire Development**

<b>SECTION A: CUSTOMER PROFILE</b>	<b>SECTION B: POSSIBLE CUSTOMER REQUIREMENT</b>
<p><b>A1: Name of Company/Institution</b> KUKUM ILP POLIMAS</p>	<p><b>B1: Machine Standard Specification</b> B1.3: Machine Brand/Name/Manufacturer B1.4: Operation Type B1.5: Drive Type B1.6: Power (kW) B1.7: Table/Clamp configuration B1.8: Clamp Type B1.9: Pressure (Nm) B1.10: Torque/Spindle Speed min<sup>-1</sup> B1.11: Load Capacity (kg) B1.12: Positioning Accuracy (mm) B1.13: D, Dimensions (mm) B1.14: W, Weight (kg)</p>
<p><b>A2: Type of customer</b> Professional/Lecturer/Instructor Management (Manager/Executive/Engineer/Assistant Engineer/etc) Maintenance (Technician/Line Leader/etc) Operator</p>	<p><b>B2: Machine Control</b> B2.15: Type of control system B2.16: Visible control located within hand reach B2.17: LCD display interface B2.18: Language options for input and output display B2.19: Data transfer options B2.20: Metric and inch measurement unit B2.21: Programming code compatibility B2.22: Graphical programming support B2.23: User storage for programs and data B2.24: All control must be short stroke push button B2.25: Flexible control console B2.26: Machine adjustment should be simple</p>
<p><b>A3: Type of Work piece Material Used/Processed</b> Wood based product Plastic based product Metal based product Composite/fiber/glass based product Product assembly and processing</p>	<p><b>B3: Machine Safety</b> B3.27: Remove mechanical hazards B3.28: Guarding of all exposed moving parts B3.29: Earth and insulation to prevent electric shock B3.30: Trip devices for puller mechanisms B3.31: Emergency stop button B3.32: Foot brake switch B3.33: Exhaust fan for cutter B3.34: Access protection B3.35: Failure for safety B3.36: Heated mould insulation</p>
	<p><b>B4: Machine Performance</b> B4.37: Sensors for warning B4.38: Alarm signal for machine error B4.39: Simple mould replacement B4.40: LED display to show current operation B4.41: High production speed B4.42: Can accommodate different types of product B4.43: Utilize small amount of resin B4.44: Rigid and high damping B4.45: Minimum noise and vibration B4.46: Zero resin spillage B4.47: Able to withstand continuous operations B4.48: Reasonable power consumption B4.49: Low operational cost</p>

	<b>B5: Machine Maintenance</b> B5.50: Easy lubrication points B5.51: Easy replacement parts B5.52: Simple part replacement B5.53: Simple assembly and disassembly B5.54: Self and periodic diagnosis and calibration B5.55: Coolant system and lighting B5.56: Quick mould change and set-up B5.57: Easy trouble shoot
	<b>B6: Machine After Sales Services</b> B6.58: Speed of supervisory/technical person B6.59: Speed of spare part delivery B6.60: Reasonable spare part price B6.61: Continuous technical consultancy B6.62: Near service center B6.63: Availability of spare parts B6.64: Alternative offer

### 3.2 Project Design

The survey was conducted to investigate and obtain information concerning the general lessons that have been learned to date, from the efforts directed at analyzing and modeling of Quality Function Deployment based on voice of customer for general machine planning. These lessons could serve as guide posts for future attempts to build forecasting model of QFD. The goal of the survey was to collect data from four different target types of customers, professional, management, maintenance and operator. There are from engineering and technical background with industrial experience, concerning their views of the resources needed for successful machine planning process in the different areas addressed within the core organizational system, in alignment with its strategy and with particular reference to the experiences in their respective organization. A survey method using questionnaire was chosen for data collection.

#### 3.2.1 Population

The population frames for this study are from the higher learning institution that involved the intensive used in operating a machine and also selected firms which used QFD as a method to measure their quality services. The sample size of types of customer for this

study is based on the sample table by Sekaran (2000). The breakdown of sample of each target is determined using proportionate stratified sampling method as shown in Table 3.2.

**Table 3.2:** Breakdown of Sample Size of Each Target

Institution	Type of Customer
Kolej Universiti Kejuruteraan Utara Malaysia (KUKUM) , Perlis	Professionals (N1) = 17 Management (N2) = 26 Maintenance (N3) = 12 Operator (N4) = 0
Polytechnic of Muadzam Shah (POLIMAS) Jitra, Kedah	Professionals (N5) = 11 Management (N6) = 10 Maintenance (N7) = 15 Operator (N8) = 101
Institute of Industrial Training (ILP) Jitra	Professionals (N9) = 17 Management (N10) = 5 Maintenance (N11) = 9 Operator (N12) = 0
TOTAL	Professionals (N13) = 45 Management (N14) = 41 Maintenance (N15) = 36 Operator (N16) = 101

Systematic sampling was used to choose elements from the population frame. The respondents were drawn from every *n*th element in the population.

### 3.2.2 Data Collection Method

The questionnaire, structured interview and focus group are used to get the information regarding to these modeling of Quality Function Deployment covered in this study.

#### i) Structured interview

The interview was conducted purposely to get in depth information on the selected machine factors with several professional and management of the institutions. Questionnaires were distributed during the interview to test the questionnaires applicability at selected technical learning institutions. Efforts were made to minimize the length of the questionnaire, the questions were pre-tested for clarify.

## ii) Questionnaire

After the interview was completed and the real questionnaire were reviewed and distributed to the selected respondent's mainly comprises of academic experts. The questionnaire was used as solicited information on the extent of effort applied to the forecasting model for QFD by the responding institution.

In designing and administering the questionnaire for this study, the various suggestions for improving response rate were incorporated as much as possible.

## iii) Focus group

All types of customers excluding the operator were involved in the focus group discussion. The information from the focus group can be used to support the knowledge in operating and selecting the best machine specification accordance to their institutions.

**Table 3.3:** Types of Customers and Possible Ways of Obtaining the Voice of Customer

	Professional	Management	Maintenance	Operator
<i>Customer Information</i>				
Structured interview		▪	▪	
Semi-structured interview				▪
Focus group	▪	▪	▪	
Questionnaire	▪	▪	▪	▪
Product screen				
Observation	▪	▪	▪	▪
User participation	▪	▪	▪	▪

## 3.3 Survey Study

The instrument used in this survey study is questionnaire. Participants of this survey study are engineers, instructor, lecturers and an operator experiencing in operating a machine. The sample was chosen by using sample random sampling method and the sample sizes are 223. The sample of this survey study is 3 institutions respondents.

### 3.3.1 Participants

Respondents involved in survey study were 45 professionals, 41 management, 36 maintenance, and 101 operators.

**Table 3.4:** Section A: Customer Profile

VARIABLE	ITEM	FREQUENCY	(%)
A1: Name of Institution/ Company	KUKUM	55	24.664
	POLIMAS	137	61.435
	ILP JITRA	31	13.901
	<b>TOTAL</b>	<b>223</b>	<b>100.000</b>
A2: Type of customer	Professionals	45	20.179
	Management	41	18.386
	Maintenance	36	16.143
	Operator	101	45.291
	<b>TOTAL</b>	<b>223</b>	<b>100.000</b>
A3: Type of work piece material used/ processed	Wood based product	6	2.439
	Plastic based product	71	28.862
	Metal based product	89	36.179
	Composite/fiber/glass based product	8	3.252
	Mixed/synthetic based product	19	7.724
	Product assembly & processing	53	21.545
	<b>TOTAL</b>	<b>246</b>	<b>100.000</b>

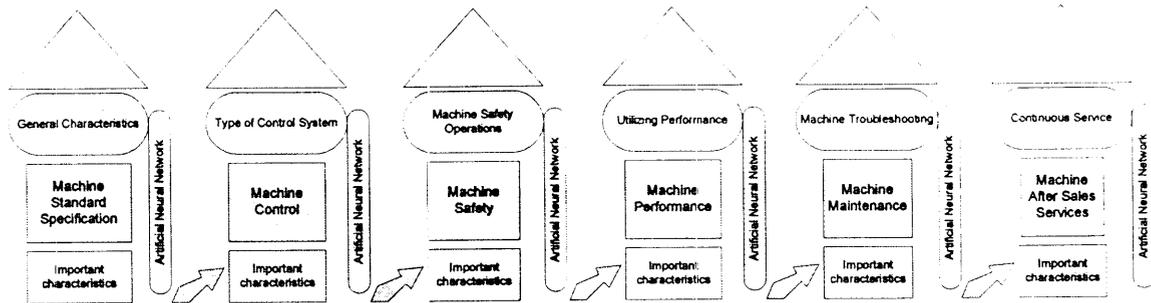
### 3.3.2 Method of Data Sampling/Procedures

Having identified the 3 technical higher learning institutions in Kedah and Perlis, the respective Director of Engineering Centre KUKUM, the head of Mechanical Engineering department POLIMAS, and Deputy Director of ILP Jitra were contacted personally whether they can give their participation on this project. If so, they were briefed the intent of the study by their contact numbers and the procedures involved by sending them an official letter, notes and questionnaire to the respondents during data collection. 3 institutions were tested by visiting their centre; overall all of them gave the best response.

To ensure their full participation, they were briefed about the purpose of the study, the voluntary nature of their participation, and the confidentiality of their responses. The questionnaires were reviewed, collected and calculated, coded and keyed-in over 2 weeks.

### 3.4 A Proposed Architecture for Analyzing QFD based on Voice of Customer (VoC)

The main research design in this study is a survey type that would be used to build QFD model and carrying out the analysis. In order to meet the objective of this study, a QFD methodology described by Clausing & Pugh, 1991 is adopted (see Fig. 3.1).



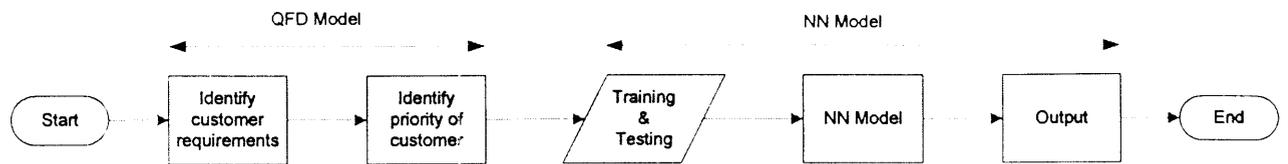
**Figure 3.1:** A Proposed Architecture for Analyzing QFD Based on Voice of Customer

For survey purposes, an instrument used is questionnaires that contain two main sections, a customer profile and possible customer requirements. For customer profile, there are three parameters used namely, name of company or institution, type of customer and type of work piece material used. For customer requirements, there are six (6) parameters according to machine standard specification, machine control, machine safety, machine performance, machine maintenance and machine after sales services. The important subject to focus is the target selected to model of QFD for industry which is type of customers. These include professional, management level, maintenance and an operator as discussed before.

### 3.5 Step to Carry Out for Building Forecasting Model

Fig. 3.2 identifies that neural network and statistical tools would be employed to carry out the analysis. This step to carry out for building forecasting model is adopted from Integrated QFD model methodology which was introduced by San Myint, 2003. The NN

technique is used to overcome QFD weakness in subjective judgments of relationship values with the help of human expert.



**Figure 3.2:** Step to Carry Out for Building Forecasting Model

NN tool would be used to establish a forecasting model for QFD based on type of customer. Some descriptive statistical techniques may also be used to support the analysis.

### 3.6 Develop QFD forecasting model

After the step to carry out for building forecasting model stages, the following phase is to develop the QFD forecasting model by identifying the parameters of the learning model, and the architecture of the network.

#### 3.6.1 Data Preparation

There were a lot of tasks needed to be carried out in this phase. All data from the questionnaire was keyed in into Microsoft Excel spreadsheet (see Fig. 3.3). The following are the list of attributes and target that were chosen to run the experiment on Multilayer Perceptron (see Table 3.5).

**Table 3.5:** The Attributes Involved in the Experiment

TYPE	INPUT VARIABLES	DOMAIN
Target	Type of customer	Professional, Management, Maintenance, Operator
Attributes	Type of work piece used	Wood, Plastic, Metal, Composite, Mixed, Product assembly
Attributes	Machine Brand/Name	US, German, Europe, Japan, Taiwan/Korea
Attributes	Operation type	Low duty, Medium, Heavy

Attributes	Drive Type	Pneumatic, Electric, Hydraulic, Manual
Attributes	Power (kW)	Low: below 1kW, Medium: 1-5kW, High-above 5kW
Attributes	Table/Clamp configuration	Horizontal/Vertical-x,y axis, Flexible-x,y,z axis
Attributes	Clamp Type	Pneumatic, Electric, Hydraulic
Attributes	Pressure (Nm)	Low, Medium, High
Attributes	Torque/Spindle Speed min <sup>-1</sup>	Low, Medium, High
Attributes	Load Capacity (kg)	Low: below 20kg, Medium: 20kg-100kg, High: 100kg-1000kg
Attributes	Positioning Accuracy (mm)	Below 0.05mm, 0.05mm-0.5mm, More than 1mm
Attributes	D, Dimensions (mm)	D<500x500x500mm, 500mm <sup>3</sup> <D≤1000mm <sup>3</sup> , More than 1000mm <sup>3</sup>
Attributes	W, Weight (kg)	0≤W<1000kg, 1000≤W≤2000kg, More than 2000kg
Attributes	Type of control system	Fully automated, Semi-automated, Manual
Attributes	Visible control located within hand reach	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	LCD display interface	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Language options for input and output display	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Data transfer options	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Metric and inch measurement unit	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Programming code compatibility	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Graphical programming support	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	User storage for programs and data	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	All control must be short stroke push button	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Flexible control console	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Machine adjustment should be simple	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Remove mechanical hazards	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Guarding of all exposed moving parts	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Earth and insulation to prevent electric shock	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Trip devices for puller mechanisms	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Emergency stop button	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Foot brake switch	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Exhaust fan for cutter	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Access protection	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Failure for safety	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Heated mould insulation	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Sensors for warning	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Alarm signal for machine error	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Simple mould replacement	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	LED display to show current operation	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	High production speed	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Can accommodate different types of product	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Utilize small amount of resin	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Rigid and high damping	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Minimum noise and vibration	Strong = 9, Medium = 3, Weak = 1, No = 0

Attributes	Zero resin spillage	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Able to withstand continuous operations	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Reasonable power consumption	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Low operational cost	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Easy lubrication points	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Easy replacement parts	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Simple part replacement	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Simple assembly and disassembly	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Self and periodic diagnosis and calibration	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Coolant system and lighting	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Quick mould change and set-up	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Easy trouble shoot	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Speed of supervisory/ technical person	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Speed of spare part delivery	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Reasonable spare part price	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Continuous technical consultancy	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Near service center	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Availability of spare parts	Strong = 9, Medium = 3, Weak = 1, No = 0
Attributes	Alternative offer	Strong = 9, Medium = 3, Weak = 1, No = 0

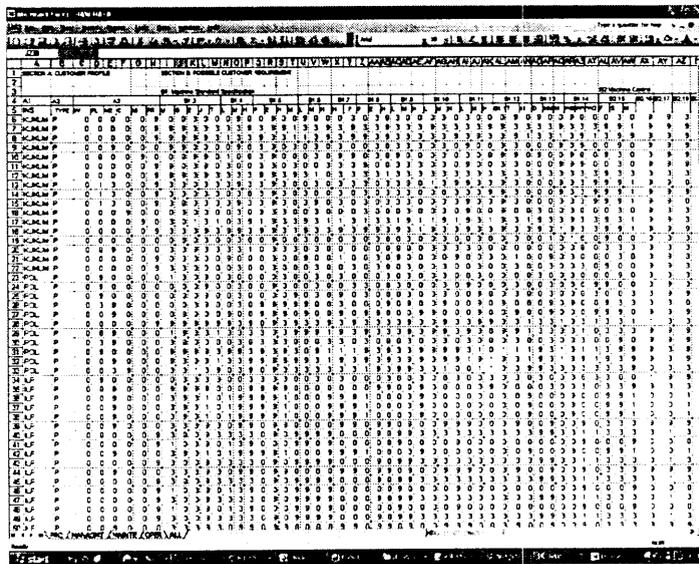


Figure 3.3: Sample of Raw Data Keyed in Microsoft Excel

Once the data has been keyed in a numerical value, the input data can be used directly for the NN, except for the target can be represented as symbol. Prior to training, the data needed to be clean and unimportant attributes were removed from the dataset as it will take a longer time to process in neural network tools and also it does not give any effects in the experiment.

### 3.6.2 Modeling Tool

The problem of this study is to build, classify or predict the QFD forecasting model based on the machine planning datasets. Multilayer Perceptron (MLP) is selected as the modeling tool in this study since it is able to classify patterns or to predict values from the datasets (SPSS, 1997). The MLP's structure consists of three layers; they are input layer, a hidden layer and an output layer. The widely used network topology in MLP is Feed Forward. In the Feed Forward topology, data is moved from the input layer to the hidden layer and finally to the output layer. The data movement is in a direction along the whole network and the result of the output is based on the input dataset.

The learning technique used in the MLP is supervised learning that is suitable for the prediction and classification purposes. It requires that each pattern consists of a set of input values and an associated desired output known as target. The desired output and the actual output are compared so that the connection weight will be adjusted.

MLP utilizes the BP algorithm to learn the pattern of the input data. BP is well known form of learning since it is easy to understand and generally applicable. In BP, the connection weight is adjusted by propagating weight changes backward from the output layer to the input layer (SPSS, 1997).

In this study, the individual entry and average value of QFD machine planning datasets have been trained and tested.

### 3.6.3 Software System

Neural Connection 2.0 is selected as a platform to train and test the neural network. Neural Connection 2.0 is a data analysis package that provides four categories of tools; they are *Input*, *Filter*, *Modeling* and *Forecasting*, and *Output* tool (SPSS, 1997). In this study, only four tools have been used, namely the Data Input, Data Output, Text Output and the Multilayer Perceptron tool.

Neural Connection delivers breakthrough tools for intelligent analysis. Neural Connection can assist in building better models to complement the traditional statistical analysis. According to SPSS Inc. and Recognition Systems Inc., 1997, Neural Connection is stated as a software system that allows user to build complex application for solving the business problems using neural networking and other techniques. The software system consists of four neural network tools and 13 other data modeling and output tools, providing flexibility for prediction, classification, time series analysis, and data segmentation.

Neural Connection is made up of three separate modular groups and a textual initialization language. The modules involved are graphical user interface, an executive, and a set of neural network and data analysis tools. The modular design of Neural Connection gives greater flexibility than standard analysis tools and allows application adaptation as required by the user, in order to gain the best results from the data. Neural Connection is a sophisticated data analysis package that uses neural networks to produce the best answers for user's problems. It is designed around a development environment, the workspace, where the user can create sophisticated and powerful solutions in a very simple way.

### Tools Involved

Tool	Description
 Input1	Tool for importing the data. Import data from files or cutting and pasting from other window application. Can be used to edit data.
 MLP1	Supervised neural network technique.
 Text1	Text Output Displays result as text and shows the success rate
 Output1	Data Output Export data to file and shows the success rate

**Figure 3.4:** Tools Involved in the Multi-Layer Perceptron Network

## Tool Setting

Fig 3.5 below shows the setting in Neural Network for the MLP Network experiment.

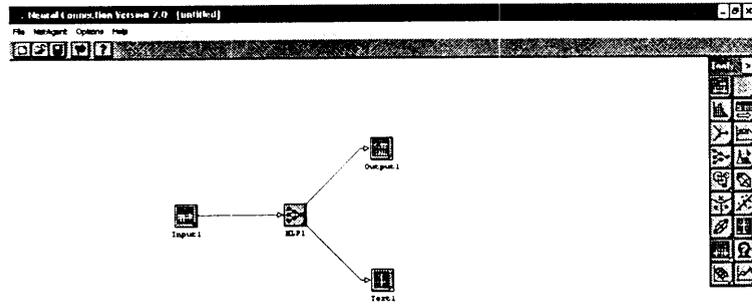


Figure 3.5: Tool Setting of Multi-Layer Perceptron Network

To run Neural Network, the input of the data must be imported from Microsoft Excel spreadsheet (see Fig 3.6) and in coma separated values form (.CSV).

	Integer A2TYPE	Integer A3W	Integer A3PL	Integer A3ME	Integer A3C	Integer A3LM	Integer A3PR
1	0	0	0	0	0	0	0
2	1	0	0	0	0	0	9
3	1	0	0	0	0	0	9
4	1	0	0	0	0	0	9
5	1	0	0	9	0	0	0
6	1	0	0	0	0	9	0
7	1	0	0	0	0	0	9
8	1	0	0	0	0	0	9
9	1	0	1	3	0	0	9
10	1	0	1	3	0	0	9
11	1	0	1	3	0	0	9
12	1	0	0	0	9	0	0
13	1	0	0	0	0	9	0
14	1	0	0	0	0	0	0
15	1	0	0	0	0	0	0
16	1	0	0	9	0	0	0
17	1	0	0	0	0	0	9
18	1	0	0	0	0	0	9
19	1	0	9	0	0	0	0
20	1	0	9	0	0	0	0
21	1	0	9	0	0	0	0
22	1	0	3	9	0	0	0
23	1	0	0	9	0	0	0
24	1	0	0	0	0	0	9
25	1	0	0	9	0	0	0
26	1	0	3	9	0	0	0
27	1	0	9	0	0	0	0
28	1	0	0	9	0	0	0
29	1	0	0	3	9	0	0
30	1	0	9	0	0	0	0

Figure 3.6: Input for the Data

To set the number of target used in the experiment, Output format would be selected to change the number of Bins according to the number of target used (see Fig 3.7).

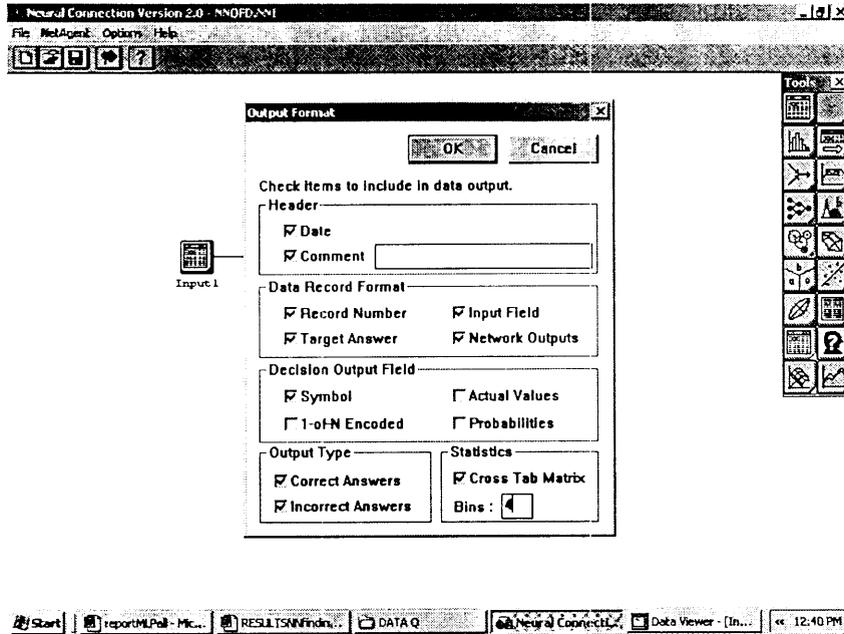


Figure 3.7: Target Setting

### MLP Network Dialog Box

All the parameter must be determined in order to run the NN. The parameters such a learning rate, momentum rate, no of epoch can be keyed in into the software as shown in Fig 3.8.

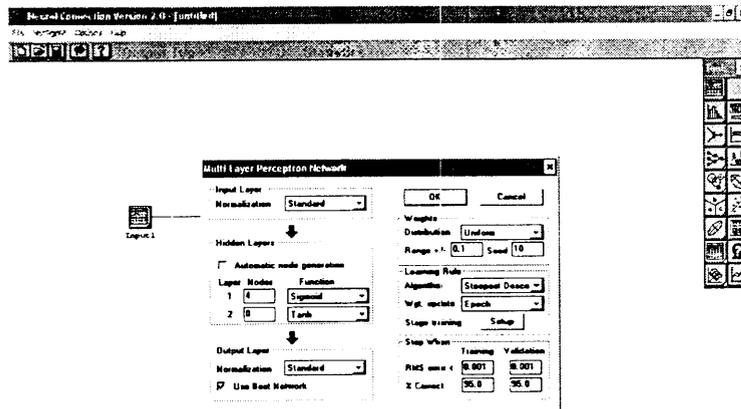


Figure 3.8: The MLP Network Dialog Box

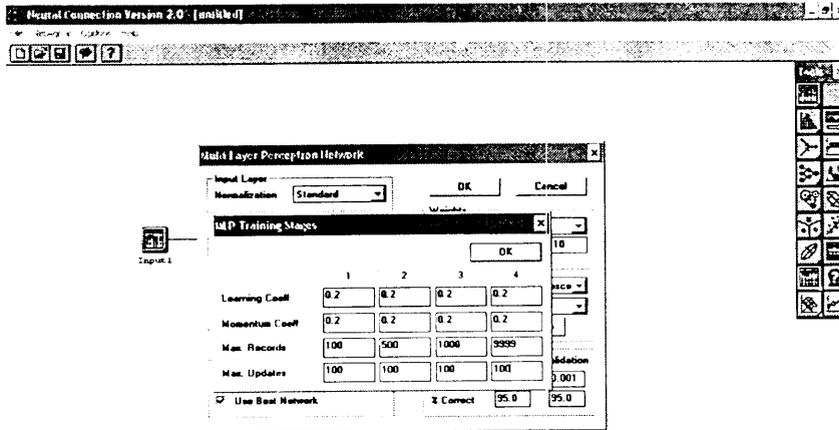


Figure 3.9: The MLP Training Stages

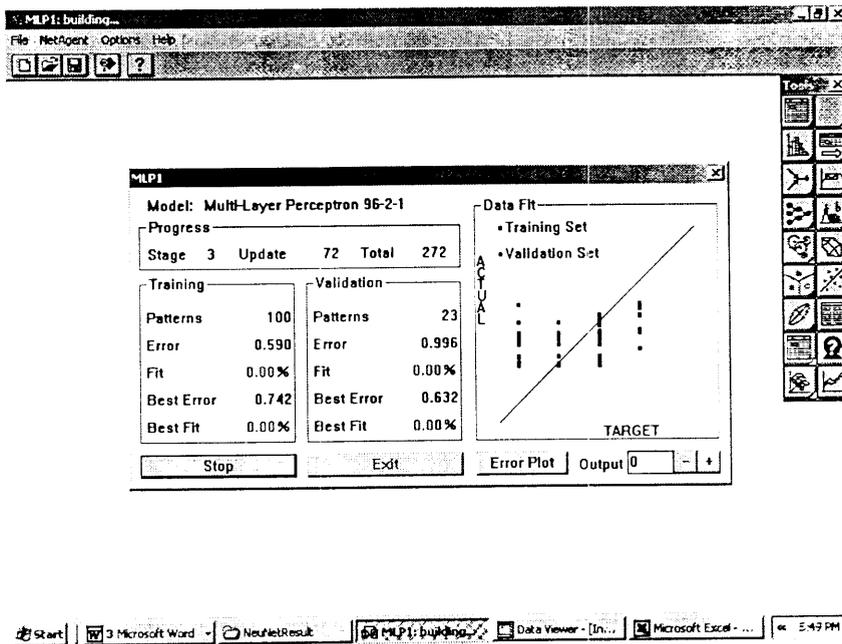


Figure 3.10: Windows for Training the Data

### 3.6.4 Neural Network Training and Testing

The Neural Network has been trained to capture the pattern of the input data and able to make generalization to the new datasets which has not been met before. The synaptic weights were stored in the memory. Once the neural network is trained, the neural network performance was tested to find out the network ability. The ability of the network is referred to as the results of the network training and testing. The network with the high testing result and low training result is identified as the best network model.

Neural Network training and testing involve several stages as shown in Fig.3.11.

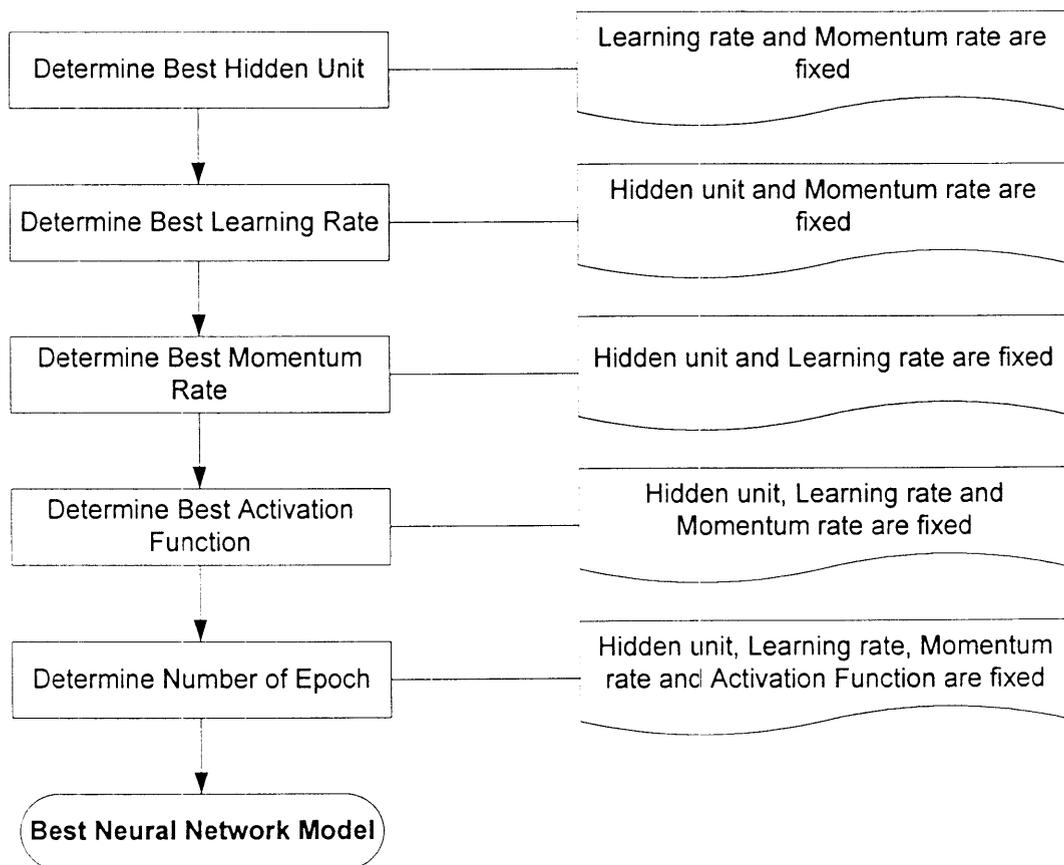


Figure 3.11: Steps of Neural Network Training and Testing

### **3.6.5 Hidden Unit Selection**

In this study, only one hidden layer has been built in the network since the second hidden layer does not produce a large improvement in performance (SPSS, 1997). Based on previous studies, there is no certain method used in determining the best number of hidden unit at the hidden layer. Usually, trial and error method is applied to determine the best number of hidden unit (Tsoukalas & Uhrig, 1997).

In this study, a set of hidden unit ranges from 2 to 20 has been experimented. The two best hidden units were selected and were tested again with different number of weight seeds to obtain the best number of hidden unit by comparing their average training and testing results.

### **3.6.6 Learning Rate Selection**

The learning process occurs when the network connection weights change so that the actual output becomes closer to the desired output. Learning rate is the main element to control the learning model in the neural network. The high learning rate was make the big change in the weight after each epoch and this gives the big variant to its value.

The network training purpose is not to memorize exactly all the training datasets but the network is trained to obtain the power of generalization so that it is able to predict correctly the new dataset which it has not been seen before.

In this study, the learning rate ranging from 0.1 to 1.0 was investigated in order to identify the learning rate which would give the best training and test results. The two best learning rates were selected and the training processes with the different weight seeds were repeated. Finally, the best learning rate was selected.

### **3.6.7 Momentum Rate Selection**

Momentum rate is connected to the learning rate in the network training. It acts as weight changing filter. The presence of the momentum can minimize the changing rate of the weight during the learning process. The latest error was found by summing the previous errors and dividing it with the total time and the result was then added to the current error. As a result, if the error for a pattern is big and in the opposite direction, the learning would not change drastically because the error has been averaged.

### **3.6.8 Activation Function Selection**

Basically, there are three types of activation functions normally been used in the neural network such as Tanh, Sigmoid and Linear Function. The selection of the activation function is based on the input data representation. Since the input data of this study is within the range 0.1 to 1.0 and is nonlinear, the activation function Sigmoid is used in the training and testing.

### **3.6.9 Number of Epoch Selection**

Stopping a training process at a certain condition is an important step to determine during the network training. There are two widely used methods as stopping criteria to stop the training; the first method is by using the tolerance error with the total Mean Square Error. In this method, the network wills the training once it reaches the situation where the total Mean Square Error is the same with the tolerance error. The second method is using the neural network or maximum cycle to stop the training. An epoch refers to a complete cycle of datasets fed into neural network.

The ability of the neural network is not necessarily improves if more number of epoch is set (Sarle, 1994). If the same input patterns have been processed iteratively, the neural network may be good in the training phase but not necessarily gives good generalization for the new dataset in the testing phase. In the over generalization, the network

remembers the given input data patterns by learning the interaction between the variables. This situation is known as over generalization. In this study, the network was trained so that it has the ability to predict the new dataset. The training result cannot indicate the real ability of the network but it can show the network ability through its testing result. Epoch is used as stopping criteria to stop the training process once the set number of neural network is reached. In this study, the number of epoch ranging from 100 to 1000 was investigated to determine the most suitable number of epoch for the QFD forecasting model. The two best neural networks selected and the experiments were repeated with different weight seeds to obtain the suitable epoch.

The results of each experiment, for individual value and average value are shown at the Appendixes B and C.

### **3.7 Logistic Regression**

Binomial (or binary) logistic regression is a form of regression which is used when the dependent is a dichotomy and the independents are continuous variables, categorical variables, or both (“Logistic Regression”, n.d.). The existence of Multinomial Logistic Regression is to handle the case of dependents with more classes.

According to SPSS Inc. (n.d), logistic regression has been described as “Logistic regression applies maximum likelihood estimation after transforming the dependent into a logit variable (the natural log of the odds of the dependent occurring or not). In this way, logistic regression estimates the probability of a certain event occurring. Logistic regression calculates changes in the log odds of the dependent, not changes in the dependent itself as OLS regression does”.

The advantages of regression analysis are the ability to relate a single dependent variable to one or more independent variables, the ability to find potential causal relationships that not only predict but explain the dependent variable makes it very powerful technique.

There is many error and diagnostic statistics help in judging the validity of the relationships. Logistic regression is being widely and easily applied on computers, and it is used commonly in sales forecasting.

The disadvantage of regression methods in forecasting is, when to forecast Y, future values of the independent variable must be known. Thus, multiple forecasts are needed to apply regression analysis and it is very difficult to confirm that a true causal model has been identified.

Logistic Regression is generally classified into 2 types, which are binomial or binary regression and multinomial regression. This study will use the SPSS 12.0 technique by using Multinomial Logistic Regression model in order to predict the QFD machine planning dataset.

To input data into SPSS software, all data must be converted into numbers including target. All the variables must be declared into SPSS software (see Fig. 3.12). The data also can be viewed in Data View (see Fig. 3.13).

Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure
1 A1 Institute	Numeric	7	0		None	None	7	Right	Nominal
2 A2 TOC	Numeric	4	0		None	None	4	Right	Nominal
3 A3 Wood	Numeric	8	2		None	None	8	Right	Nominal
4 Plastic	Numeric	7	2		None	None	8	Right	Nominal
5 Metal	Numeric	2	1		None	None	8	Right	Nominal
6 Composite	Numeric	1	0		None	None	8	Right	Nominal
7 Mixed	Numeric	2	1		None	None	8	Right	Nominal
8 Product	Numeric	2	1		None	None	8	Right	Nominal
9 B1 3US	Numeric	4	2		None	None	8	Right	Nominal
10 German	Numeric	7	2		None	None	8	Right	Nominal
11 Europe	Numeric	8	2		None	None	8	Right	Nominal
12 Japan	Numeric	13	2		None	None	8	Right	Nominal
13 Taiwan	Numeric	2	1		None	None	8	Right	Nominal
14 B1 #Low	Numeric	8	2		None	None	8	Right	Nominal
15 Medium	Numeric	8	2		None	None	8	Right	Nominal
16 High	Numeric	11	2		None	None	8	Right	Nominal
17 B1 SPneu	Numeric	4	2		None	None	8	Right	Nominal
18 Elec	Numeric	1	0		None	None	8	Right	Nominal
19 Hydraul	Numeric	1	0		None	None	8	Right	Nominal
20 Manual	Numeric	1	0		None	None	8	Right	Nominal
21 B1 ELow	Numeric	4	2		None	None	8	Right	Nominal
22 B1 EM	Numeric	1	0		None	None	8	Right	Nominal
23 B1 EH	Numeric	1	0		None	None	8	Right	Nominal
24 B1 7ton	Numeric	4	2		None	None	8	Right	Nominal
25 Vertical	Numeric	1	0		None	None	8	Right	Nominal
26 B1 BPneu	Numeric	4	2		None	None	8	Right	Nominal
27 Elect	Numeric	1	0		None	None	8	Right	Nominal
28 Hyd	Numeric	1	0		None	None	8	Right	Nominal
29 B1 9LG	Numeric	4	2		None	None	8	Right	Nominal
30 Me	Numeric	1	0		None	None	8	Right	Nominal
31 H	Numeric	1	0		None	None	8	Right	Nominal
32 B1 10L	Numeric	5	2		None	None	8	Right	Nominal

Figure 3.12: Variable View in SPSS

The screenshot shows the SPSS Data View window. The menu bar includes File, Edit, View, Data, Transform, Analyze, Graphs, Utilities, Add-ons, Windows, and Help. The toolbar contains icons for Reports, Descriptive Statistics, Compare Groups, General Linear Model, Residual Plots, Correlations, Split-Cell, Loglinear, Classify, Data Reduction, Scale, Nonparametric Tests, Time Series, Survival, Multiple Response, Weights, and 2-Stage Least Squares. The data grid has columns: Atrial, Atrial, Atrial, Atrial, Metal, Composite, Metal, Product, B1, B3, German, Europe, Japan, Taiwan, and B1,4,5,6. The rows are numbered 8 through 37.

Case	Atrial	Atrial	Atrial	Atrial	Metal	Composite	Metal	Product	B1	B3	German	Europe	Japan	Taiwan	B1,4,5,6
8	1	00	00	00	00	00	00	90	900	900	900	900	900	30	10
9	1	00	00	00	90	00	00	00	900	900	900	900	900	00	00
10	1	00	00	00	00	00	90	00	300	00	00	900	900	00	10
11	1	00	00	00	00	00	00	90	900	00	300	900	900	00	30
12	1	00	00	00	00	00	00	90	900	900	300	900	900	30	30
13	1	00	100	30	00	00	00	90	300	300	00	300	300	30	30
14	1	00	100	30	00	00	00	90	300	300	00	300	300	30	30
15	1	00	100	30	00	00	00	90	300	00	300	300	300	30	30
16	1	00	00	00	00	90	00	00	300	00	00	00	00	00	00
17	1	00	00	00	00	00	90	00	300	00	100	300	300	10	00
18	1	00	00	00	00	00	00	90	300	300	300	300	900	30	90
19	1	00	00	00	00	00	00	00	00	00	00	00	300	00	00
20	1	00	00	00	90	00	00	00	300	300	900	300	300	30	30
21	1	00	00	00	00	00	00	90	00	300	00	00	00	00	00
22	1	00	00	00	00	00	00	90	300	300	00	00	900	00	30
23	1	00	900	00	00	00	00	00	100	300	00	00	900	00	00
24	1	00	900	00	00	00	00	00	00	00	00	00	900	00	00
25	1	00	900	00	00	00	00	00	00	00	300	900	00	00	00
26	1	00	300	90	00	00	00	00	900	00	00	00	00	00	90
27	1	00	00	90	00	00	00	00	90	900	900	900	900	90	90
28	1	00	00	00	00	00	00	90	900	900	900	900	900	10	30
29	1	00	00	90	00	00	00	00	300	100	00	00	00	00	00
30	1	00	300	90	00	00	00	00	900	900	900	900	900	30	90
31	1	00	900	00	00	00	00	00	900	300	300	900	900	10	30
32	1	00	00	90	00	00	00	00	300	300	100	300	900	90	00
33	1	00	00	30	90	00	00	00	00	300	300	300	300	30	00
34	1	00	900	00	00	00	00	00	900	900	900	900	900	00	00
35	1	00	00	90	00	00	00	00	300	900	300	100	00	00	10
36	1	00	00	90	00	00	00	00	300	900	300	100	00	00	10
37	1	00	00	90	00	00	00	00	300	900	300	100	00	00	10

Figure 3.13: Data View in SPSS

To apply logistic regression in SPSS, the menu Analyze will be chosen (see Fig.3.14).

The screenshot shows the SPSS Analyze menu open. The menu items are: Reports, Descriptive Statistics, Compare Groups, General Linear Model, Residual Plots, Correlations, Split-Cell, Loglinear, Classify, Data Reduction, Scale, Nonparametric Tests, Time Series, Survival, Multiple Response, Weights, and 2-Stage Least Squares. The 'Logistic Regression' option is highlighted. The background shows the same data grid as Figure 3.13.

Figure 3.14: Menu Bar to choose Logistic Regression

### 3.8 Spearman's rho Correlation

**Spearman's rho:** Nonparametric correlation between two ordinal variables. Kendall, Spearman and the Pearson Product Moment Correlation are equivalent.

$$\text{Spearman's } \rho = 1 - \frac{6D^2}{n(n^2-1)} \quad (10)$$

where

$D = \text{difference between rank of } x \text{ and rank of } y: r_x - r_y$

When the proportion of ties is small, the ties may be ignored. When the proportion of ties is large, they may not be ignored. A correction for ties needs to be made. The correction for ties is performed by giving each tied rank the average score for all of the ranks that are tied.

#### Spearman's rho corrected for tied ranks

Daniel, W. (1978) gives the formula for the Spearman correlation corrected for tied ranks.

$$\begin{aligned} T_x &= \frac{t_x^3 - t_x}{12} \\ T_y &= \frac{t_y^3 - t_y}{12} \\ \sum x^2 &= \frac{n^3 - n}{12} - \sum T_x \\ \sum y^2 &= \frac{n^3 - n}{12} - \sum T_y \\ r_s &= \frac{\sum x^2 + \sum y^2 - \sum d^2}{2\sqrt{\sum x^2 + \sum y^2}} \end{aligned} \quad (11)$$

It should be noted that Kendall discovered that the Spearman's rho is equivalent to a Pearson Product Moment Correlation for continuous variables, which is now to be derived.

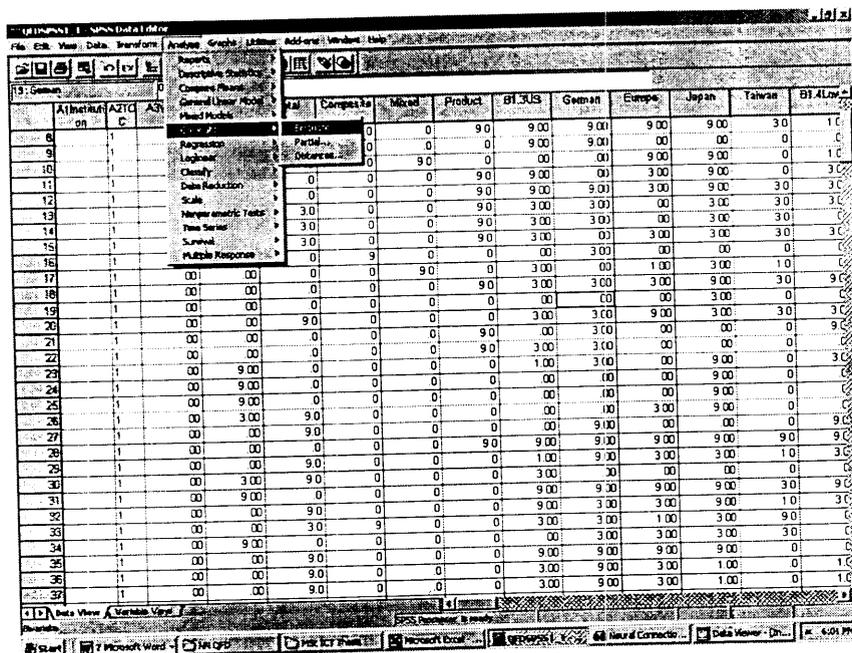


Figure 3.15: Spearman's rho Correlation

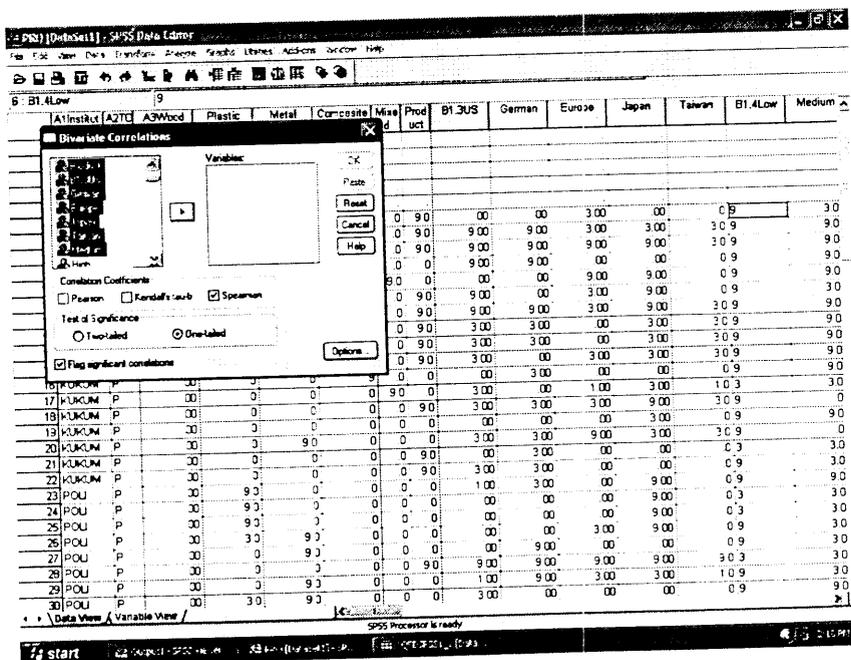


Figure 3.16: Independent Variable Selected to Spearman's rho

### **3.9 Conclusion**

This chapter describes the methodology used in this study. The data for preparation using Microsoft Excel is also discussed. The architecture of the QFD methodology was built through training and testing the network to obtain the parameter of the learning model and the network architecture for developing a suitable NN QFD performance model. In the next chapter, the results of the experiments are presented.

## CHAPTER 4

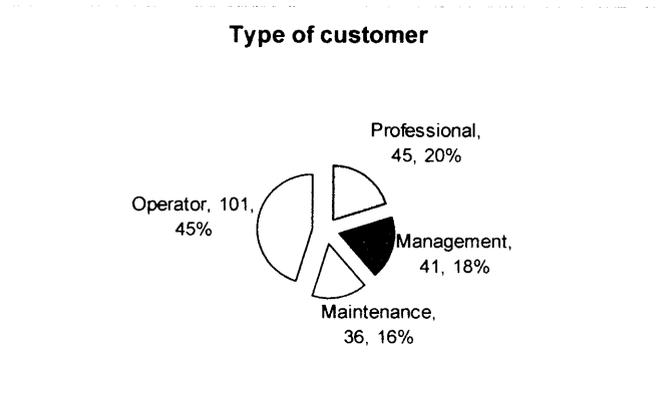
### RESULTS & FINDINGS

This section discusses the result and analysis from the various experiments that have been conducted to explore the effect of each prediction variable against the targeted output. The analysis is written based on the sections provided in the questionnaires.

#### 4.1 The Convenient Sampling Dataset

The survey was conducted to investigate and obtain information concerning and analyzing of Quality Function Deployment for general machine planning. These lessons could serve as guide posts for future attempts to build forecasting model of QFD. The goal of the survey was to collect data from four different target voice of customers, professional, management, maintenance and operator. They are from engineering and technical background with industrial experience, concerning their views of the resources needed for successful machine planning process in different areas addressed within the core organizational system, in alignment with its strategy and with particular reference to the experiences in their respective organization. A survey method using questionnaire was chosen for data collection.

A total of 300 questionnaires were distributed to various customers, and 223 questionnaires were returned (74.3%). This indicates the returned rate is 74.3 percent, which is higher than 10% expected. The distribution of customers with respect to their group type is illustrated in Fig. 4.1.



**Figure 4.1: Pie Chart of Type's Voice of Customer**

## 4.2 Description of respondents

For the initial analysis, the Customer Profile and Possible Customer Requirement were used as independent variables and the types of customers as the dependent variable.

### 4.2.1 Type of customers

For this analysis, types of customers are considered in this study are, (1) Professional/Lecturer/Instructor, (2) Management (Manager/Executive/Engineer/Assistant Engineer), (3) Maintenance (Technician/Line Leader) and (4) Operator. The distribution of the respondent in this study is shown in Table 4.1.

**Table 4.1: Types of Customers**

Type of customer	Total Respondent	Percentage (%)
Professional	45	20.179
Management	41	18.386
Maintenance	36	16.144
Operator	101	45.291
Total	<b>223</b>	100

#### **4.2.2 Professionals/Lecturer/Instructor (1)**

Professional/Lecturer/Instructor is represented as number 1. This group comprises of those who are really involved in teaching how to operate the machine, either theoretical based or practical based. For convenient sampling, the respondents are selected from KUKUM, POLIMAS (Mechanical Engineering Department) and ILP, Jitra. At KUKUM, they are referred to as Instructor Engineer, while at ILP and POLIMAS they are known as Lecturer and Instructor. Group number 1 is 20.179% from overall sample. It is about 45 persons from three selected institution above.

#### **4.2.3 Management (Manager/Executive/Engineer/Assistant Engineer) (2)**

Management is for those who are really involved as a decision maker, such as Dean and Deputy Dean for faculty, Managing Director, Senior Executive, Engineer and Assistant Engineer. This group usually having more experience in handling the heavy machine, and also involved in selecting or forecasting the need for a machine at their institution. About 41 person or 18.386% are willingly to involve as a respondents for this study.

#### **4.2.4 Maintenance (Technician/Line Leader) (3)**

Maintenance group are globally expert from occurs in operating machine. They also ready to settle and troubleshoot a problem happen while machine was operating. For this study, around 36 people (16.144%) from 100% work as the industrial technician almost 10 years.

#### **4.2.5 Operator (4)**

The operators are POLIMAS students, the student who used to work before pursuing their study. They are in final semester and have a good technical knowledge to answer the questionnaires. They gave the exact answer for all questions. 101 operators (45.291%) were selected from 3 different classes (DKM 5B, DTP 6A, DTP 6B).

### 4.3 Pseudo R-Square

An attempt was made to obtain a logistic regression model. The overall was computed and the Pseudo R Square results are shown in Table 4.2.

**Table 4.2:** Pseudo R–Square  
**Pseudo R-Square**

Cox and Snell	.937
Nagelkerke	1.000
McFadden	1.000

Pseudo R Square is an Aldrich and Nelson’s coefficient that serves as an analog to the square contingency coefficient, with an interpretation like R square. Its maximum is less than 1. It maybe used in either dichotomy or multinomial logistic regression. *The Cox and Snell’s* R-square is an attempt to mimic the interpretation of multiple R-square based on the likelihood, but its maximum can be (and usually is) less than 1.0, making it difficult to interpret.

The *Nagelkerke’s R-square* is a further modification of the Cox and Snell coefficient to assure that it can vary from 0 to 1. That is, Nagelkerke’s R-square divides Cox and Snell R-square by its maximum in order to achieve a measure ranging from 0 to1. Therefore Nagelkerke’s R-square will be normally higher than the Cox and Snell measure. Thus, the percentage of Nagelkerke’s R-square for this experiment is **100.0%** while the percentage of Cox and Snell R-square is **93.7%**. The *McFadden’s R-square* (100.0%) is a measure scalar that varies between 0 and (somewhat close to) 1 that is similar like the R Square in a Linear Probability model.

As a conclusion, the *Cox and Snell*, *Nagelkerke*, or *McFadden* in the Table 4.2 above is an attempt to provide a logistic analogy to R-square in the Multiple Linear Regression. Taking all values individually, the regression result is shown in Table 4.2. Although the

Pseudo R-Square produces 100%, no coefficient values have been generated for the logistic regression model. Hence, the model is ignored.

The next sections describe analysis performed based on the section indicated in the questionnaires.

#### **4.4 Spearman's rho Correlation**

The Spearman correlation coefficient, a nonparametric alternative to the Pearson correlation coefficient, replaces the actual data values with ranks. This correlation is a rank order correlation coefficient which also measures association at the ordinal level. In other word, Spearman is simply the Pearson correlation when the data values are replaced by ranks.

##### **4.4.1 Customer Profile**

Further analysis was conducted to explore the relationship between *types of work piece* with respect to voice of customers (see Table 4.3). Based on Table 4.3, all significant correlations at the 0.01 level (1-tailed) are highlighted. The significant attributes include *wood* at  $p = 0.00$ , ( $r = 0.776$ ), *plastic*  $p = 0.00$ , ( $r = -0.266$ ) and *composite*  $p = 0.00$ , ( $r = 0.402$ ) out of six type of work piece used. Out of these, *wood* has the strongest (0.776) relationship with voice of customers. This shows that customers prefer *wood* type to other work piece of material. This may be due to the fact that wood is cheaper in price, and easily available. Furthermore, the *wood* specimen can be bought in various sizes and types. The other three types of work piece that do not have significant correlations are *metal*, *mixed*, and *product assembly*.

**Table 4.3: Type of Work piece Material Used/Processed**

Spearman's rho			Type Of Customer
Type Of Customer	Correlation Coefficient	Sig. (1-tailed)	1.
	N		223
<b>Wood</b>	<b>Correlation Coefficient</b>	<b>Sig. (1-tailed)</b>	<b>.776**</b>
	N		<b>.000</b>
			<b>223</b>
<b>Plastic</b>	<b>Correlation Coefficient</b>	<b>Sig. (1-tailed)</b>	<b>-.266**</b>
			<b>.000</b>
Metal	Correlation Coefficient	Sig. (1-tailed)	.009
			.449
<b>Composite</b>	<b>Correlation Coefficient</b>	<b>Sig. (1-tailed)</b>	<b>.402**</b>
			<b>.000</b>
Mixed	Correlation Coefficient	Sig. (1-tailed)	.061
			.183
Product	Correlation Coefficient	Sig. (1-tailed)	-.304
			.000

\*\* Correlation is significant at the 0.01 level (1-tailed).

\* Correlation is significant at the 0.05 level (1-tailed).

#### 4.4.2 Possible Customer Requirements

This section describe machine specification requirement specified by the customers. Results based on Spearman's rho correlation for each machine specification categories are discussed in accordance to the section written in the questionnaire.

##### 4.4.2.1 Machine Standard Specification

Machine Standard Specification comprises of 12 items, namely *Machine Brand, Operation Type, Drive Type, Power, Table/Clamp Configuration, Clamp Type, Pressure, Torque/Spindle, Load Capacity, Positioning Accuracy, Dimension* and *Weight*.

##### B1.3: Machine Brand/Name/Manufacturer

For *machine brand*, several are investigated such as from *US made, German, Europe, Japan* and *Taiwan*. The significant correlation coefficient between type of customer and

*US machine manufacturer* is  $p = 0.00$  and ( $r = -0.324$ ), *German made*  $p = 0.004$ , ( $r = 0.179$ ), *Japan made*  $p = 0.001$ , ( $r = -0.216$ ) and *Taiwan made*  $p = 0.00$ , ( $r = 0.578$ ). All the correlation stated above are significant at the 0.01 level (1-tailed). The result showed that Taiwan made (0.578) has the strongest relationship among machine brand name or manufacturer (see Table 4.4).

**Table 4.4:** Machine Brand/Name/Manufacturer

			Type Of Customer
Spearman's rho	<b>US made</b>	<b>Correlation Coefficient</b>	<b>-.324**</b>
		<b>Sig. (1-tailed)</b>	<b>.000</b>
		<b>N</b>	<b>223</b>
	German	Correlation Coefficient	.032
		Sig. (1-tailed)	.315
	<b>Europe</b>	<b>Correlation Coefficient</b>	<b>.179**</b>
		<b>Sig. (1-tailed)</b>	<b>.004</b>
	<b>Japan</b>	<b>Correlation Coefficient</b>	<b>-.216**</b>
		<b>Sig. (1-tailed)</b>	<b>.001</b>
	<b>Taiwan</b>	<b>Correlation Coefficient</b>	<b>.578**</b>
		<b>Sig. (1-tailed)</b>	<b>.000</b>

#### **B1.4: Operation Type**

Among *low duty*, *medium duty* and *heavy duty* items, only *operation type* of *heavy duty operation type* achieved a significant correlation  $p = 0.001$ , ( $r = .208$ ) as shown in Table 4.5. The result indicates that customers prefer *heavy duty operating type* of machine. This type of machine normally is more robust, and can be used to perform multiple tasks such as sanding, sawing, cutting, pivoting, threading, dowelling and drilling process.

**Table 4.5:** Operation Type

			Type Of Customer
Spearman's rho	Low duty	Correlation Coefficient	-.064
		Sig. (1-tailed)	.172
		N	223
	Medium	Correlation Coefficient	-.100
		Sig. (1-tailed)	.068
	Heavy	<b>Correlation Coefficient</b>	<b>.208**</b>
		<b>Sig. (1-tailed)</b>	<b>.001</b>

### B1.5: Drive Type

For machine standard specification, *electrical*, *hydraulic* and *manual* machine drive type have significant correlation at  $p = 0.007$ , ( $r = -0.163$ ),  $p = 0.00$ , ( $r = 0.332$ ) and  $p = 0.00$ , ( $r = .229$ ). The hydraulic drive type at  $p = 0.00$ , ( $r = 0.332$ ) is the most significant relationship among this drive type. Only pneumatic drive type does not have a significant level out of four drive type categories.

Table 4.6: Drive Type

			Type Of Customer
Spearman's rho	Pneumatic	Correlation Coefficient	.045
		Sig. (1-tailed)	.252
		N	223
	Electric	Correlation Coefficient	-.163**
		Sig. (1-tailed)	.007
	Hydraulic	Correlation Coefficient	.332**
		Sig. (1-tailed)	.000
	Manual	Correlation Coefficient	.229**
		Sig. (1-tailed)	.000

### B1.6: Power (kW)

According to the *power in kilo Watt* for machine standard specification, all types of power consumption had been selected by all type of customer as significant value. *Low power* is defined as *below 1 kilo Watt*; *medium* is *1-5 kW* and *high power* is *above 5 kW*. *Low*, *Medium* and *High* powers have significant correlation in both 0.01 levels and 0.05 levels. *Low power* and *medium power* have significant correlation at  $p = 0.042$ , ( $r = 0.116$ ) and  $p = 0.050$ , ( $r = 0.110$ ), and *high power* has correlation that is significant at  $p = 0.00$ , ( $r = 0.353$ ). *High machine power* is the most significant at  $p = 0.00$ , ( $r = 0.353$ ) rather than low and medium power.

Table 4.7: Power (kW)

			Type Of Customer
Spearman's rho	Low	Correlation Coefficient	.116*
		Sig. (1-tailed)	.042
		N	223
	Medium	Correlation Coefficient	.110*
		Sig. (1-tailed)	.050
	High	Correlation Coefficient	.353**
		Sig. (1-tailed)	.000

### B1.7: Table/Clamp Configuration

The *table and clamp configuration* usually designed in two types, *horizontal/vertical (xy) axis* and *flexible (xyz) axis*. Currently, a machine have 5 to 9 axis based on the manufacturing process needed, either milling or turning process. Only *flexible axis clamp configuration* has a significant correlation at  $p = 0.00$ , ( $r = 0.343$ ).

**Table 4.8:** Table/Clamp Configuration

			Type Of Customer
Spearman's rho	Horizontal/Vertical - x,y axis	Correlation Coefficient	.090
		Sig. (1-tailed)	.090
		N	223
	Flexible – x,y,z axis	Correlation Coefficient	<b>.343**</b>
		Sig. (1-tailed)	<b>.000</b>

### B1.8: Clamp type

The *clamp types* have 3 different clamping, *pneumatic*, *electrical* and *hydraulic*. For this study, all clamp type have a correlation coefficient at  $p = 0.00$ , ( $r = 0.289$ ) for pneumatic,  $p = 0.00$ , ( $r = 0.245$ ) for electrical clamp and  $p = 0.00$ , ( $r = 0.308$ ) for hydraulic clamp. The *hydraulic clamp type* is the strongest (0.308) relationship similar to *hydraulic drive type*.

**Table 4.9:** Clamp type

			Type Of Customer
Spearman's rho	Pneumatic	Correlation Coefficient	<b>.289**</b>
		Sig. (1-tailed)	<b>.000</b>
		N	223
	Electric	Correlation Coefficient	<b>.245**</b>
		Sig. (1-tailed)	<b>.000</b>
	Hydraulic	Correlation Coefficient	<b>.308**</b>
		Sig. (1-tailed)	<b>.000</b>

### B1.9: Pressure (Nm)

In general, the *pressure (Nm)* for machine standard specification divided into three main types, *low pressure*, *medium pressure* and *High pressure*. Based on Spearman's rho in Table 4.10, correlation coefficient is significant at the 0.01 level (1-tailed) for *low*

*pressure*  $p = 0.002$ , ( $r = 0.197$ ) and *high pressure*  $p = 0.00$ , ( $r = 0.362$ ). The *high pressure* is the strongest (0.362) relationship with other type of machine pressure.

**Table 4.10:** Pressure (Nm)

			Type Of Customer
Spearman's rho	Low	Correlation Coefficient Sig. (1-tailed) N	.197** .002 223
	Medium	Correlation Coefficient Sig. (1-tailed)	-.069 .154
	High	Correlation Coefficient Sig. (1-tailed)	.362** .000

#### B1.10: Torque/Spindle Speed ( $\text{min}^{-1}$ )

*Low* and *high torque/spindle speed* ( $\text{min}^{-1}$ ) have the significant correlation at  $p = 0.00$ , ( $r = 0.318$ ) and  $p = 0.00$ , ( $r = 0.284$ ). This correlation is significant at the 0.01 level (1-tailed). *Low torque spindle speed* is the strongest (0.318) relationship with the others.

**Table 4.11:** Torque/Spindle Speed ( $\text{min}^{-1}$ )

			Type Of Customer
Spearman's rho	Low	Correlation Coefficient Sig. (1-tailed) N	.318** .000 223
	Medium	Correlation Coefficient Sig. (1-tailed)	-.006 .465
	High	Correlation Coefficient Sig. (1-tailed)	.284** .000

#### B1.11: Load Capacity (kg)

*Load capacities* (kg) for machine standard specification have all significant value. For a load capacity *low than 20kg*, the significant correlation is  $p = 0.034$ , ( $r = 0.123$ ) and it is significant at the 0.05 level (1-tailed). For *medium load capacity, 20 kg to 100 kg* the correlation coefficient is  $p = 0.012$ , ( $r = 0.151$ ) and also significant at the 0.05 level. Otherwise, *high load capacity* has correlation coefficient at  $p = 0.000$ , ( $r = 0.413$ ) at the

0.01 level. *High load capacity* refers to a machine with the standard of *100 kg - 1000 kg* and this is the strongest (0.413) relationship with the machine load capacity.

**Table 4.12: Load Capacity (kg)**

			Type Of Customer
Spearman's rho	Low	Correlation Coefficient	.123*
		Sig. (1-tailed)	.034
		N	223
	Medium	Correlation Coefficient	.151*
		Sig. (1-tailed)	.012
	High	Correlation Coefficient	.413**
		Sig. (1-tailed)	.000

### B1.12: Positioning Accuracy (mm)

All types of *Positioning Accuracy (mm)* are significant at the 0.01 level and 0.05 levels (1-tailed). For positioning accuracy *Below 0.05 mm*, correlation coefficient is  $p = 0.011$ , ( $r = 0.154$ ) significant at the 0.05 level (1-tailed). For *0.05 mm to 0.5 mm*, correlation coefficient is  $p = 0.046$ , ( $r = 0.113$ ), significant at the 0.05 level (1-tailed). The last one, *More than 1 mm*, correlation is significant at the 0.01 level (1-tailed) at  $p = 0.000$ , ( $r = 0.520$ ) it is the strongest (0.520) relationship.

**Table 4.13: Positioning Accuracy (mm)**

			Type Of Customer
Spearman's rho	Below 0.05 mm	Correlation Coefficient	.154*
		Sig. (1-tailed)	.011
		N	223
	0.05 mm – 0.5 mm	Correlation Coefficient	.113*
		Sig. (1-tailed)	.046
	More than 1 mm	Correlation Coefficient	.520**
		Sig. (1-tailed)	.000

### B1.13: D, Dimensions, mm (Width x Height x Length)

*Dimension* machine standard specification decision is the important categories to locate the machine in the product or process layout. In other words, it should suit the size of the area allocated by the shop floor of machine. From this study, all valuable findings

showed that it have correlation that is significant at the 0.01 level (1-tailed). When dimension,  $D < 500 \times 500 \times 500 \text{ mm}$ , correlation coefficient is  $p = 0.001$ , ( $r = 0.200$ ) and it is significant at the 0.01 level (1-tailed). For the actual specification,  $500 \text{ mm}^3 < D \leq 1000 \text{ mm}^3$ , the significant correlation is  $p = 0.002$ , ( $r = 0.192$ ). For the last one, *more than 1000 mm<sup>3</sup>*, correlation is significant at  $p = 0.000$ , ( $r = 0.414$ ). Dimension *more than 1000 mm<sup>3</sup>* is the strongest (0.414). All the correlation is significant at the 0.01 level (1-tailed).

**Table 4.14:** D, Dimensions, mm (Width x Height x Length)

			Type Of Customer
Spearman's rho	$D < 500 \times 500 \times 500 \text{ mm}$	Correlation Coefficient	.200**
		Sig. (1-tailed)	.001
		N	223
	$500 \text{ mm}^3 < D \leq 1000 \text{ mm}^3$	Correlation Coefficient	.192**
		Sig. (1-tailed)	.002
	More than 1000 mm <sup>3</sup>	Correlation Coefficient	.414**
		Sig. (1-tailed)	.000

#### B1.14: W, Weight (kg)

The last standard for machine specification in this study is *weight* for the machine. All type of customer is considered that only the best weight of machine is applicable in their operating area. For  $0 \leq W < 1000 \text{ kg}$  has correlation coefficient at  $p = 0.211$ , ( $r = 0.054$ ), that not significant at any level. Otherwise, machine weight  $1000 \leq W \leq 2000 \text{ kg}$  has significant correlation at  $p = 0.001$ , ( $r = 0.207$ ). For machine weight *More than 2000 kg*, its' significant correlation is  $p = 0.000$ , ( $r = 0.414$ ). The strongest relationship is *more than 2000 kg*, with (0.414) significant correlation coefficient (see Table 4.15).

**Table 4.15:** W, Weight (kg)

			Type Of Customer
Spearman's rho	$0 \leq W < 1000 \text{ kg}$	Correlation Coefficient	.054
		Sig. (1-tailed)	.211
		N	223
	$1000 \leq W \leq 2000 \text{ kg}$	Correlation Coefficient	.207**
		Sig. (1-tailed)	.001
	More than 2000 kg	Correlation Coefficient	.414**
		Sig. (1-tailed)	.000

#### 4.4.2.2 Machine Control

A *machine control* criterion was generated based on the control system for the machine as proposed by Abdul Rahman & Mohd Shariff (2003). Items include in this category are *Types of Control System, Visible Control Located within Hand Reach, LCD Display Interface, Language Options for Input and Output Display, Data Transfer Options, Metric and Inch Measurement Unit, Programming Code Compatibility, Graphical Programming Support, User Storage for Programs and Data, All Control must be Short Stroke Push Button, Flexible Control Console and Machine Adjustment should be Simple.*

With reference to three choices of control system, only *manual control system* has significant correlation at  $p = 0.000$ , ( $r = 0.332$ ) rather than fully and semi-automated. The machine with *visible control located within hand reach* has significant correlation at  $p = 0.000$ , ( $r = -0.315$ ). *LCD display interface* has correlation significant at  $p = 0.031$ , ( $r = -0.125$ ). For the *user storage for programs and data* and its significant correlation is  $p = 0.011$ , ( $r = 0.154$ ). Based on the correlation results, *manual* is the strongest type of control system for machine specification. This could be due to the reason that the process involved in manufacturing process with wood work piece selected before comes from manual machine control. In addition, all types of customers either technical or non-technical background inevitably would be able to operate this manual control machine. For machine control option, it concludes that only four out of fourteen criteria achieved the significant value for correlation coefficient (see Table 4.16).

**Table 4.16:** Machine Control

			Type Of Customer
Spearman's rho	Type of control system Fully automated	Correlation Coefficient	-.053
		Sig. (1-tailed)	.214
		N	223
	Semi-automated	Correlation Coefficient	.037
		Sig. (1-tailed)	.292
	<b>Manual</b>	<b>Correlation Coefficient</b>	<b>.332**</b>
		<b>Sig. (1-tailed)</b>	<b>.000</b>
	<b>Visible control located</b>	<b>Correlation Coefficient</b>	<b>-.315**</b>

<b>within hand reach</b>	<b>Sig. (1-tailed)</b>	<b>.000</b>
<b>LCD display interface</b>	<b>Correlation Coefficient</b>	<b>-.125*</b>
	<b>Sig. (1-tailed)</b>	<b>.031</b>
Language options for input and output display	Correlation Coefficient	-.002
	Sig. (1-tailed)	.488
Data transfer options	Correlation Coefficient	-.019
	Sig. (1-tailed)	.391
Metric and inch measurement unit	Correlation Coefficient	-.053
	Sig. (1-tailed)	.215
Programming code compatibility	Correlation Coefficient	-.034
	Sig. (1-tailed)	.307
Graphical programming support	Correlation Coefficient	.017
	Sig. (1-tailed)	.398
<b>User storage for programs and data</b>	<b>Correlation Coefficient</b>	<b>.154*</b>
	<b>Sig. (1-tailed)</b>	<b>.011</b>
All control must be short stroke push button	Correlation Coefficient	.087
	Sig. (1-tailed)	.098
Flexible control console	Correlation Coefficient	.092
	Sig. (1-tailed)	.085
Machine adjustment should be simple	Correlation Coefficient	-.007
	Sig. (1-tailed)	.459

#### 4.4.2.3 Machine Safety

*Machine safety* is the third important segment for general machine specification. There are ten items in this section, namely ***Remove Mechanical Hazards, Guarding of all Exposed Moving Parts, Earth and Insulation to Prevent Electric Shock, Trip Devices for Puller Mechanism, Emergency Stop Button, Foot Brake Switch, Exhaust Fan for Cutter, Access Protection, Failure for Safety and Heated Mould Insulation.***

Based on Table 4.17, only four criteria out of ten have four significant correlations at 0.01 level (1-tailed). The significant items include *earth and insulation to prevent electric shock*  $p = 0.007$ , ( $r = -0.164$ ), *emergency stop button*  $p = 0.003$ , ( $r = -0.187$ ), *foot*

*brake switch*  $p = 0.000$ , ( $r = 0.235$ ) and the last one is *exhaust fan for cutter*  $p = 0.007$ , ( $r = 0.165$ ). *Foot brake switch* has the strongest (0.235) relationship with type of customer.

*Foot Brake Switch* is preferable to other machine safety type since it is the most commonly used for wood material. It seems reasonable that this type of machine safety achieves significant correlation due to the facts that most material used is wood as indicated earlier.

**Table 4.17: Machine Safety**

			Type Of Customer
Spearman's rho	Remove mechanical hazards	Correlation Coefficient Sig. (1-tailed) N	-.077 .128 223
	Guarding of all exposed moving parts	Correlation Coefficient Sig. (1-tailed)	.024 .360
	<b>Earth and insulation to prevent electric shock</b>	<b>Correlation Coefficient Sig. (1-tailed)</b>	<b>-.164** .007</b>
	Trip devices for puller mechanism	Correlation Coefficient Sig. (1-tailed)	.054 .211
	<b>Emergency stop button</b>	<b>Correlation Coefficient Sig. (1-tailed)</b>	<b>-.187** .003</b>
	<b>Foot brake switch</b>	<b>Correlation Coefficient Sig. (1-tailed)</b>	<b>.235** .000</b>
	<b>Exhaust fan for cutter</b>	<b>Correlation Coefficient Sig. (1-tailed)</b>	<b>.165** .007</b>
	Access protection	Correlation Coefficient Sig. (1-tailed)	.083 .109
	Failure for safety	Correlation Coefficient Sig. (1-tailed)	-.046 .245
	Heated mould insulation	Correlation Coefficient Sig. (1-tailed)	.079 .119

#### 4.4.2.4 Machine Performance

*Machine performance* have thirteen important elements that consist of *Sensors for Warning, Alarm Signal for Machine Error, Simple Mould Replacement, LED Display to Show Current Operation, High Production Speed, Can Accommodate Different Types of Product, Utilize Small Amount of Resin, Rigid and High Damping, Minimum Noise and Vibration, Zero Resin Spillage, Able to Whist and Continuous Operations, Reasonable Power Consumption* and *Low Operational Cost*.

Based on results exhibited in Table 4.18, *utilize small amount of resin, rigid and high damping*, and *zero resin spillage* have significant values at the 0.01 level (1-tailed). Among these, the strongest relationship for machine performance is *utilize small amount of resin*  $p = 0.000$ , ( $r = 0.289$ ). At 0.05 level (1-tailed), only *simple mould replacement* has significant correlation is  $p = 0.013$ , ( $r = 0.149$ ).

**Table 4.18:** Machine Performance

			Type Of Customer
Spearman's rho	Sensors for warning	Correlation Coefficient	-.005
		Sig. (1-tailed)	.468
		N	223
	Alarm signal for machine error	Correlation Coefficient	-.012
		Sig. (1-tailed)	.431
	<b>Simple mould replacement</b>	<b>Correlation Coefficient</b>	<b>.149*</b>
		<b>Sig. (1-tailed)</b>	<b>.013</b>
	LED display to show current operation	Correlation Coefficient	.051
		Sig. (1-tailed)	.226
	High production speed	Correlation Coefficient	-.008
		Sig. (1-tailed)	.453
	Can accommodate different types of product	Correlation Coefficient	.097
		Sig. (1-tailed)	.074
<b>Utilize small amount of resin</b>	<b>Correlation Coefficient</b>	<b>.289**</b>	
	<b>Sig. (1-tailed)</b>	<b>.000</b>	
<b>Rigid and high damping</b>	<b>Correlation Coefficient</b>	<b>.201**</b>	
	<b>Sig. (1-tailed)</b>	<b>.001</b>	
Minimum noise and vibration	Correlation Coefficient	.072	
	Sig. (1-tailed)	.141	
<b>Zero resin spillage</b>	<b>Correlation Coefficient</b>	<b>.242**</b>	
	<b>Sig. (1-tailed)</b>	<b>.000</b>	

Able to withstand continuous operations	Correlation Coefficient Sig. (1-tailed)	.078 .122
Reasonable power consumption	Correlation Coefficient Sig. (1-tailed)	-.028 .341
Low operational cost	Correlation Coefficient Sig. (1-tailed)	-.030 .329

#### 4.4.2.5 Machine Maintenance

Machine Maintenance contains several precaution steps in preserving lifetime of a machine. In this questionnaire, machine maintenance is measured by several items such as *Easy Lubrication Points*, *Easy Replacement Parts*, *Simple Part Replacement*, *Simple Assembly and Disassembly*, *Self and Periodic Diagnose and Calibration*, *Coolant System and Lighting*, *Quick Mould Change* and *Set-up and Easy Trouble Shoot*.

Out of these items, *easy lubrication points* is  $p = 0.011$ , ( $r = -0.154$ ), *simple part replacement* is  $p = 0.024$ , ( $r = -0.133$ ), *simple assembly and disassembly* is  $p = 0.032$ , ( $r = -0.125$ ), *easy trouble shoot* is  $p = 0.030$ , ( $r = -0.126$ ) have significant correlation with customers voices (see Table 4.19). However, the strongest negative correlation is shown by *easy lubrication points*.

Table 4.19: Machine Maintenance

			Type Of Customer
Spearman's rho	<b>Easy lubrication points</b>	<b>Correlation Coefficient</b>	<b>-.154*</b>
		<b>Sig. (1-tailed)</b>	<b>.011</b>
		<b>N</b>	<b>223</b>
	Easy replacement parts	Correlation Coefficient	-.008
		Sig. (1-tailed)	.450
	<b>Simple part replacement</b>	<b>Correlation Coefficient</b>	<b>-.133*</b>
		<b>Sig. (1-tailed)</b>	<b>.024</b>
<b>Simple assembly and disassembly</b>	<b>Correlation Coefficient</b>	<b>-.125*</b>	
	<b>Sig. (1-tailed)</b>	<b>.032</b>	
Self and periodic diagnose and calibration	Correlation Coefficient	-.002	
	Sig. (1-tailed)	.487	
Coolant system and	Correlation Coefficient	-.090	

lighting	Sig. (1-tailed)	.091
Quick mould change and set-up	Correlation Coefficient Sig. (1-tailed)	.064 .170
Easy trouble shoot	Correlation Coefficient Sig. (1-tailed)	-.126* .030

#### 4.4.2.6 Machine after Sales Services

For machine after sales services, there are 7 items, including *Speed of Supervisory/Technical Person, Speed of Spare Part Delivery, Reasonable Spare Part Price, Continuous Technical Consultancy, Near Service Center, Availability of Spare Parts, and Alternative Offer*.

Among these 7 items, *availability of spare parts* shows significant correlation with voice of customer at  $p = 0.027$ , ( $r = -0.129$ ). The results indicate that when customers show an interest in buying a specific machine, one of the most important criteria that they would consider is after sales services. This is to ensure that the machine they bought can be maintained, serviced or replaced the parts whenever it is necessary. Therefore, the *availability of spare parts* becomes important item in machine after sales services section.

**Table 4.20: Machine after Sales Services**

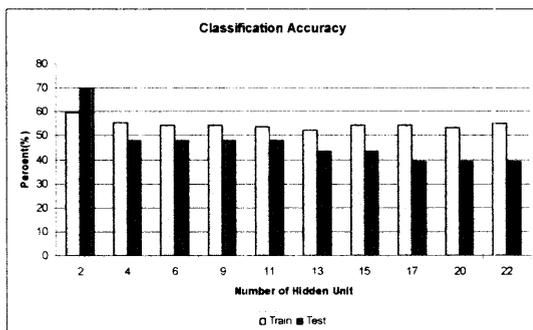
			Type Of Customer
Spearman's rho	Speed of supervisory/technical person	Correlation Coefficient	-.065
		Sig. (1-tailed)	.169
		N	223
	Speed of spare part delivery	Correlation Coefficient	-.073
		Sig. (1-tailed)	.138
	Reasonable spare part price	Correlation Coefficient	-.103
		Sig. (1-tailed)	.062
	Continuous technical consultancy	Correlation Coefficient	-.006
		Sig. (1-tailed)	.465
	Near service center	Correlation Coefficient	.076
		Sig. (1-tailed)	.129
	<b>Availability of spare parts</b>	<b>Correlation Coefficient</b>	<b>-.129*</b>
		<b>Sig. (1-tailed)</b>	<b>.027</b>
	Alternative offer	Correlation Coefficient	.067
		Sig. (1-tailed)	.161

## 4.5 QFD Neural Network Model

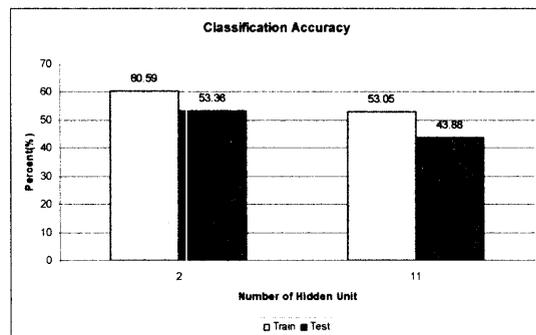
The analysis using Neural Network (NN) is performed in two ways. First, each individual entry of the questionnaire would be considered as an attribute for each pattern in NN dataset. The second method is to get the average value for each section in the questionnaire as an entity for NN attributes.

### 4.5.1 Individual Entry

In order to determine the most suitable number of hidden units, the dataset was trained with various hidden units ranging from 2 to 20. The results illustrated in Fig. 4.2(a) indicate that hidden unit 2 and 11 obtained highest test and least training accuracy for both training and testing. A set of networks with hidden unit 2 and 11 were further trained to determine which hidden is more appropriate to be used in the next experiment. The results depicted in Fig. 4.2(b) show that a network with 2 hidden units obtained higher classification accuracy than a network with 11 hidden units (53.36% versus 43.88%).

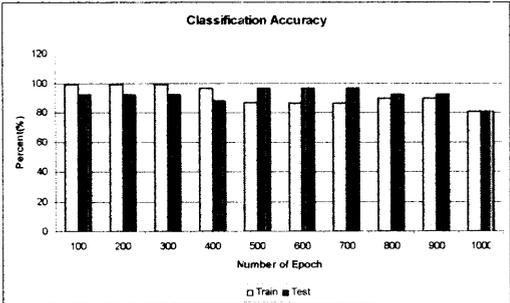


**Figure 4.2(a):** Classification accuracies for different number of

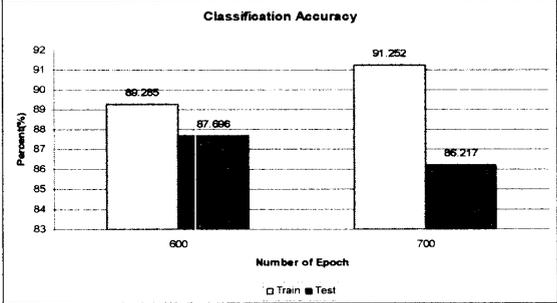


**Figure 4.2(b):** Average classification accuracies for network trained with hidden unit 2 and 11

Experiments have been conducted to determine the suitable number of epoch prior to determining the backpropagation training parameters. For experimental purposes, the learning rate is 0.1 and the momentum rate was set to 0.3. Based on the results exhibited in Fig. 4.3(a), epochs 600, and 700 obtained the highest test results with 96.25% and 86.59% classification accuracy. These two number of epochs were further investigated by varying weight seeds in order to determine the most suitable number of epoch for the problem at hand. The results displayed in Fig. 4.3(b) show that a set of network trained up to 600 epoch achieved the highest average test result with 87.696% accuracy.



**Figure 4.3(a):** Classification accuracies for different number of epoch



**Figure 4.3(b):** Average classification accuracies for network trained up to 600 and 700 epochs

Similar experiments were conducted to determine the learning rate and the momentum rate for Backpropagation learning algorithm. The experimental results show that learning rate 0.1 obtained 40.01% classification accuracy whilst momentum rate of 0.3 achieved 44.78%. Once again the number of epoch was investigated based on the selected training parameters of Backpropagation. The Neural Network architecture and training parameters on individual entry for classifying QFD machine planning datasets are summarized in Table 4.21.

The summary of the best model to classify the QFD for machine planning datasets individual entry is listed as below:

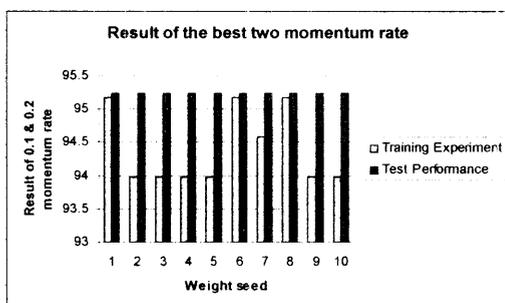
**Table 4.21:** NN model for each value

Parameter	Value
Architecture	Multilayer Perceptron
Learning Algorithm	Backpropagation
Input Node	97
Hidden Node	2
Output Node	4
Learning Rate	0.1
Momentum Rate	0.3
Activation Function	Sigmoid
Number of Epoch	600

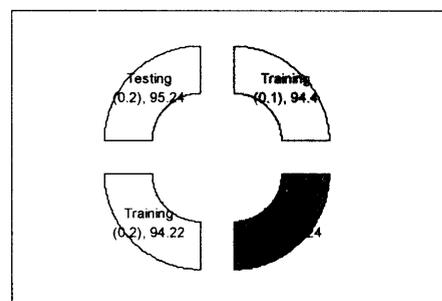
#### 4.5.2 Average Value

Similar experiments have been conducted by averaging values of items for Type of Work piece, Machine Standard Specification, Machine Control, Machine Safety, Machine Performance, Machine Maintenance and Machine after Sales Service.

Based on the results shown in Fig.4.4(a), the results of 0.1 and 0.2 momentum rates constantly at 95.24% for test performance but varies for training experiment. The least average training result was produced when the momentum rate was set to 0.2, which are 94.22% rather than 94.40% for 0.1 momentum rate (see Fig.4.4 (b)). Therefore, in order to conduct the further experiments, the momentum rate 0.2 has been selected.



**Figure 4.4(a):** Bar graph of the best two momentum rate



**Figure 4.4(b):** Pie chart of the average of 0.1 and 0.2 momentum rate (Test & Train)

According to Fig. 4.5, the average test result was obtained the same result for both Sigmoid and Tanh function (95.24%). The results only for training performance produced different results (94.46%) for Sigmoid and 94.70% for Tanh. Therefore, in order to conduct the further experiments, the Sigmoid activation function has been selected because of the least percentage rather than Tanh activation function.

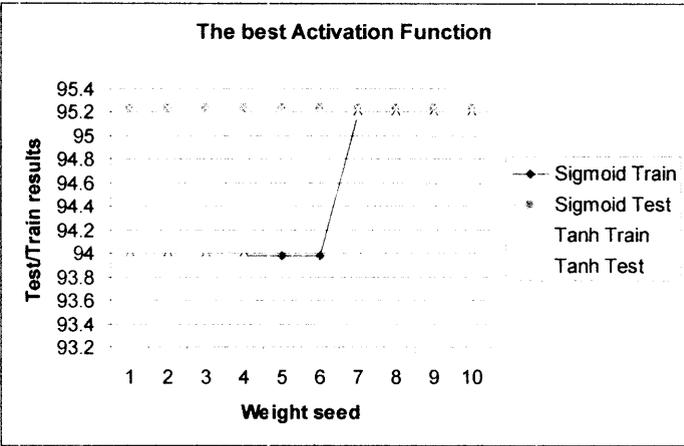


Figure 4.5: Line graph for the best Activation Function

Based on the results shown in Fig. 4.6, the highest average test result was produced when the epoch was set to 100 that are 87.621%. When the hidden unit is equal to 4, learning rate is equal to 0.2, momentum rate is equal to 0.2, and activation function is set to sigmoid, the epoch of 100 has been considered the best compared to epoch of 400.

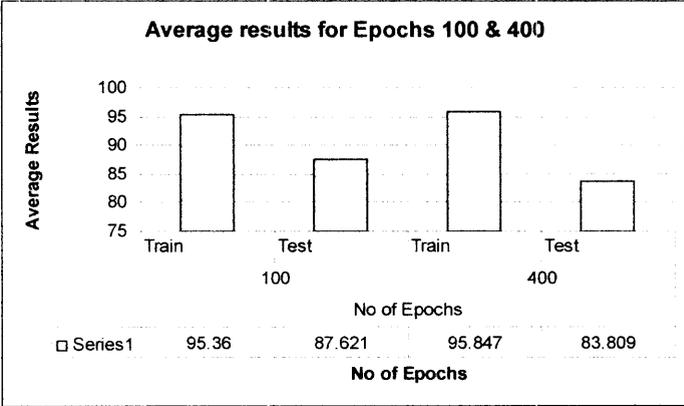


Figure 4.6: Average results for No of Epochs 100 & 400

For brevity, the results are summarized in Table 4.22.

**Table 4.22:** NN model for average value

<b>Parameter</b>	<b>Value</b>
Architecture	Multilayer Perceptron
Learning Algorithm	Backpropagation
Input Node	97
Hidden Node	4
Output Node	4
Learning Rate	0.2
Momentum Rate	0.2
Activation Function	Sigmoid
Number of Epoch	100

#### 4.6 Conclusion

Hundreds of experiments have been conducted to establish a forecasting NN model in this study. For both models, the architecture of NN model can be expressed as 97-2/4-4 or 97 input nodes, 2 or 4 hidden nodes and 4 output nodes. Both models used sigmoid activation function, backpropagation (BP) learning algorithm with slightly different learning and momentum rates. To this end, the performances of both models are presented in Table 4.23. Based on the results, the datasets with individual value achieves higher percentage accuracy (87.696%). Therefore, Neural Network (NN) model summarized in Table 4.23 is chosen to represent the QFD model based on voice of customer with architecture of 97-2-4.

**Table 4.23:** NN Model Performance

<b>Multi-Layer Perceptron (MLP) (Individual Value)</b>	<b>Multi-Layer Perceptron (MLP) (Average Value)</b>
87.696%	87.621%

## CHAPTER 5

### CONCLUSION AND RECOMMENDATION

This chapter wrapping up the contribution of the study, as well as presenting the problems and limitations encountered in conducting the study. In addition, the discussion on the recommendation for the future work is also presented.

#### 5.1 Conclusion

Data mining is an activity which involves a lot of trial and error experiments. However, it is an interesting study once the hidden information within the data is uncovered. This study attempts to explore manufacturing sector focusing on Quality Function Deployment (QFD) since a lot of interesting data that can be mined and analyzed. The results show that the accuracy using NN is 87.696% for individual entry and 87.621% for average value. QFD is one of the most valuable tools that can be used when developing a new product. It is a structured method where all customer requirements can be analyzed and built in during the design stage. To ensure its effectiveness, the use of QFD technique must be integrated with the design process and not carried out separately. In this project, it was carried out for a general machine specification by using NN approach and also statistical approach to support the findings.

From this study, it concludes that for the average value, the best learning rate is 0.2 while 0.2 for the best momentum rate. Sigmoid activation function has been chosen as it produced the highest test percentage. For the best epoch, 100 is selected as it represents

the highest average test percentage that is **87.621%**. In addition, for individual entry, the best learning rate is 0.1 while 0.3 for the best momentum rate. For the best epoch, epoch of 600 has been selected as it represents the highest test percentage that is **87.696%**.

In summary, the findings from the experiments conducted indicate that the significant correlations with customer voices are summarized in Table 5.1.

**Table 5.1: Correlation Summary**

Section	Significance item	Significant values	Spearman's rho Correlation
Type of work piece material used	Wood	p = 0.000	r = 0.776
Machine Standard Specification	Heavy Duty Operation Type	P = 0.001	r = 0.208
Machine Control	Manual Control System	P = 0.000	r = 0.332
Machine Safety	Foot Brake Switch	P = 0.000	r = 0.235
Machine Performance	Utilize Small Amount Of Resin	P = 0.000	r = 0.289
Machine Maintenance	Easy Lubrication Point	P = 0.011	r = -0.154
Machine After Sales Service	Availability of Spare Parts	P = 0.027	r = -0.129

These correlations help to explain the relationship between attributes used in the study. To complete the study, NN forecasting model has been established with **87.696%** accuracy in determining the customer voices based on QFD. The study indicates that the approach has some potential in providing some information regarding the relationship between QFD and the customers, as well as predicting the type of customer if QFD information is provided. Hence, the study reveals the type of machine and type of operation that are favorable to customer prior to acquiring the machines for their industrial usage.

## 5.2 Problems and Limitation

The problems in conducting the study are as follows:

- **Data**

The main problem encountered during the study is incomplete data. Some respondent did not provide complete results. Most of them did not know the exact information about the machine specification at their institutions.

- **Size of respondent**

The size of the respondents is not as large as expected since industrial firm did not give their feedback for this study. At first, a total of 1000 respondents have been planned including industrial sector. Thus, only respondent at technical institution have been covered and the copied questionnaire about 500, only 300 has used.

The limitations of the study are follows:

- **Sample of respondents**

The respondents considered in this study have technical experiences and engineering background. These targets are too small compared to others. It might be an interesting discovery to explore the pattern from various backgrounds of respondents around the country.

- **Time constraint**

This study has been done in the duration of 2 months study. Due to time constraint, only technical institution at northern area can be covered.

## 5.3 Recommendation and Future Work

For future extension, it is an advantage to find the respondents from various technical institutions and also from industrial sectors. There is also a need for further studies that will help to determine the types of problem situations where NN will yield superior predictions.

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## APPENDIX A: RAW DATA

SECTION A: CUSTOMER PROFILE

SECTION B: POSSIBLE CUSTOMER REQUIREMENT

B1: Machine Standard Specification

A1	A2	A3																	B1.3				B1.4				B1.5				B1.6				B1.7	
INS	TYPE	W	PL	ME	C	MI	PR	U	G	E	J	T	L	M	H	P	E	H	M	L	M	H	H	F												
KUKUM	P	0	0	0	0	0	9	0	0	3	0	0	0	9	0	0	9	0	0	9	0	0	0	3												
KUKUM	P	0	0	0	0	0	9	9	9	3	3	3	3	9	3	9	9	1	3	3	9	3	9													
KUKUM	P	0	0	0	0	0	9	9	9	9	3	1	3	3	9	3	3	1	1	3	9	3	9													
KUKUM	P	0	0	9	0	0	0	9	9	0	0	0	9	0	3	3	0	3	0	3	0	3	0													
KUKUM	P	0	0	0	0	9	0	0	0	9	9	0	1	0	0	3	9	0	0	3	0	9	9													
KUKUM	P	0	0	0	0	9	9	0	3	9	0	3	0	0	3	3	0	3	0	3	3	3														
KUKUM	P	0	0	0	0	9	9	9	3	9	3	3	3	3	9	9	3	9	3	1	0	3	3													
KUKUM	P	0	1	3	0	0	9	3	3	0	3	3	3	9	3	9	3	0	3	0	3	3	3													
KUKUM	P	0	1	3	0	0	9	3	3	0	3	3	0	3	0	3	9	3	0	3	0	3	0													
KUKUM	P	0	1	3	0	0	9	3	0	3	3	3	3	9	3	3	9	3	0	3	9	0	3													
KUKUM	P	0	0	0	9	0	0	0	3	0	0	0	3	0	3	3	0	3	0	3	0	0	0													
KUKUM	P	0	0	0	9	0	0	0	3	0	1	3	1	0	3	9	1	9	3	3	9	3	1													
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KUKUM	P	0	0	0	0	0	0	0	0	3	0	3	0	0	0	0	9	0	3	0	3	0	0													
KUKUM	P	0	0	9	0	0	0	3	3	9	3	3	3	1	0	3	3	3	0	3	0	0	0													
KUKUM	P	0	0	0	0	9	0	3	0	0	0	9	0	0	3	0	0	9	0	0	1	0														
KUKUM	P	0	0	0	0	9	3	3	0	0	0	3	0	0	3	0	0	3	0	3	0	0	3													
POLI	P	0	9	0	0	0	0	1	3	0	9	0	3	0	0	0	3	0	3	0	3	0	3													
POLI	P	0	9	0	0	0	0	0	0	9	0	0	3	0	0	9	0	0	0	3	0	0	3													
POLI	P	0	9	0	0	0	0	0	0	9	0	0	3	0	0	0	0	9	0	3	0	9	0													
POLI	P	0	3	9	0	0	0	0	0	3	9	0	3	0	9	9	9	9	9	0	3	0	0													
POLI	P	0	0	9	0	0	0	0	9	0	0	0	9	0	0	9	9	9	0	9	0	9	0													
POLI	P	0	0	9	0	0	0	9	9	9	9	9	3	9	0	9	3	9	3	9	3	9	9													
POLI	P	0	0	9	0	0	0	1	9	3	3	1	3	3	3	3	9	9	9	1	9	3														
POLI	P	0	3	9	0	0	0	3	0	0	0	0	3	0	3	3	3	0	0	3	3	0														
POLI	P	0	9	0	0	0	0	9	9	9	3	9	9	3	9	3	9	9	1	1	1	1														
POLI	P	0	0	9	0	0	0	9	3	3	9	1	3	3	9	9	9	9	3	1	9	3														
POLI	P	0	0	3	9	0	0	3	3	1	3	9	0	3	9	0	9	3	3	3	3	3														
ILP	P	0	9	0	0	0	0	0	3	3	3	3	0	0	3	3	3	0	3	0	3	0														
ILP	P	0	0	9	0	0	0	9	9	9	0	0	9	9	9	0	0	9	9	0	0	0														
ILP	P	0	0	9	0	0	0	3	9	3	1	0	1	9	9	9	9	1	0	0	9	9														
ILP	P	0	0	9	0	0	0	3	9	3	1	0	1	9	9	9	9	1	0	0	9	9														
ILP	P	0	0	9	0	0	0	3	3	3	9	3	0	9	9	0	9	9	0	0	9	9														
ILP	P	0	0	9	0	0	9	3	0	0	9	3	3	3	0	9	0	9	9	9	9	0														
ILP	P	0	0	0	0	9	1	0	3	9	0	1	3	9	0	0	0	9	9	9	9	0														
ILP	P	0	0	9	0	0	0	3	3	3	9	3	0	9	9	0	0	0	0	0	9	9														
ILP	P	0	0	9	0	0	9	3	0	0	9	3	3	3	0	9	9	9	9	9	9	0														
ILP	P	0	0	0	0	9	1	0	3	9	0	1	3	9	0	0	0	9	9	0	9	0														
ILP	P	0	0	0	0	9	3	0	0	9	3	3	3	0	9	0	9	9	9	9	9	0														
ILP	P	0	0	0	0	9	1	0	3	9	0	1	3	9	0	0	0	9	9	0	9	0														
ILP	P	0	0	9	0	0	0	3	3	3	9	3	0	9	9	0	0	0	0	0	9	9														
KUKUM	MG	0	0	0	0	0	0	0	0	0	3	0	0	3	0	0	9	0	0	3	0	0	3													

KUKUM	MG	0	0	9	0	0	0	3	3	9	3	3	3	1	0	3	3	3	0	3	0	0	0
KUKUM	MG	0	0	0	0	0	9	0	3	0	0	0	9	0	0	3	0	0	9	0	0	0	1
KUKUM	MG	0	0	0	0	0	9	0	0	3	0	0	9	0	0	9	0	0	9	0	0	0	3
KUKUM	MG	0	1	3	0	0	9	3	0	3	3	3	9	3	3	9	3	3	9	3	0	3	9
KUKUM	MG	0	0	0	9	0	0	0	3	0	0	0	3	0	3	3	3	0	3	0	0	3	0
KUKUM	MG	0	0	9	0	0	0	3	3	9	3	3	3	1	0	3	3	3	0	3	0	0	0
KUKUM	MG	0	0	0	0	9	0	3	0	0	0	9	0	0	3	0	0	0	9	0	0	0	1
KUKUM	MG	0	0	0	0	9	3	3	0	0	0	3	0	0	3	0	0	3	0	0	3	0	0
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	1	3	3	9	3	3	1	1	3	9	3	9
KUKUM	MG	0	0	9	0	0	9	9	0	0	0	9	0	0	3	3	0	3	0	3	0	3	0
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	1	3	3	9	3	3	1	1	3	9	3	9
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	0	3	0	3	0	3	0
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9	3	9	3	1	0	3
KUKUM	MG	0	0	0	0	9	9	9	9	9	3	3	3	9	3	3	9						

KUKUM	MT	0	0	0	0	0	9	0	3	0	0	0	9	0	0	0	3	0	0	9	0	0	1	0
POLI	MT	0	9	0	0	0	0	1	3	0	9	1	1	9	3	0	9	9	3	9	3	1	3	9
POLI	MT	0	3	9	0	0	0	0	0	0	9	0	0	3	0	0	3	0	3	0	3	0	3	9
POLI	MT	0	0	9	0	0	0	0	0	0	9	0	9	9	0	1	3	0	9	3	3	3	3	3
POLI	MT	0	0	9	0	0	0	9	0	0	9	0	3	9	0	3	1	3	1	3	1	3	3	3
POLI	MT	0	9	0	0	0	0	1	3	0	0	9	0	9	0	0	9	0	9	0	9	0	9	0
POLI	MT	0	3	9	0	0	0	3	0	0	0	0	3	0	0	3	3	3	0	0	0	3	3	0
POLI	MT	0	9	0	0	0	0	9	9	9	3	9	9	3	9	3	9	3	9	3	0	9	1	1
POLI	MT	0	0	3	9	0	0	3	3	1	3	9	0	3	9	0	9	3	3	3	3	3	3	3
POLI	MT	0	0	9	0	0	0	1	9	3	3	1	3	3	3	3	3	9	9	9	1	9	3	3
POLI	MT	0	0	9	0	0	0	9	3	3	9	1	3	3	9	9	9	9	9	3	1	9	3	3
POLI	MT	0	9	0	0	0	0	1	3	0	9	0	3	0	0	0	3	0	0	3	0	3	0	3
POLI	MT	0	9	0	0	0	0	0	0	0	9	0	0	3	0	0	9	0	0	3	0	0	3	0
POLI	MT	0	9	0	0	0	0	0	0	0	9	0	0	3	0	0	0	0	9	0	3	0	9	0
POLI	MT	0	3	9	0	0	0	0	0	3	9	0	0	3	0	9	9	9	9	9	0	0	3	0
POLI	MT	0	0	9	0	0	0	0	9	0	0	9	0	9	9	9	9	9	9	0	0	3	0	0
POLI	MT	0	0	9	0	0	0	9	9	9	9	9	3	9	0	9	3	9	3	3	9	3	9	9
ILP	MT	0	0	0	0	0	9	9	9	9	9	9	9	3	9	0	9	3	9	3	3	9	3	9
ILP	MT	0	0	9	0	1	0	0	0	3	1	3	9	9	9	9	1	0	9	9	9	9	1	0
ILP	MT	0	0	9	0	1	0	0	0	3	1	3	9	9	9	9	1	0	9	9	9	9	1	0
ILP	MT	0	0	9	0	0	0	3	0	3	9	3	3	0	9	0	0	9	3	3	0	9	0	9
ILP	MT	0	0	0	0	3	0	3	9	0	9	3	0	9	0	0	0	9	3	3	0	9	0	9
ILP	MT	0	0	0	0	1	0	0	9	3	9	1	0	9	0	0	0	3	9	0	0	0	0	9
ILP	MT	0	0	9	0	1	0	0	0	3	1	3	9	9	9	9	1	0	9	9	9	9	1	0
ILP	MT	0	0	0	0	3	0	3	9	0	9	3	0	9	0	0	0	9	3	3	0	9	0	9
ILP	MT	0	0	9	0	0	0	3	0	3	9	3	3	0	9	9	0	9	9	0	9	9	0	9
DTP 6B	O	0	9	9	0	0	0	0	9	0	9	0	0	3	0	9	3	0	0	0	3	0	3	3
DTP 6B	O	0	9	0	0	0	0	0	0	9	0	0	3	0	9	3	0	0	0	3	0	3	3	3
DTP 6B	O	0	9	0	0	0	0	0	0	1	9	3	1	3	1	1	9	1	9	9	3	3	1	9
DTP 6B	O	1	1	3	0	9	0	0	0	9	0	9	0	9	0	9	9	9	0	9	0	9	9	0
DTP 6B	O	0	9	0	0	0	0	0	0	0	9	0	9	0	9	9	9	9	0	9	9	0	9	0
DTP 6B	O	0	0	9	0	0	0	0	0	3	0	3	0	0	0	0	0	3	0	3	0	9	0	9
DTP 6B	O	9	0	3	0	0	0	0	0	9	0	9	0	9	0	9	0	9	0	9	0	9	0	9
DTP 6B	O	0	3	3	3	9	9	0	0	9	0	0	3	0	0	0	0	3	9	0	0	9	0	9
DTP 6B	O	0	9	9	9	9	9	0	0	0	9	0	9	0	3	3	3	3	3	0	0	9	0	9
DTP 6B	O	0	9	9	0	0	0	0	0	9	0	9	0	0	0	0	0	9	0	3	0	9	0	9
DTP 6B	O	0	3	9	0	0	0	0	0	9	0	9	0	0	3	0	0	0	3	0	0	3	0	9
DTP 6B	O	0	3	9	0	0	0	0	0	9	0	9	0	0	0	0	0	3	0	0	3	0	0	9
DTP 6B	O	0	0	9	0	0	0	0	0	9	0	9	0	0	0	0	0	9	0	9	0	0	0	9
DTP 6B	O	0	0	9	0	0	0	0	0	9	0	9	0	0	0	0	0	9	0	9	0	0	0	9
DTP 6B	O	0	0	9	0	0	0	0	0	9	0	9	0	0	0	0	0	9	9	9	0	9	0	9
DTP 6B	O	0	0	9	0	0	0	0	0	9	0	9	0	0	0	0	0	9	0	9	0	9	0	9
DTP 6B	O	0	0	9	0	0	0	0	0	9	0	9	0	0	0	0	0	9	0	9	0	9	0	9
DTP 6B	O	0	0	9	0	0	0	0	0	9	0	9	0	0	0	0	0	9	0	9	0	9	0	9
DTP 6B	O	0	9	9	0	0	0	0	0	9	0	9	0	9	1	9	9	0	3	3	9	9	9	9
DTP 6B	O	0	9	9	0	0	0	0	0	9	0	9	0	0	0	0	9	0	9	0	9	0	9	0

DTP 6B	O	0	0	9	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	9	0	9	0
DTP 6B	O	9	9	9	0	0	0	0	0	0	0	9	0	0	9	0	0	9	0	9	0	9	0	9	0
DTP 6B	O	0	0	9	0	0	0	0	0	0	0	3	9	3	9	3	0	9	0	9	0	9	0	3	0
DTP 6A	O	0	0	9	0	0	0	0	0	0	9	9	9	1	3	3	3	9	9	9	1	9	3	1	3
DTP 6A	O	0	0	9	0	0	0	0	0	3	9	9	9	1	3	3	3	9	9	9	1	9	3	1	3
DTP 6A	O	0	9	0	0	0	0	0	0	9	0	0	0	9	0	0	0	3	0	0	3	0	0	3	0
DTP 6A	O	0	0	9	0	0	0	0	9	9	3	9	1	3	9	3	9	1	3	9	3	9	3	9	9
DTP 6A	O	0	9	0	0	0	0	0	3	9	9	1	0	9	3	3	9	3	9	1	3	9	3	9	3
DTP 6A	O	0	0	9	0	0	0	0	9	9	1	9	1	3	3	3	9	9	9	9	1	3	3	3	3
DTP 6A	O	0	9	0	0	0	0	0	9	9	3	1	3	3	9	9	3	1	9	9	3	1	9	3	3
DTP 6A	O	0	9	9	0	0	0	0	9	0	0	3	3	9	1	1	1	3	3	3	3	3	3	3	9
DTP 6A	O	0	9	0	0	0	0	0	9	0	0	3	3	3	3	9	9	9	9	3	3	3	9	9	9
DTP 6A	O	0	9	0	0	0	0	0	3	9	3	3	1	3	3	9	9	3	3	1	3	3	9	3	1
DTP 6A	O	0	0	9	0	0	0	0	9	3	1	9	3	3	3	1	3	9	3	3	1	3	9	3	9
DTP 6A	O	0	0	9	0	0	0	0	9	3	1	9	3	3	3	1	3	9	3	3	1	1	3	3	9
DTP 6A	O	0	0	9	0	0	0	0	9	3	1	9	3	3	3	1	3	9	3	3	1	1	3	3	9
DTP 6A	O	0	0	9	0	0	0	0	9	3	1	9	3	3	3	1	3	9	3	3	1	1	3	3	9
DTP 6A	O	0	0	9	0	0	0	0	9	3	1	9	3	3	3	1	3	9	3	3	1	1	3	3	9
DTP 6A	O	0	0	9	0	0	0	0	9	3	1	9	3	3	3	1	3	9	3	3	1	1	3	3	9
DTP 6A	O	0	9	0	0	0	0	0	3	9	9	3	3	3	9	9	9	9	9	9	9	9	9	9	9
DTP 6A	O	0	9	0	0	0	0	0	1	3	1	3	3	9	3	1	9	9	3	1	1	3	3	3	9
DTP 6A	O	0	0	0	0	0	0	0	9	9	3	9	9	1	9	9	9	9	9	9	9	9	9	9	9
DTP 6A	O	0	0	9	0	0	0	0	3	9	3	3	1	3	3	3	9	3	3	3	1	3	3	3	9
DTP 6A	O	0	0	9	0	0	0	0	3	3	3	9	9	1	3	9	3	9	3	3	3	3	3	3	9
DTP 6A	O	0	9	0	0	0	0	0	3	3	3	9	9	1	3	9	9	9	9	9	9	9	9	9	9
DTP 6A	O	0	9	0	0	0	0	0	3	1	3	3	1	3	3	3	3	3	3	3	1	3	3	3	9
DTP 6A	O	0	0	0	0	0	0	0	9	3	0	9	1	3	3	9	9	9	9	9	9	9	9	9	9
DTP 6A	O	0	0	0	0	0	0	0	9	3	3	3	3	9	3	3	9	9	9	9	9	9	9	9	9
DTP 6A	O	0	9	0	0	0	0	0	3	3	3	3	9	9	9	9	9	9	9	9	9	9	9	9	9
DTP 6A	O	0	0	0	0	0	0	0	1	3	0	9	3	1	3	9	9	9	9	9	9	9	9	9	9
DKM 5B	O	0	0	0	0	9	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	9	0	9	0
DKM 5B	O	0	9	0	0	0	0	0	9	9															

DKM 5B O	0	9	0	0	0	3	9	3	9	3	3	3	0	9	3	3	1	3	3	3	1	1	
DKM 5B O	0	0	9	0	0	0	9	3	1	3	3	0	3	0	9	0	0	0	3	0	0	9	9
DKM 5B O	0	0	0	0	0	9	0	0	0	9	0	0	3	0	0	3	0	0	0	0	0	9	0
DKM 5B O	0	0	0	0	0	9	9	9	9	3	9	3	1	9	9	9	9	9	9	9	9	9	9
DKM 5B O	0	9	0	0	0	0	9	9	9	3	9	9	1	9	9	9	9	9	9	9	9	9	9
DKM 5B O	0	0	9	0	0	0	3	9	3	9	9	9	3	3	3	3	3	3	3	3	3	9	3
DKM 5B O	0	0	9	0	0	0	3	9	9	9	1	3	9	9	9	9	9	9	9	9	9	9	9
DKM 5B O	0	9	0	0	0	0	9	9	9	9	3	9	9	1	9	9	9	9	9	9	9	9	9
DKM 5B O	0	0	0	0	9	0	9	3	3	3	3	9	9	3	3	3	3	3	3	3	3	9	9
DKM 5B O	0	9	0	0	0	0	9	9	9	9	3	3	3	9	9	3	1	3	3	1	1	3	3
DKM 5B O	0	0	9	0	0	3	3	9	3	9	1	9	3	9	9	3	9	1	3	3	9	3	9
DKM 5B O	0	0	0	0	0	9	3	9	3	3	9	9	3	3	9	9	9	3	3	9	9	3	3
DKM 5B O	0	0	0	0	9	0	3	9	9	9	3	3	9	9	9	9	9	3	3	9	9	9	9
DKM 5B O	0	9	0	0	0	0	9	0	0	0	0	9	0	0	9	0	0	0	0	3	0	3	0
DKM 5B O	0	0	0	0	9	0	9	9	3	9	3	3	3	9	9	9	9	9	3	9	9	9	9
DKM 5B O	0	0	0	0	9	0	3	3	1	9	1	3	9	1	3	1	9	9	3	1	9	9	3
DKM 5B O	0	0	0	0	9	0	3	3	9	0	3	3	3	9	3	1	0	3	3	9	3	9	9
DKM 5B O	0	0	0	0	9	0	3	3	9	3	3	9	9	3	3	9	9	3	3	9	3	9	9
DKM 5B O	0	0	0	0	9	0	3	9	9	9	3	3	9	9	9	9	9	3	3	9	3	9	3
DKM 5B O	0	0	0	0	9	0	9	9	9	9	1	9	3	1	9	9	9	3	9	3	9	3	9
DKM 5B O	0	0	9	0	0	0	1	3	0	9	1	3	9	1	3	1	3	3	3	3	9	3	3
DKM 5B O	0	0	0	0	9	0	9	9	3	3	9	3	9	3	3	9	9	3	9	3	9	3	9
DKM 5B O	0	0	0	0	9	0	9	3	9	1	3	3	9	9	3	1	1	3	9	3	9	3	9
DKM 5B O	9	0	0	0	0	0	3	9	0	1	0	9	3	1	9	1	3	9	1	3	3	9	9
DKM 5B O	0	9	0	0	0	0	3	1	3	9	1	3	3	9	3	9	3	1	9	3	9	9	3
DKM 5B O	0	0	0	0	9	0	9	9	3	3	9	3	3	3	9	9	3	9	1	3	3	3	3
DKM 5B O	0	0	9	0	0	0	3	3	9	9	3	1	3	1	3	3	1	3	3	3	3	3	3
DKM 5B O	0	9	0	0	0	0	0	9	1	3	3	9	1	9	3	3	3	9	1	3	3	9	9
DKM 5B O	0	0	9	0	0	0	0	9	0	0	3	3	3	3	1	3	9	9	9	9	9	3	3

B2:Machine Control																				B2.16	B2.17	B2.18							
B1.8			B1.9			B1.10			B1.11			B1.12			B1.13			B1.14			B2.15								
P	E	H	L	M	H	L	M	H	L	M	H	B1.11	T	M	D	MM	M	WO	WI	W2	F	S	M						
0	3	0	3	0	0	0	3	0	3	0	0	0	9	0	9	0	0	9	0	0	0	3	0	9	9	3			
3	3	9	3	3	3	9	3	3	3	3	9	9	3	3	3	9	3	3	3	9	3	3	9	9	1	9	9	9	
9	3	9	3	3	3	3	9	3	9	3	9	3	3	9	1	3	3	1	3	9	1	3	9	9	9	9	9		
0	3	0	3	3	3	0	3	0	9	0	0	3	3	0	0	9	0	9	0	9	0	0	9	0	9	9	9		
0	3	0	9	0	0	0	3	0	3	0	0	9	9	0	9	0	0	9	0	9	0	0	9	3	0	3	9	9	
9	0	0	3	3	3	0	3	0	9	0	0	3	3	0	0	9	9	0	0	9	9	0	0	3	0	9	9	9	
3	3	1	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	9	3	3	3	3	3	
3	0	3	3	9	0	1	3	9	9	3	3	9	3	9	3	0	0	9	3	3	9	9	9	1	9	9	0		
3	0	3	3	3	0	0	3	3	9	3	9	9	3	0	0	9	3	3	9	9	3	9	9	9	1	9	9	0	
3	0	3	3	3	0	0	3	3	9	3	3	9	3	9	3	0	0	3	3	3	9	9	9	1	9	9	0		
3	0	0	3	0	0	3	0	9	0	0	3	0	0	3	0	0	0	9	9	0	0	3	0	0	9	9	3	3	
1	3	3	1	9	1	1	9	1	9	3	1	9	3	1	9	3	1	9	3	3	9	3	9	3	1	9	9	3	
9	9	3	9	3	1	9	3	3	9	3	3	9	3	3	9	3	1	9	3	3	9	9	1	9	9	9	9		
0	3	0	0	3	0	0	3	0	0	3	0	0	0	3	0	1	0	1	0	0	9	0	0	0	3	3	3		
0	3	0	9	0	0	0	9	0	0	3	0	0	3	0	1	0	0	9	0	3	0	0	0	3	0	3	9	3	
0	3	0	0	3	0	0	3	0	0	3	0	0	3	0	0	3	0	0	3	0	0	3	0	9	0	9	9	3	
0	0	3	0	3	0	0	3	0	0	3	0	0	0	0	3	0	0	3	0	0	0	0	9	0	0	3	3	3	
3	0	0	3	0	0	0	3	0	9	0	0	0	3	0	0	3	0	0	9	0	0	0	9	0	0	3	9	3	
0	0	9	0	9	0	0	9	0	9	0	9	0	9	0	9	0	0	9	0	9	0	0	9	3	3	3	3	0	
9	9	0	0	9	9	0	9	0	0	9	0	0	9	0	0	9	0	0	9	0	0	9	9	9	0	9	3	9	
3	3	3	9	3	3	9	3	3	9	9	3	3	9	9	3	3	1	3	3	1	3	3	1	1	3	3	1	3	
9	3	3	9	3	9	9	3	9	3	9	3	9	3	9	9	1	3	3	3	1	0	3	3	9	9	9	9	9	
3	0	0	3	0	0	3	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	9	0	0	9	9	9	
9	3	9	3	9	9	9	9	9	9	3	1	0	1	1	1	9	3	1	3	1	1	3	9	9	9	9	3	9	
9	3	9	9	9	3	9	9	1	9	1	9	3	1	9	3	1	9	3	1	9	9	1	9	3	9	9	0	3	3
1	9	3	9	9	3	3	1	0	0	1	1	3	3	9	9	3	3	3	3	3	3	3	9	0	3	9	0	3	3
0	0	3	0	0	3	0	0	3	0	0	3	0	0	3	0	3	0	0	0	3	3	0	0	1	9	9	9	9	
0	9	9	0	0	9	0	0	0	0	0	9	0	0	0	0	9	0	0	0	9	0	0	9	1	0	0	0	1	
1	0	0	0	3	9	0	0	0	0	0	0	0	0	0	9	0	0	0	9	0	0	9	9	1	0	0	0	1	
1	0	0	0	3	9	0	0	0	0	0	0	0	0	0	9	0	0	0	9	0	0	9	9	1	0	0	0	1	
0	9	9	0	9	0	0	9	9	9	0	0	3	9	0	0	9	0	9	0	9	0	3	3	3	9	0	0	9	
0	9	0	9	9	3	3	3	3	3	3	3	3	3	3	3	9	9	3	3	1	1	3	3	3	3	1	3	3	
0	0	0	9	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	9	0	0	9	0	0	9	0	0	0	
1	0	0	0	3	9	0	0	9	9	9	0	0	3	9	0	9	0	9	0	9	0	0	9	0	0	9	0	0	0
0	9	0	9	9	3	3	3	3	3	3	3	3	3	3	9	9	3	3	1	1	3	3	3	3	1	3	3	1	3
0	9	0	9	9	0	0	9	9	9	0	0	3	9	0	9	0	9	0	9	0	9	0	3	3	3	9	9	9	9
0	9	0	9	9	3	3	3	3	3	3	3	3	3	3	9	9	3	3	1	1	3	3	3	3	1	3	3	1	3
0	0	0	9	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	9	0	0	0	0	0	0
0	9	0	9	9	3	3	3	3	3	3	3	3	3	3	9	9	3	3	1	1	3	3	3	3	1	3	3	1	3
0	9	9	0	9	0	0	9	9	9	0	0	3	9	0	9	0	9	0	9	0	0	9	0	0	9	0	0	0	0
0	9	9	0	9	0	0	9	9	9	0	0	3	9	0	9	0	9	0	9	0	0	9	0	3	3	3	9	9	9
0	3	0	0	3	0	0	3	0	0	3	0	0	3	0	0	1	0	1	0	0	9								





















## APPENDIX B: RESULTS OF NN FOR INDIVIDUAL ENTRY

## 1.0 The Hidden Unit Experiment

*Learning rate = 0.1*

*Momentum rate = 0.1*

*Activation function = Sigmoid*

*Stopping criteria = 95%*

**Table 1:** Result on the experiment of the suitable hidden unit

No of hidden unit	Accuracy (%)	
	Train	Test
2	59.89	69.57
4	55.49	47.83
6	54.40	47.83
9	54.40	47.83
11	53.85	47.83
13	52.20	43.48
15	54.40	43.48
17	54.40	39.13
20	53.30	39.13
22	54.95	39.13

## 2.0 The Hidden Unit 2 and 11 Experiment

*Learning rate = 0.1*

*Momentum rate = 0.1*

*Activation function = Sigmoid*

*Stopping criteria = 95%*

**Table 2:** Results on the experiment of hidden unit 2 and 11

Weight seed	Hidden unit			
	2		11	
	Train	Test	Train	Test
1	58.24	47.83	53.85	47.83
2	63.74	56.52	53.85	47.83
3	59.34	52.17	52.75	43.48
4	58.79	56.52	50.00	39.13
5	60.44	52.17	53.30	47.83
6	61.54	52.17	53.30	39.13
7	62.09	52.17	54.40	47.83
8	57.69	52.17	52.20	39.13
9	65.38	52.17	54.40	47.83
10	56.59	60.87	52.75	43.48
13	62.64	52.17	52.75	39.13
<b>Average</b>	<b>60.59</b>	<b>53.36</b>	<b>53.05</b>	<b>43.88</b>

### Comparison

Hidden unit	Train	Test
2	60.59	53.36
11	53.05	43.88

**RESULT: HIDDEN UNIT : 2**

### 3.0 The Learning Rate Experiment

*Hidden unit = 2*

*Momentum rate = 0.1*

*Activation function = Sigmoid*

*Number of epoch = 100*

**Table 3:** Results on the experiment of the suitable learning rate

Learning rate	2	
	Train	Test
0.1	58.24	47.83
0.2	58.24	47.83
0.3	58.24	43.48
0.4	19.23	43.48
0.5	60.44	39.13
0.6	68.68	39.13
0.7	68.68	39.13
0.8	60.99	39.13
0.9	60.99	39.13
1.0	18.13	43.48

Input Data Set : Test

!

! Fri Jun 23 15:53:35 2006

**\*\* Confusion Matrix For Output 1 \*\***

!

! True      Predicted

! ----      -

!    1.0+ 1.75+ 2.5+ 3.25+

! 1.0+ 0    2    1    0

! 1.75+ 0    4    2    1

! 2.5+ 0    2    3    1

! 3.25+ 1    0    2    4

!

! Total number of targets : 23

!

! Total correct : 11

!

! Percentage correct : **47.83%**

Output Error Measures

=====

Output:    RMS Error:    Mean Absolute: Mean  
Absolute %:

-----      -----      -----      -----  
1      0.931565      0.703983      25.700975

**Figure 3(a): Testing Performance at Learning Rate: 0.1 & 0.2**

Input Data Set : Training

!  
! Fri Jun 23 15:54:28 2006

\*\* Confusion Matrix For Output 1 \*\*

!  
! True      Predicted  
! ----      -  
!    1.0+ 1.75+ 2.5+ 3.25+  
! 1.0+ 17  17  1  0  
! 1.75+ 4  22  3  0  
! 2.5+ 1  16  9  1  
! 3.25+ 0  4  29  58

!  
! Total number of targets : 182  
!  
! Total correct : 106  
!  
! Percentage correct : **58.24%**

Output Error Measures

=====  
Output:    RMS Error:    Mean Absolute:    Mean Absolute  
%:  
-----  
          1    0.721032    0.578394    19.566501 %

**Figure 3(b): Training Performance at Learning Rate: 0.1 & 0.2**

#### 4.0 The Learning Rate of 0.1 and 0.2 Experiment

*Hidden unit = 2*

*Momentum rate = 0.1*

*Activation function = Sigmoid*

*Number of epoch = 100*

**Table 4:** Result he best learning rate with different weight seeds

Weight seed	Learning Rate			
	0.1		0.2	
	Train	Test	Train	Test
1	18.13	43.48	54.95	47.83
2	54.40	39.18	53.30	47.83
3	54.40	39.18	65.38	30.43
4	70.33	30.43	47.80	26.09
5	46.15	30.43	56.04	39.13
6	45.60	30.43	66.48	30.43
7	60.99	34.78	69.23	34.78
8	54.40	47.83	63.19	39.13
9	51.66	47.83	58.79	39.13
10	50.55	56.52	59.34	39.13
<b>Average</b>	<b>50.661</b>	<b>40.01</b>	<b>59.45</b>	<b>37.391</b>

**RESULT: LEARNING RATE : 0.1**

## 5.0 The Momentum Rate Experiment

*Number of hidden unit = 2      Learning Rate = 0.1*

**Table 5:** Result the most suitable momentum rate

<b>Momentum Rate</b>	<b>2</b>	
	<b>Train</b>	<b>Test</b>
0.1	64.29	60.87
0.2	64.29	60.87
0.3	52.75	60.87
0.4	52.75	39.13
0.5	58.79	52.17
0.6	58.79	52.17
0.7	21.43	43.48
0.8	21.43	43.48
0.9	59.34	52.17
1.0	59.34	58.79

```

Input Data Set : Test
!
! Fri Jun 23 17:30:29 2006
!
!
!
** Confusion Matrix For Output 1 **
!
! True      Predicted
! ----      -
! 1.0+ 1.75+ 2.5+ 3.25+
! 1.0+ 1  1  1  0
! 1.75+ 1  4  2  0
! 2.5+ 0  2  3  1
! 3.25+ 0  1  0  6
!
! Total number of targets : 23
!
! Total correct : 14
!
! Percentage correct : 60.87%

```

Output Error Measures

---

Output:	RMS Error:	Mean Absolute:	Mean Absolute %:
-----	-----	-----	-----
1	0.761409	0.571303	20.857103 %

**Figure 5(a): Confusion Matrix for Test Performance at Momentum Rate 0.1**

```

Input Data Set : Training
!
! Fri Jun 23 17:32:27 2006
!
! ** Confusion Matrix For Output 1 **
!
! True      Predicted
! ----      -
! 1.0+ 1.75+ 2.5+ 3.25+
! 1.0+ 22  13  0  0
! 1.75+ 10  17  2  0
! 2.5+  2  16  8  1
! 3.25+ 1   4  16  70
!
! Total number of targets : 182
!
! Total correct : 117
!
! Percentage correct : 64.29%

Output Error Measures
=====
Output:  RMS Error:  Mean Absolute:  Mean Absolute %:
-----  -
1      0.708903    0.594435    20.109127 %

```

**Figure 5(b): Confusion Matrix for Training Performance at Momentum Rate 0.1**

Input Data Set : Test

!

! Fri Jun 23 17:35:56 2006

\*\* Confusion Matrix For Output 1 \*\*

!

! True        Predicted

! ----        -

!    1.0+ 1.75+ 2.5+ 3.25+

! 1.0+ 1    1    1    0

! 1.75+ 1    4    2    0

! 2.5+ 0    2    3    1

! 3.25+ 0    1    0    6

!

! Total number of targets : 23

!

! Total correct : 14

!

! Percentage correct : **60.87%**

Output Error Measures

=====

Output:    RMS Error:    Mean Absolute:    Mean Absolute %:

-----

1    0.761409    0.571303    20.857103 %

**Figure 5(c):** Confusion Matrix for Test Performance at **Momentum Rate 0.3**

```

Input Data Set : Training
!
! Fri Jun 23 17:36:46 2006

! ** Confusion Matrix For Output 1 **
!
! True      Predicted
! ----      -
! 1.0+ 1.75+ 2.5+ 3.25+
! 1.0+ 14  19  2  0
! 1.75+ 2  24  3  0
! 2.5+ 1  16  10  0
! 3.25+ 0  6  37  48
!
! Total number of targets : 182
!
! Total correct : 96
!
! Percentage correct : 52.75%

Output Error Measures
=====

Output:  RMS Error:  Mean Absolute:  Mean Absolute %:
-----  -
1      0.857339    0.726094    24.563046 %

```

**Figure 5(d):** Confusion Matrix for Training Performance at Momentum Rate 0.3

## 6.0 The Momentum Rate of 0.1 and 0.3 Experiment

Number of hidden unit = 2

Learning Rate = 0.1

**Table 6:** Result of the experiment of momentum rate 0.1 and 0.3

Weight seed	Momentum Rate			
	0.1		0.3	
	Train	Test	Train	Test
1	58.79	34.78	16.48	43.48
2	15.93	39.13	63.74	39.13
3	48.35	43.48	48.90	47.83
4	56.04	47.83	56.59	52.17
5	42.86	39.13	50.55	39.13
6	14.84	26.09	56.59	52.17
7	56.04	43.48	56.04	47.83
8	15.38	26.09	62.64	43.48
9	14.84	17.39	53.85	43.48
10	39.13	45.60	47.80	39.13
<b>Average</b>	<b>36.22</b>	<b>36.30</b>	<b>51.318</b>	<b>44.783</b>

**RESULT : MOMENTUM RATE : 0.3**

## 7.0 The Activation Function Experiment

*Hidden unit = 2*

*Momentum rate = 0.3*

*Learning rate = 0.1*

*No of epoch = 100*

**Table 7: Result on the Activation Function Experiment**

Weight seed	Linear		Sigmoid		Tanh	
	Train	Test	Train	Test	Train	Test
1	52.75	39.13	16.48	43.48	16.48	43.48
2	17.58	34.78	17.58	34.78	17.58	34.78
3	17.03	21.74	17.03	21.74	17.03	21.74
4	15.38	30.43	15.38	17.39	15.38	30.43
5	16.48	30.43	42.31	43.48	16.48	30.43
6	15.93	30.43	14.84	26.09	15.93	30.43
7	14.29	21.74	33.52	43.48	14.29	21.74
8	14.84	26.09	14.84	26.09	14.84	26.09
9	15.93	30.43	15.93	30.43	15.93	30.43
10	14.84	26.09	14.84	26.09	14.84	26.09
<b>Average</b>	19.505	29.129	20.275	31.305	15.878	29.564

**RESULT : BEST ACTIVATION FUNCTION : SIGMOID**

## 8.0 The Epochs Unit Experiment

*Hidden unit = 2*

*Learning rate = 0.1*

*Momentum rate = 0.3*

*Activation function = Sigmoid*

**Table 8:** Result on the experiment of the suitable epoch number

<b>Epoch</b>	<b>Train</b>	<b>Test</b>
100	99.34	92.17
200	99.34	92.17
300	99.34	92.17
400	96.37	87.83
500	87.14	96.52
600	86.59	96.52
700	86.59	96.52
800	89.34	92.17
900	89.34	92.17
1000	80.66	80.43

## 9.0 The 600 and 700 No. Of Epoch Experiment

Table 9: Result on the experiment of epoch no.600 and 700

Weight seed	No of Epochs			
	600		700	
	Train	Test	Train	Test
1	89.34	86.52	89.34	86.52
2	94.84	83.48	95.49	89.13
3	80.44	87.83	89.78	83.48
4	88.24	92.17	89.89	83.48
5	95.49	89.13	90.66	80.43
6	88.24	92.17	89.78	86.52
7	86.04	87.83	94.40	84.78
8	93.19	87.83	86.15	87.83
9	89.89	83.48	89.89	93.48
10	87.14	86.52	97.14	86.52
<b>Average</b>	<b>89.285</b>	<b>87.696</b>	<b>91.252</b>	<b>86.217</b>

**RESULT : NO OF EPOCHS : 600**

## 10.0 The Neural Network Model

Table 10: NN model for each value

Parameter	Value
Architecture	Multilayer Perceptron
Learning Algorithm	Backpropagation
Input Node	97
Hidden Node	2
Output Node	4
Learning Rate	0.1
Momentum Rate	0.3
Activation Function	Sigmoid
Number of Epoch	600

APPENDIX C: RESULTS OF NN FOR AVERAGE VALUE

## 11.0 The Hidden Units Experiment

*Learning rate = 0.1*

*Momentum rate = 0.1*

*Activation function = Sigmoid*

*Stopping criteria = 95%*

**Table 11:** Result on the experiment of the suitable hidden unit

No of hidden unit	Accuracy	
	Train	Test
2	86.14 %	71.43 %
4	86.14 %	76.19 %
6	85.54 %	71.43 %
9	84.34 %	71.43 %
11	84.94 %	71.43 %
13	84.34 %	71.43 %
15	78.92 %	47.62 %
17	79.52 %	52.38 %
20	83.13 %	71.43 %
22	83.73 %	66.67 %

## 12.0: The Hidden Unit 4 & 20 Experiment

*Learning rate = 0.1*

*Momentum rate = 0.1*

*Activation function = Sigmoid*

*Stopping criteria = 95%*

**Table 12:** Results on the experiment of hidden unit 2 and 11

Weight seed	Hidden unit			
	4		20	
	Train	Test	Train	Test
1	86.14	76.19	84.94	71.43
2	86.14	71.43	83.73	71.43
3	85.54	76.19	83.73	71.43
4	85.54	76.19	83.73	71.43
5	86.14	66.67	83.73	71.43
6	86.14	76.19	84.34	71.43
7	86.14	76.19	83.73	71.43
8	86.75	76.19	83.73	71.43
9	86.14	71.43	84.94	71.43
10	86.14	76.19	84.34	71.43
13	86.14	76.19	84.34	71.43
<b>Average</b>	<b>86.09</b>	<b>74.46</b>	<b>84.12</b>	<b>71.43</b>

### Comparison

Hidden unit	Train	Test
4	86.09	74.46
20	84.12	71.43

**RESULT: HIDDEN UNIT : 4**

### 13.0: The Learning Rate Experiment

*Hidden unit = 4*

*Momentum rate = 0.1*

*Activation function = Sigmoid*

*Number of epoch = 100*

**Table 13(a):** Results on the experiment of the suitable learning rate

Learning rate	4	
	Train	Test
0.1	94.58	95.24
0.2	93.37	95.24
0.3	93.37	95.24
0.4	94.58	95.24
0.5	93.37	95.24
0.6	93.98	95.24
0.7	93.98	95.24
0.8	93.37	95.24
0.9	93.37	95.24
1.0	95.78	95.24

**Table 13(b):** Comparing training performance

Learning rate	Training performance
0.2, 0.3, 0.5, 0.8, 0.9	93.37
0.6, 0.7, 1.0	93.98
0.1, 0.4	94.58

#### 14.0: The Learning Rate of 0.2 and 0.9 Experiment

*Hidden unit = 4*

*Momentum rate = 0.1*

*Activation function = Sigmoid*

*Number of epoch = 100*

**Table 14:** Result the learning rate 0.2 and 0.9

Weight seed	Learning Rate			
	0.2		0.9	
	Train	Test	Train	Test
1	93.98	95.24	93.37	95.24
2	95.18	95.24	95.18	95.24
3	93.98	95.24	93.37	95.24
4	93.98	95.24	95.18	95.24
5	93.98	95.24	92.77	95.24
6	93.98	95.24	95.18	95.24
7	93.98	95.24	95.18	95.24
8	93.98	95.24	95.18	95.24
9	93.98	95.24	95.18	95.24
10	93.98	95.24	95.18	95.24
<b>Average</b>	<b>94.10</b>	<b>95.24</b>	<b>94.557</b>	<b>95.24</b>

**RESULT: LEARNING RATE : 0.2**

## 15.0 The Momentum Rate

*Number of hidden unit = 4*      *Learning Rate = 0.2*

**Table 15:** Result the most suitable momentum rate

Momentum Rate	4	
	Train	Test
0.1	93.98	95.24
0.2	93.98	95.24
0.3	95.18	95.24
0.4	95.18	95.24
0.5	95.18	95.24
0.6	95.18	95.24
0.7	95.18	95.24
0.8	95.18	95.24
0.9	95.18	95.24
1.0	95.18	95.24

## 16.0: The Momentum Rate of 0.1 and 0.2 Experiment

Number of hidden unit = 4

Learning Rate = 0.2

Table 16: Result of the experiment of momentum rate 0.1 and 0.3

Weight seed	Momentum Rate			
	0.1		0.2	
	Train	Test	Train	Test
1	95.18	95.24	93.98	95.24
2	93.98	95.24	93.98	95.24
3	93.98	95.24	93.98	95.24
4	93.98	95.24	93.98	95.24
5	93.98	95.24	93.98	95.24
6	95.18	95.24	93.98	95.24
7	94.58	95.24	95.18	95.24
8	95.18	95.24	93.98	95.24
9	93.98	95.24	95.18	95.24
10	93.98	95.24	93.98	95.24
<b>Average</b>	<b>94.40</b>	<b>95.24</b>	<b>94.22</b>	<b>95.24</b>

**RESULT : MOMENTUM RATE : 0.2**

### 17.0: The Activation Function Experiment

*Hidden unit = 4*

*Momentum rate = 0.2*

*Learning rate = 0.2*

*No of epoch = 100*

**Table 17:** Result on the Activation Function Experiment

Weight seed	Linear		Sigmoid		Tanh	
	Train	Test	Train	Test	Train	Test
1	-	-	93.98	95.24	93.98	95.24
2	-	-	93.98	95.24	93.98	95.24
3	-	-	93.98	95.24	93.98	95.24
4	-	-	93.98	95.24	93.98	95.24
5	-	-	93.98	95.24	95.18	95.24
6	-	-	93.98	95.24	95.18	95.24
7	-	-	95.18	95.24	95.18	95.24
8	-	-	95.18	95.24	95.18	95.24
9	-	-	95.18	95.24	95.18	95.24
10	-	-	95.18	95.24	95.18	95.24
<b>Average</b>	-	-	<b>94.46</b>	<b>95.24</b>	<b>94.70</b>	<b>95.24</b>

**RESULT : BEST ACTIVATION FUNCTION : SIGMOID**

### 18.0: The number of Epochs Experiment

*Hidden unit = 4*

*Learning rate = 0.2*

*Momentum rate = 0.2*

*Activation function = Sigmoid*

**Table 18:** Result on the number of Epochs Experiment

<b>Epoch</b>	<b>Train</b>	<b>Test</b>
100	94.58	90.48
200	96.39	80.95
300	96.39	80.95
400	94.58	90.48
500	96.39	80.95
600	96.99	85.71
700	96.39	80.95
800	96.99	85.71
900	96.99	85.71
1000	96.99	85.71

## 19.0: The 100 and 400 No. Of Epoch Experiment

**Table 19:** Result on the experiment of epoch no.100 and 400

Weight seed	No of Epochs			
	100		400	
	Train	Test	Train	Test
1	95.18	90.48	94.58	90.48
2	95.18	90.48	94.58	90.48
3	95.18	90.48	94.58	90.48
4	95.18	90.48	96.39	80.95
5	95.18	90.48	96.39	80.95
6	95.18	90.48	96.39	80.95
7	95.78	80.95	96.39	80.95
8	95.78	80.95	96.39	80.95
9	95.18	90.48	96.39	80.95
10	95.78	80.95	96.39	80.95
<b>Average</b>	<b>95.36</b>	<b>87.621</b>	<b>95.847</b>	<b>83.809</b>

**RESULT : NO OF EPOCHS : 100**

## 20.0: The Neural Network Model

**Table 20:** NN model for each value

Parameter	Value
Architecture	Multilayer Perceptron
Learning Algorithm	Backpropagation
Input Node	97
Hidden Node	4
Output Node	4
Learning Rate	0.2
Momentum Rate	0.2
Activation Function	Sigmoid
Number of Epoch	100

## APPENDIX D: SPEARMAN'S RHO CORRELATION RESULT

# Nonparametric Correlations

[DataSet1] D:\NN QFD\DATA Q\QFDGPSS1\_1.sav

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Correlations

		A2TOC	A3Wood	Plastic	Metal	
Spearman's rho	A2TOC	Correlation Coefficient	1.000	.776**	.266**	.009
		Sig. (1-tailed)		.000	.000	.449
		N	228	223	223	223
A3Wood		Correlation Coefficient	.776**	1.000	-.240**	-.047
		Sig. (1-tailed)	.000		.000	.244
		N	223	223	223	223
Plastic		Correlation Coefficient	-.266**	-.240**	1.000	-.007
		Sig. (1-tailed)	.000	.000		.458
		N	223	223	223	223
Metal		Correlation Coefficient	.009	-.047	-.007	1.000
		Sig. (1-tailed)	.449	.244	.458	
		N	223	223	223	223
Composite		Correlation Coefficient	.402**	.438**	-.191**	-.250**
		Sig. (1-tailed)	.000	.000	.002	.000
		N	223	223	223	223
Mixed		Correlation Coefficient	.061	-.007	-.061	-.016
		Sig. (1-tailed)	.183	.456	.183	.406
		N	223	223	223	223
Product		Correlation Coefficient	-.304**	-.163**	.012	-.327**
		Sig. (1-tailed)	.000	.008	.427	.000
		N	223	223	223	223
B1.3US		Correlation Coefficient	-.324**	-.260**	.033	-.022
		Sig. (1-tailed)	.000	.000	.310	.370
		N	223	223	223	223
German		Correlation Coefficient	.032	.076	-.192**	-.009
		Sig. (1-tailed)	.315	.130	.002	.447
		N	223	223	223	223
Europe		Correlation Coefficient	.179**	.229**	-.226**	.064
		Sig. (1-tailed)	.004	.000	.000	.170
		N	223	223	223	223
Japan		Correlation Coefficient	-.216**	-.236**	.140*	-.060
		Sig. (1-tailed)	.001	.000	.018	.185
		N	223	223	223	223
Taiwan		Correlation Coefficient	.578**	.565**	-.195**	-.047
		Sig. (1-tailed)	.000	.000	.002	.240
		N	223	223	223	223
B1.4Low		Correlation Coefficient	-.064	-.062	-.142*	-.038
		Sig. (1-tailed)	.172	.177	.017	.288
		N	223	223	223	223
Medium		Correlation Coefficient	-.100	-.104	.011	.043
		Sig. (1-tailed)	.068	.062	.434	.262
		N	223	223	223	223
High		Correlation Coefficient	.208**	.268**	-.178**	.162**
		Sig. (1-tailed)	.001	.000	.004	.008
		N	223	223	223	223
B1.5Pneu		Correlation Coefficient	.045	.119*	-.045	.175**
		Sig. (1-tailed)	.252	.039	.253	.004
		N	223	223	223	223

Correlations

			A2TOC	A3Wood	Plastic	Metal
Spearman's rho	Elec	Correlation Coefficient	-.163**	-.019	-.044	.096
		Sig. (1-tailed)	.007	.390	.255	.077
		N	223	223	223	223
	Hydrau	Correlation Coefficient	.332**	.333**	.024	.240**
		Sig. (1-tailed)	.000	.000	.359	.000
		N	223	223	223	223
	Manual	Correlation Coefficient	.229**	.164**	-.210**	.047
		Sig. (1-tailed)	.000	.007	.001	.243
		N	223	223	223	223
	B1.6Low	Correlation Coefficient	.116*	.010	-.262**	-.092
		Sig. (1-tailed)	.042	.441	.000	.085
		N	223	223	223	223
	B1.6M	Correlation Coefficient	-.110*	.130*	.013	-.038
		Sig. (1-tailed)	.050	.026	.423	.288
		N	223	223	223	223
	B1.6H	Correlation Coefficient	.353**	.290**	-.296**	.019
		Sig. (1-tailed)	.000	.000	.000	.388
		N	223	223	223	223
	B1.7Hori	Correlation Coefficient	.090	.198**	-.002	.196**
		Sig. (1-tailed)	.090	.002	.488	.002
		N	223	223	223	223
	Vertical	Correlation Coefficient	.343**	.394**	-.279**	-.085
		Sig. (1-tailed)	.000	.000	.000	.104
		N	223	223	223	223
	B1.8Pneu	Correlation Coefficient	.289**	.240**	-.001	-.109
		Sig. (1-tailed)	.000	.000	.494	.053
		N	223	223	223	223
	Elect	Correlation Coefficient	.245**	.349**	-.442**	-.080
		Sig. (1-tailed)	.000	.000	.000	.117
		N	223	223	223	223
	Hyd	Correlation Coefficient	.308**	.323**	-.016	.047
		Sig. (1-tailed)	.000	.000	.404	.242
		N	223	223	223	223
	B1.9Lo	Correlation Coefficient	-.197**	.220**	-.204**	-.169**
		Sig. (1-tailed)	.002	.000	.001	.006
		N	223	223	223	223
	Me	Correlation Coefficient	-.069	.019	.033	.091
		Sig. (1-tailed)	.154	.388	.313	.088
		N	223	223	223	223
	Hi	Correlation Coefficient	.362**	.373**	-.267**	.074
		Sig. (1-tailed)	.000	.000	.000	.136
		N	223	223	223	223
	B1.10Li	Correlation Coefficient	.318**	.349**	-.229**	.014
		Sig. (1-tailed)	.000	.000	.000	.415
		N	223	223	223	223
	Mm	Correlation Coefficient	-.006	.055	.046	.021
		Sig. (1-tailed)	.465	.208	.246	.380
		N	223	223	223	223

Correlations

			A2TOC	A3Wood	Plastic	Metal
Spearman's rho	Hh	Correlation Coefficient	.284**	.239**	-.177**	-.041
		Sig. (1-tailed)	.000	.000	.004	.273
		N	223	223	223	223
	B1.11LB	Correlation Coefficient	.123*	.145*	-.092	-.042
		Sig. (1-tailed)	.034	.015	.086	.264
		N	223	223	223	223
	MB	Correlation Coefficient	.151*	.147*	.020	.060
		Sig. (1-tailed)	.012	.014	.385	.187
		N	223	223	223	223
	HB	Correlation Coefficient	.413**	.467**	-.171**	-.105
		Sig. (1-tailed)	.000	.000	.005	.059
		N	223	223	223	223
	B1.12BMM	Correlation Coefficient	.154*	.231**	-.071	-.005
		Sig. (1-tailed)	.011	.000	.145	.472
		N	223	223	223	223
	MMT	Correlation Coefficient	.113*	.083	-.152*	-.067
		Sig. (1-tailed)	.046	.109	.012	.160
		N	223	223	223	223
	MM1	Correlation Coefficient	.520**	.539**	-.344**	-.003
		Sig. (1-tailed)	.000	.000	.000	.480
		N	223	223	223	223
	B1.13DMM	Correlation Coefficient	.200**	.219**	-.207**	-.196**
		Sig. (1-tailed)	.001	.000	.001	.002
		N	223	223	223	223
	D500	Correlation Coefficient	.192**	.216**	-.165**	-.073
		Sig. (1-tailed)	.002	.001	.007	.140
		N	223	223	223	223
	D1000	Correlation Coefficient	.414**	.460**	-.163**	-.056
		Sig. (1-tailed)	.000	.000	.007	.204
		N	223	223	223	223
	B1.14WO	Correlation Coefficient	.054	.126*	-.084	-.085
		Sig. (1-tailed)	.211	.031	.106	.102
		N	223	223	223	223
	W1000	Correlation Coefficient	.207**	.271**	-.191**	.038
		Sig. (1-tailed)	.001	.000	.002	.287
		N	223	223	223	223
	W2000	Correlation Coefficient	.414**	.357**	.076	-.009
		Sig. (1-tailed)	.000	.000	.130	.447
		N	223	223	223	223
	B2.15F	Correlation Coefficient	-.053	.036	.039	.170**
		Sig. (1-tailed)	.214	.298	.282	.005
		N	223	223	223	223
	Semi	Correlation Coefficient	.037	.086	.059	.113*
		Sig. (1-tailed)	.292	.100	.191	.047
		N	223	223	223	223
	Manual	Correlation Coefficient	.332**	.351**	-.077	.100
		Sig. (1-tailed)	.000	.000	.125	.069
		N	223	223	223	223

Correlations

			A2TOC	A3Wood	Plastic	Metal
Spearman's rho	B2 16	Correlation Coefficient	-.315**	-.272**	.215**	.071
		Sig. (1-tailed)	.000	.000	.001	.145
		N	223	223	223	223
	B2 17	Correlation Coefficient	-.125*	-.021	.161**	-.024
		Sig. (1-tailed)	.031	.379	.008	.360
		N	223	223	223	223
	B2 18	Correlation Coefficient	-.002	.122*	.012	.009
		Sig. (1-tailed)	.488	.035	.428	.446
		N	223	223	223	223
	B2 19	Correlation Coefficient	-.019	.102	.193**	.100
		Sig. (1-tailed)	.391	.064	.002	.068
		N	223	223	223	223
	B2 20	Correlation Coefficient	-.053	.114*	.154*	.081
		Sig. (1-tailed)	.215	.045	.011	.115
		N	223	223	223	223
	B2 21	Correlation Coefficient	-.034	.071	.293**	.176**
		Sig. (1-tailed)	.307	.147	.000	.004
		N	223	223	223	223
	B2 22	Correlation Coefficient	.017	.147*	.235**	.074
		Sig. (1-tailed)	.398	.014	.000	.135
		N	223	223	223	223
	B2 23	Correlation Coefficient	.154*	.177**	.215**	.185**
		Sig. (1-tailed)	.011	.004	.001	.003
		N	223	223	223	223
	B2 24	Correlation Coefficient	.087	.168**	.213**	.141*
		Sig. (1-tailed)	.098	.006	.001	.018
		N	223	223	223	223
	B2 25	Correlation Coefficient	.092	.217**	.091	-.012
		Sig. (1-tailed)	.085	.001	.088	.430
		N	223	223	223	223
	B2 26	Correlation Coefficient	-.007	.114*	.194**	.147*
		Sig. (1-tailed)	.459	.045	.002	.014
		N	223	223	223	223
	B3 27	Correlation Coefficient	-.077	.035	.132*	.088
		Sig. (1-tailed)	.128	.302	.025	.095
		N	223	223	223	223
	B3 28	Correlation Coefficient	.024	.130*	.188**	.194**
		Sig. (1-tailed)	.360	.026	.002	.002
		N	223	223	223	223
	B3 29	Correlation Coefficient	-.164**	.042	.224**	.021
		Sig. (1-tailed)	.007	.266	.000	.376
		N	223	223	223	223
	B3 30	Correlation Coefficient	.054	.238**	.105	.000
		Sig. (1-tailed)	.211	.000	.059	.498
		N	223	223	223	223
	B3 31	Correlation Coefficient	-.187**	.011	.242**	.069
		Sig. (1-tailed)	.003	.438	.000	.153
		N	223	223	223	223

Correlations

			A2TOC	A3Wood	Plastic	Metal
Spearman's rho	B3 32	Correlation Coefficient	.235**	.252**	.052	.064
		Sig. (1-tailed)	.000	.000	.221	.172
		N	223	223	223	223
	B3 33	Correlation Coefficient	.165**	.227**	.138*	.108
		Sig. (1-tailed)	.007	.000	.020	.054
		N	223	223	223	223
	B3 34	Correlation Coefficient	.083	.176**	.056	.007
		Sig. (1-tailed)	.109	.004	.203	.458
		N	223	223	223	223
	B3 35	Correlation Coefficient	-.046	.106	.133*	.027
		Sig. (1-tailed)	.245	.057	.024	.343
		N	223	223	223	223
	B3 36	Correlation Coefficient	.079	.160**	.081	-.045
		Sig. (1-tailed)	.119	.008	.115	.252
		N	223	223	223	223
	B4 37	Correlation Coefficient	-.005	.066	.242**	.013
		Sig. (1-tailed)	.468	.164	.000	.423
		N	223	223	223	223
	B4 38	Correlation Coefficient	-.012	.193**	.241**	-.027
		Sig. (1-tailed)	.431	.002	.000	.344
		N	223	223	223	223
	B4 39	Correlation Coefficient	.149*	.251**	.193**	.165**
		Sig. (1-tailed)	.013	.000	.002	.007
		N	223	223	223	223
	B4 40	Correlation Coefficient	.051	.214**	.132*	.114*
		Sig. (1-tailed)	.226	.001	.024	.045
		N	223	223	223	223
	B4 41	Correlation Coefficient	-.008	.111*	.228**	.039
		Sig. (1-tailed)	.453	.049	.000	.279
		N	223	223	223	223
	B4 42	Correlation Coefficient	.097	.195**	.260**	.032
		Sig. (1-tailed)	.074	.002	.000	.319
		N	223	223	223	223
	B4 43	Correlation Coefficient	.289**	.310**	.138*	-.014
		Sig. (1-tailed)	.000	.000	.020	.417
		N	223	223	223	223
	B4 44	Correlation Coefficient	.201**	.235**	.193**	-.052
		Sig. (1-tailed)	.001	.000	.002	.218
		N	223	223	223	223
	B4 45	Correlation Coefficient	.072	.130*	.290**	-.071
		Sig. (1-tailed)	.141	.026	.000	.146
		N	223	223	223	223
	B4 46	Correlation Coefficient	.242**	.262**	.203**	-.012
		Sig. (1-tailed)	.000	.000	.001	.426
		N	223	223	223	223
	B4 47	Correlation Coefficient	.078	.106	.301**	-.052
		Sig. (1-tailed)	.122	.057	.000	.222
		N	223	223	223	223

Correlations

			A2TOC	A3Wood	Plastic	Metal
Spearman's rho	B4 48	Correlation Coefficient	-.028	.128*	.130*	.009
		Sig. (1-tailed)	.341	.028	.026	.446
		N	223	223	223	223
B4 49		Correlation Coefficient	-.030	.088	.329**	-.080
		Sig. (1-tailed)	.329	.095	.000	.117
		N	223	223	223	223
B5 50		Correlation Coefficient	-.154*	-.016	.177**	.032
		Sig. (1-tailed)	.011	.409	.004	.315
		N	223	223	223	223
B5 51		Correlation Coefficient	-.008	.168**	.251**	.018
		Sig. (1-tailed)	.450	.006	.000	.395
		N	223	223	223	223
B5 52		Correlation Coefficient	-.133*	.057	.286**	-.084
		Sig. (1-tailed)	.024	.199	.000	.105
		N	223	223	223	223
B5 53		Correlation Coefficient	-.125*	.054	.321**	-.089
		Sig. (1-tailed)	.032	.212	.000	.093
		N	223	223	223	223
B5 54		Correlation Coefficient	-.002	.127*	.266**	.026
		Sig. (1-tailed)	.487	.030	.000	.350
		N	223	223	223	223
B5 55		Correlation Coefficient	-.090	-.002	.228**	.088
		Sig. (1-tailed)	.091	.488	.000	.096
		N	222	222	222	222
B5 56		Correlation Coefficient	.064	.145*	.312**	.032
		Sig. (1-tailed)	.170	.015	.000	.317
		N	223	223	223	223
B5 57		Correlation Coefficient	-.126*	-.046	.299**	-.039
		Sig. (1-tailed)	.030	.248	.000	.283
		N	223	223	223	223
B6 58		Correlation Coefficient	-.065	.007	.184**	.124*
		Sig. (1-tailed)	.169	.461	.003	.032
		N	223	223	223	223
B6 59		Correlation Coefficient	-.073	.116*	.170**	.108
		Sig. (1-tailed)	.138	.042	.005	.054
		N	223	223	223	223
B6 60		Correlation Coefficient	-.103	.020	.036	.043
		Sig. (1-tailed)	.062	.384	.296	.261
		N	223	223	223	223
B6 61		Correlation Coefficient	-.006	.117*	.057	-.081
		Sig. (1-tailed)	.465	.041	.197	.114
		N	223	223	223	223

Correlations

			A2TOC	A3Wood	Plastic	Metal
Spearman's rho	B6 62	Correlation Coefficient	.076	.218**	.009	.055
		Sig. (1-tailed)	.129	.001	.446	.206
		N	223	223	223	223
B6 63		Correlation Coefficient	-.129*	.078	.038	-.049
		Sig. (1-tailed)	.027	.123	.287	.232
		N	223	223	223	223
B6 64		Correlation Coefficient	.067	.213**	-.104	-.040
		Sig. (1-tailed)	.161	.001	.061	.277
		N	223	223	223	223

APPENDIX E: QUESTIONNAIRE USED



**ANALYZING QUALITY FUNCTION DEPLOYMENT (QFD)  
BASED ON VOICE OF CUSTOMER (VoC)**

**Researcher: Norshahrizan bt Nordin (85644)**

**What is QFD?**

QFD is one of most valuable tools that can be used when developing a new product. It is a structured method where all customer requirements can be analyzed and built in during the design stage.

**Dear respondent,**

As part and partial of MSc ICT (UUM) requirement, I am conducting a research on the title of "Modelling of Quality Function Deployment for Industry". The research focuses on the machine planning by preparing the actual machine specifications using QFD before buying is made, purposely to reduce under/over specification of the machine and to promote fully machine utilization.

**INSTRUCTION:**

This questionnaire consists of **TWO** main sections (Section A and B). Please read and understand the questions before answering them. Then, **TICK**  or **SELECT** the box or complete the answer in the space provided

**SECTION A: CUSTOMER PROFILE**

**A1: Name of Company/Institution:** \_\_\_\_\_

**1 A2: Type of customer**

- Operator
- Maintenance (Technician/Line Leader/etc)
- Management (Manager/Executive/Engineer/Assistant Engineer/etc)
- Profesional/Lecturer/Instructor/etc

**2 A3: Type of Workpiece Material Used/Processed**

- Wood based product
- Plastic based product
- Metal based product
- Composite/fibre/glass based product
- Mixed/Synthetic based product
- Product assembly and processing

**SECTION B: POSSIBLE CUSTOMER REQUIREMENT**

		Relationship			
No	B1: Machine Standard Specification	Strong = 9	Medium =3	Weak = 1	No = 0
3	Machine Brand/Name/Manufacturer				
	US made				
	German made				
	Europe made				
	Japan made				
	Taiwan/Korea made				
4	Operation type				
	Low duty				
	Medium duty				
	Heavy duty				
5	Drive type				
	Pneumatic				
	Electric				
	Hydraulic				
	Manual				
6	Power (kW)				
	Low : below 1 kW				
	Medium : 1 - 5 kW				
	High - above 5 kW				
7	Table/Clamp configuration				
	Horizontal/Vertical - x, y axis				
	Flexible - x, y, z axis				
8	Clamp type				
	Pneumatic				
	Electric				
	Hydraulic				
9	Pressure (Nm)				
	Low				
	Medium				
	High				
10	Torque/Spindle Speed min <sup>-1</sup>				
	Low				
	Medium				
	High				
11	Load Capacity (kg)				
	Low, below 20 kg				
	Medium, 20 kg to 100 kg				
	High, 100 kg - 1000 kg				
12	Positioning Accuracy (mm)				
	Below 0.05 mm				
	0.05 mm to 0.5 mm				
	More than 1 mm				
13	D, Dimensions, mm (Width x Height x Length)				
	D < 500 x 500 x 500 mm				
	500 mm <sup>3</sup> < D ≤ 1000 mm <sup>3</sup>				
	More than 1000 mm <sup>3</sup>				
14	W, Weight (kg)				
	0 ≤ W < 1000 kg				
	1000 ≤ W ≤ 2000 kg				
	More than 2000 kg				

No	B2: Machine Control	Strong = 9	Medium =3	Weak = 1	No = 0
15	Type of control system				
	Fully automated				
	Semi-automated				
	Manual				
16	Visible control located within hand reach				
17	LCD display interface				
18	Language options for input and output display				
19	Data transfer options				
20	Metric and inch measurement unit				
21	Programming code compatibility				
22	Graphical programming support				
23	User storage for programs and data				
24	All control must be short stroke push button				
25	Flexible control console				
26	Machine adjustment should be simple				

No	B3: Machine Safety	Strong = 9	Medium =3	Weak = 1	No = 0
27	Remove mechanical hazards				
28	Guarding of all exposed moving parts				
29	Earth and insulation to prevent electric shock				
30	Trip devices for puller mechanism				
31	Emergency stop button				
32	Foot brake switch				
33	Exhaust fan for cutter				
34	Access protection				
35	Failure for safety				
36	Heated mould insulation				

No	B4: Machine Performance	Strong = 9	Medium =3	Weak = 1	No = 0
37	Sensors for warning				
38	Alarm signal for machine error				
39	Simple mould replacement				
40	LED display to show current operation				
41	High production speed				
42	Can accommodate different types of product				
43	Utilize small amount of resin				
44	Rigid and high damping				
45	Minimum noise and vibration				
46	Zero resin spillage				
47	Able to withstand continuous operations				
48	Reasonable power consumption				
49	Low operational cost				

No	B5: Machine Maintenance	Strong = 9	Medium =3	Weak = 1	No = 0
50	Easy lubrication points				
51	Easy replacement parts				
52	Simple part replacement				
53	Simple assembly and disassembly				
54	Self and periodic diagnosis and calibration				
55	Coolant system and lighting				
56	Quick mould change and set-up				
57	Easy trouble shoot				

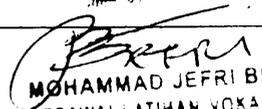
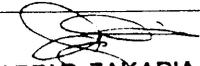
No	B6: Machine After Sales Services	Strong = 9	Medium =3	Weak = 1	No = 0
58	Speed of supervisory/technical person				
59	Speed of spare part delivery				
60	Reasonable spare part price				
61	Continous technical consultancy				
62	Near service center				
63	Availability of spare parts				
64	Alternative offer				

**THANK YOU FOR YOUR TIME AND EFFORT. YOUR RESPONSES WILL BE  
HELD IN STRICTEST CONFIDENCE**

APPENDIX F: PROOF OF SURVEY ATTENDANCE



ADALAH DISAHKAN BAHAWA PELAJAR INI, NORSHHRIZAN BT NORDIN (85644), PROGRAM SARJANA SAINS TEKNOLOGI MAKLUMAT DAN KOMUNIKASI (MSc ICT) UUM TELAH DATANG MENJALANKAN KAJI SELIDIK DI TEMPAT BERIKUT.

NAMA INSTITUSI / SYARIKAT	TARIKH & MASA	PENGESAHAN
PELIMAS BANDAR DARULAMAN 06000 Jitra, Kedah	22 MEI 2006 / 11 <sup>00</sup> a.m	 <b>MOHAMAD FIZA BIN HJ. ISMAIL</b> Ketua Juruteknik Jabatan Kejuruteraan Mekanikal Politeknik Sultan Abdul Halim Mu'adzam Shah Jitra
MOHAMED JEFFRI BIN JAAFAR INSTITUT LATIHAN PERINDUSTRIAN JITHA  NO. PIA 04-9161426 FAK (04-9162367)	22/5/2006 / 3 <sup>00</sup> pm	 <b>MOHAMMAD JEFFRI BIN JAAFAR</b> PEGAWAI LATIHAN VOKASIONAL INSTITUT LATIHAN PERINDUSTRIAN JITHA
PUSAT KEJURUTERAAN KUKUM, 02000 KUALA PERLIS, PERLIS	25/5/2006/ 9.30 a.m	 <b>SABRI B. ZAKARIA</b> Jurutera Pengajar Pusat Kejuruteraan Kolej Universiti Kejuruteraan Utara Malaysia
PELIMAS BANDAR DARULAMAN 06000 Jitra, Kedah	29 MEI 06 / 10 <sup>30</sup> a.m	 <b>MOHAMAD FIZA BIN HJ. ISMAIL</b> Ketua Juruteknik Jabatan Kejuruteraan Mekanikal Politeknik Sultan Abdul Halim Mu'adzam Shah Jitra, Kedah Darul Aman.

APPENDIX G: LETTER OF PERMISSION TO CONDUCT A SURVEY



# UNIVERSITI UTARA MALAYSIA

06010 UUM Sintok, Kedah Darul Aman, Malaysia. Tel: 604 - 928 4000

*Pusat Pengajian Siswazah*

*'KEDAH MAJU 2010'*

UUM/HEA/PPS/PEL : 85644

09 Mei 2006  
10 Rabiulakhir 1427H

## KEPADA SESIAPA YANG BERKENAAN

Tuan / Puan

## PERMOHONAN UNTUK MENGUMPUL DATA DAN MAKLUMAT

Dengan ini disahkan bahawa Norshahrizan Nordin (no. matrik 85644) merupakan pelajar siswazah program Sarjana Sains (Teknologi Maklumat & Komunikasi) secara Separuh Masa di Universiti Utara Malaysia.

Pelajar ini perlu mengutip serta mengumpul data/maklumat daripada pelbagai sumber yang telah dikenalpasti untuk membolehkan mereka memenuhi keperluan penyediaan Kertas Projek/Tesis.

Sehubungan dengan itu, kami amat berbesar hati sekiranya pihak tuan/puan dapat memberi kerjasama dan bantuan kepada pelajar berkenaan dalam usaha tersebut. Segala maklumat yang diperolehi daripada soal selidik ini akan dirahsiakan.

Sekian, terima kasih.

**"AKADEMIK CEMERLANG UUM TERBILANG"**  
**"ILMU BUDI BAKTI"**

Saya yang menurut perintah

**MAIMUNAH H.J. MOHAMAD**

Penolong Pengarah

b.p. Pengarah

Tel : 04-9283167 / Faks : 04-9284019

E-mail : [maimunah@uum.edu.my](mailto:maimunah@uum.edu.my)



# UNIVERSITI UTARA MALAYSIA

06010 UUM Sintok, Kedah Darul Aman, Malaysia. Tel: 604 - 928 4000

Norshahrizan bt Nordin (85644),  
Pelajar Sarjana Teknologi Maklumat & Komunikasi,  
Fakulti Teknologi Maklumat,  
Universiti Utara Malaysia,  
06010 Sintok,  
Kedah.

24 Mei 2006

Melalui,  
Penyelia Tesis,  
Prof Madya Fadzilah Siraj,  
Fakulti Teknologi Maklumat,  
Universiti Utara Malaysia,  
06010 Sintok,  
Kedah.

  
PROF. MADYA FADZILAH SIRAJ  
Pensyarah  
Fakulti Teknologi Maklumat  
Universiti Utara Malaysia

Kepada,  
Yang Berusaha,  
En. Abdul Rahman Mohd. Saad  
Pengarah Pusat Kejuruteraan KUKUM  
02000 Kuala Perlis,  
Perlis.

## PERMOHONAN MENGADAKAN KAJI SELIDIK (QUESTIONNAIRE)

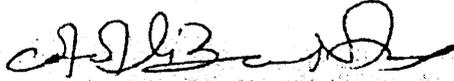
Adalah saya seperti nama diatas ingin membuat permohonan untuk mengadakan kaji selidik di jabatan Tuan untuk projek sarjana saya yang bertajuk **Modelling of Quality Function Deployment (QFD) for Industry**.

Sehubungan dengan itu, saya bercadang untuk mengadakan sesi kaji selidik melalui penyerahan borang kaji selidik tersebut pada **25 Mei 2006 (Khamis), bermula jam 9.00 pagi**.

Besarlah harapan saya agar saya diberi kebenaran untuk melakukan kaji selidik tersebut di jabatan Tuan.

Sekian, harap maklum dan terlebih dahulu diucapkan ribuan terima kasih di atas pertimbangan yang diberikan oleh pihak Tuan.

Yang Benar,

  
(NORSHHRIZAN BT NORDIN)



Norshahrizan bt Nordin (85644),  
Pelajar Sarjana Teknologi Maklumat & Komunikasi,  
Fakulti Teknologi Maklumat,  
Universiti Utara Malaysia,  
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Melalui,  
Penyelia Tesis,  
Prof Madya Fadzilah Siraj,  
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Kedah.

  
PROF MADYA FADZILAH SIRAJ  
Pensyarah  
Fakulti Teknologi Maklumat  
Universiti Utara Malaysia

Kepada,  
Yang Berusaha,  
Pengarah,  
Institut Latihan Perindustrian Jitra (ILP JITRA),  
Bandar Darulaman, 06000 Jitra, Kedah.

#### **PERMOHONAN MENGADAKAN KAJI SELIDIK (QUESTIONNAIRE)**

Adalah saya seperti nama diatas ingin membuat permohonan untuk mengadakan kaji selidik di jabatan Tuan untuk projek sarjana saya yang bertajuk **Modelling of Quality Function Deployment (QFD) for Industry**.

Sehubungan dengan itu, saya bercadang untuk mengadakan sesi kaji selidik melalui penyerahan borang kaji selidik tersebut pada **22 Mei 2006 (Isnin), bermula jam 10.00 pagi**.

Besarliah harapan saya agar saya diberi kebenaran untuk melakukan kaji selidik tersebut di jabatan Tuan.

Sekian, harap maklum dan terlebih dahulu diucapkan ribuan terima kasih di atas pertimbangan yang diberikan oleh pihak Tuan.

Yang Benar,

  
(NORSHAHORIZAN BT NORDIN)  
85644

Norshahrizan bt Nordin (85644),  
Pelajar Sarjana Teknologi Maklumat & Komunikasi,  
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PROF. MADYA FADZILAH SIRAJ  
Pensyarah  
Fakulti Teknologi Maklumat  
Universiti Utara Malaysia

Melalui,  
Penyelia Tesis,  
Prof Madya Fadzilah Siraj,  
Fakulti Teknologi Maklumat,  
Universiti Utara Malaysia,  
06010 Sintok,  
Kedah.

*Disokong*  
*fadzilah*

Kepada,  
Yang Berusaha,  
Ketua Jabatan Kejuruteraan Mekanikal,  
Ketua Jabatan Kejuruteraan Awam,  
Ketua Jabatan Kejuruteraan Elektrik,  
Politeknik Sultan Abdul Halim Mu'adzam Shah (POLIMAS),  
Bandar Darulaman, 06000 Jitra, Kedah.

### PERMOHONAN MENGADAKAN KAJI SELIDIK (QUESTIONNAIRE)

Adalah saya seperti nama diatas ingin membuat permohonan untuk mengadakan kaji selidik di jabatan Tuan untuk projek sarjana saya yang bertajuk **Modelling of Quality Function Deployment (QFD) for Industry**.

Sehubungan dengan itu, saya bercadang untuk mengadakan sesi kaji selidik melalui penyerahan borang kaji selidik tersebut pada **22 Mei 2006 (Isnin)**, bermula jam **8.30 pagi**.

Besarliah harapan saya agar saya diberi kebenaran untuk melakukan kaji selidik tersebut di jabatan Tuan.

Sekian, harap maklum dan terlebih dahulu diucapkan ribuan terima kasih di atas pertimbangan yang diberikan oleh pihak Tuan.

Yang Benar,

  
(NORSHAHRIZAN BT NORDIN)  
85644