QUALITY FUNCTION DEPLOYMENT ANALYSIS BASED ON NEURAL NETWORK AND STATISTICAL RESULTS

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Abstract: *QFD is a method of translating high-level objectives into concrete actions and metrics. It is one of the techniques that aims to fulfill the customers' satisfaction at the very beginning, namely the product design phase. This study focuses on the development of general QFD for machine specification selection so that it later can be used for any kind of machine evaluation prior to purchasing the machines. A set of questionnaires was used as an instrument and was distributed to 223 respondents. NN models were generated and statistical methods were used to explain the relationship between attributes in this study. The findings from the experiments conducted exhibit that the significant correlations of QFD with customer voices help to explain the relationship between attributes. The study also indicates that NN forecasting model has been established with 12.30 percent misclassification error in determining the customer voices based on QFD versus 6.3 percent using regression. This indicates that the approach has the 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.*

Keywords: Quality Function Deployment (QFD), Voice of Customer, Neural Network, Machine Planning

1. INTRODUCTION

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. To succeed in developing new products or improve an existing one is not easy. Studies indicate that as much as somewhere between 35 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 and 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 study 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 "a system for designing product or service based on customer demands and involving all members of the producer or supplier organization" (King, 1987).

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 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. In another study,

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), this study presents alternative ways to identify the relationship between QFD and customer voices. 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 an IT tool in manufacturing and product development will torch the light towards the creation of the QFD forecasting model. Statistical techniques were utilized to support the findings in this study.

2. RELATED WORKS

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.
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Figure 1 shows that 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 (Omar *et al.*, 1999).

For QFD DSS, neural network could be used, such that Customer demands, engineering characteristics and engineering solutions are interconnected. The engineering solutions are considered as the input, and customer satisfaction rating as the output.

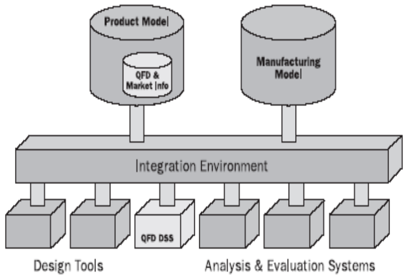

Figure 1 An architecture for future computer-aided engineering systems
Source: Harding & Popplewell (1996)

NN is an important technology of Artificial Intelligence, which have been widely used, in recent years, for manufacturing process monitoring using output pattern recognition (Guh & Tannock, 1999). NNs are found to be a good alternative to traditional analytical techniques for the modelling of complex manufacturing process. This is due to the fact that the number of process variables involved, and the non-linear nature of problems. One of the major NN applications is forecasting since NN can provide a valid alternative to such conventional approaches as time series and regressions.

Compared to the traditional statistical methods, NNs 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.* 1996; Zhang *et al.* 1998).

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) as shown in Figure 2.

A number of successful implementations of neural networks process modelling have been reported and summarized in Table 1.

A framework of an intelligent quality function deployment (IQFD) for discrete assembly environment of QFD as well as the project's profile has been described by San Myint (2003). Wimalin and Tannock (2005) applied a neural network process model based on historical data to Taguchi experimental design for manufacturing optimization process. QFD with applied statistics techniques have been employed to facilitate the translation of prioritized set of customer requirements into a set of system level requirements during conceptual design (Yu & Fu, 2004).

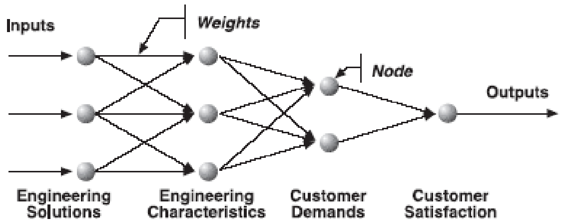

Figure 2 Artificial neural network: design theory and their interrelationship
Source: Zhang et al. (1996)

Table 1. The Applications of Neural Networks in Process Modeling

Author (Year)	Process / Production	Training Data	Architecture / learning algorithm
Wimalin and James (2005)	Production of hollow wide cord fan blades for aircraft engines (Rolls Royce)	EX	MLP
Yu and Fu (2004)	Ship design principle	AC	BP
Rajam and Selladurai (2004)	Flexible manufacturing process (FMS)	EX & SIM	BP
Jimenez-Marquez *et al.* (2003)	Cheese manufacturing	AC	MLP/QN
Heider *et al.* (2002)	Thermoplastic tow placement process	SIM	MLP/BP
Benardos and Vosniakos (2002)	CNC face milling	EX	MLP/LM
Hsieh and Tong (2001)	IC manufacturing	EX	MLP/BP
Cook *et al.* (2000)	Particleboard manufacturing	AC	AP
Nascimento *et al.*(2000)	Chemical process	AC & SIM	MLP/BP
Raj *et al.*(2000)	Metal forming and machining	SIM	MLP/LM
Edwards *et al.* (1999)	Paper making industry	AC	MLP
Ko *et al.*(1999)	Metal forming process	EX & SIM	MLP/BP
Yarlagadda and Chiang (1999)	Pressure die casting	AC & SIM	MLP/LM

Notes: 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

To improve QFD, fuzzy logic is an alternative method to be utilized since fuzzy logic exhibits some useful features for exploitating QFD. For example, Vivianne and Hefin (2000) review methods and techniques to assist QFD by integrating Fuzzy Logic to prioritize engineering characteristics in QFD by addressing the issue of defining non-crisp customer attributes. 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 (Raj *et al.,* 2000).

QFD could also be integrated with World Wide Web (WWW, web) technology to provide QFD services on the Internet/Intranets (Huang & Mak, 2002). The resulting web-based QFD system requires no installation or maintenance on the client side but offers remote and simultaneous accesses and therefore supports better teamwork. The web-based QFD system is the synchronization of multiple clients, whether online active or joining the project late. Any change made by one user is reflected to other users instantly.

The QFD approach was first adopted to translate quality requirements for mobile services to technical (design) requirements for design purpose. Two most important design requirements were identified in the QFD process and they are the need for emergency service and the need for good telehealthcare provider (Xiaosong & Petri, 2007). The concept of Wireless Information Device (WID) is integrated into the architecture to enhance service mobility, personalization and security.

Through the combination of dynamic quality function deployment and statistical process control on core process parameters, dynamic QFD became a critical methodology for improving manufacturing capabilities. Managing the manufacturing interface with other functions and with value chain partners can potentially encode years of problem-solving experience and problem-solving information, whereby a significant degree of technical engineering knowledge is transferred to the production worker (Vivianne & Hefin, 2000).

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 modelling and presents the potential techniques for building a model. Modelling QFD by using NNs and statistical techniques are proposed and compared to identify QFD specification based on customer voices.

3. METHODOLOGY

To build QFD model, experiments were conducted to determine the learning parameters for establishing NN model. In order to meet the objective of this study, a QFD methodology described by (Hauser & Clausing, 1998) is adopted (see Figure 3).

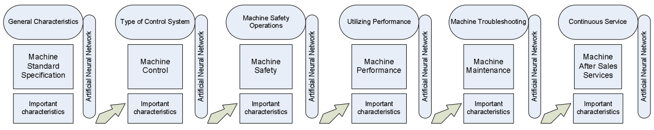

Figure 3 A Proposed Architecture For Analyzing QFD For Customer Voice

To collect data for NN modelling, questionnaires that contains two main sections: a customer profile and possible customer requirements were distributed to respondents. 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) 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 target selected to model QFD for industry, which is the type of customers. These include professional, management level, maintenance and an operator. A questionnaire was constructed based on the study by (Abdul Rahman & Abdul Rahim, 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 (Herzwum *et al.*, 1998).

NN and statistical tools were employed to carry out the analysis. The approach for building forecasting model is adopted from Integrated QFD model methodology (as shown in Figure 4) 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.

4. RESULTS

The survey was conducted in order to investigate and obtain information concerning Quality Function Deployment for general machine planning process. The information obtained serve as guideline for future attempts to build forecasting model of QFD. Data was collected from four different voice of customers's types: 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 total of 300 questionnaires were distributed to various customers, and 223 questionnaires were returned (74.3%). The distribution of customers with respect to their group type is illustrated in Figure 5. Based on Figure 5, the

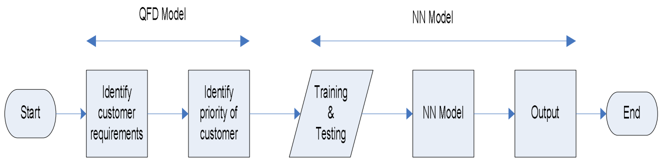

Figure 4 Step To Carry Out For Building Forecasting Model

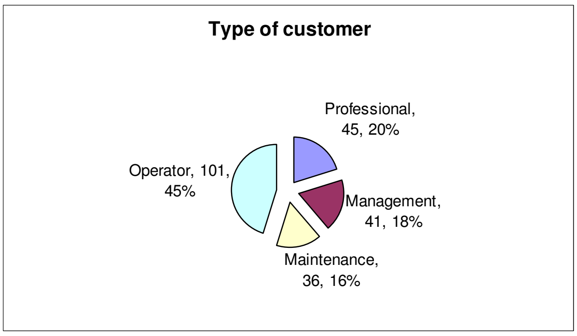

Figure 5 Type's voice of customer

highest percentage for voice of customers' type is contributed by operator (45%), followed by Professional (20*, Management (18%) and Maintenance (16%).

Professional group comes from those who are really involved in teaching how to operate the machine, either in terms of theory or practice. This group is selected from three tertiary, and institutions of higher learning in the northern part of Malaysia. Management respondents refers to those who are really involved as decision makers, such as the Dean and Deputy Dean for a faculty, Managing Director, Senior Executive, Engineer and Assistant Engineer. This group usually has more experience in handling the heavy machine, and also involved in selecting or forecasting the need for a machine at their respective institutions.

Maintenance group comprises of experts from small to big matter in operating machine. They are responsible in solving and troubleshooting a problem that may occur while machine is in operation. For this study, around 36 people (16%) from 100% work as the industrial technician for almost 10 years. The operator comes from tertiary students who have working experience before pursuing their study.

4.1 Neural Network Approach to QFD with Respect to Voice of Customer

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.

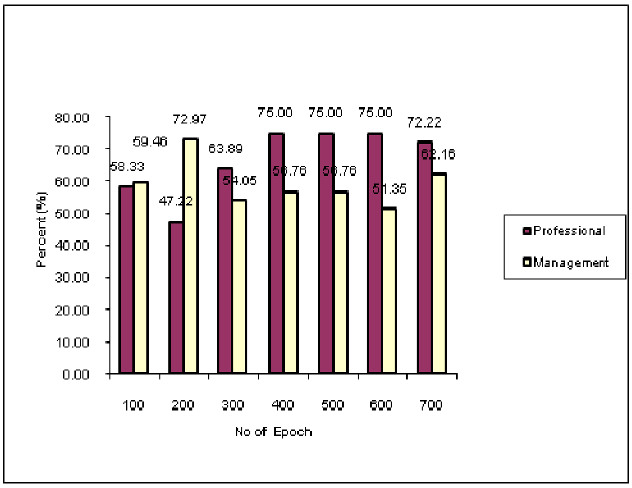

Figure 6(a) Percentage of Correctly Trained Patterns With Respect to PROFESSIONAL and MANAGEMENT

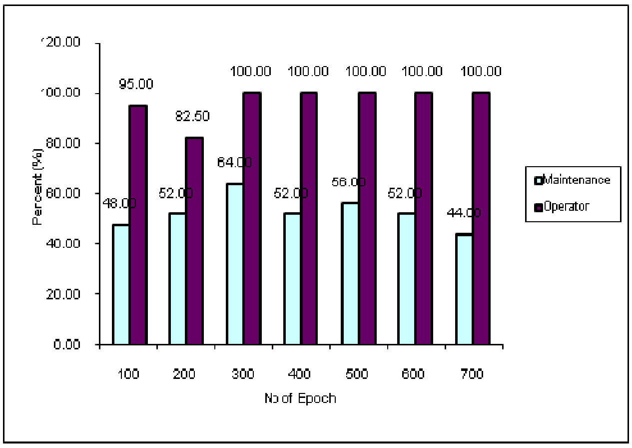

Figure 6(b) Percentage of Correctly Trained Patterns With Respect to MAINTENANCE and OPERATOR

Considering each question as an input to NN, the results based on confusion matrix with regards to Types of customers are illustrated in Figure 6(a) and 6(b).

Closer inspection on the confusion matrix indicates that NN is able to train patterns of type OPERATOR correctly when epoch is set to 300. Based on the bar charts, further investigation is carried out for epoch 400, 500 and 600. Results based on confusion matrix also reveal that patterns of type PROFESSIONAL is normally mistaken as MANAGEMENT and so is vice versa. In this study, the analysis concentrates on the training failures in order to get some insight as to why such confusion is taking place. The initial step is to study the training patterns that fail to learn. The experimental results show that the option NO that has been included in the questionnaire has affected the learning. Thus, the representation of 0 in the questionnaire coding needs to be treated cautiously prior to including such representation when transferring the information from respondent's questionnaire to numerical or symbolic representation.

Table 2. The Correlation results on the Type of Customers with Machine Characteristics based on successful train patterns

Type of Customer with respect to Machine Characteristics (N=143)		Significant Values	Correlation Coefficient
Machine Standard Specification	Machine Brand (Europe)	.139(*)	.048
Machine Safety	Trip devices for puller mechanism	.167(*)	.023
Machine Performance	Utilize small amount of resin	-.174(*)	.019
Machine Maintenance	Quick mould change and set-up	-.151(*)	.036
Machine After Sales Services	Speed of supervisory/ technical person	-.211(**)	.006
	Continuous technical consultancy	.139(*)	.048

Table 3. Correlation summary for the whole data set

Type of Customer with respect to Machine Characteristics (N= 223)		Significant Values	Correlation Coefficient
Type of work piece material used	Plastic	p = 0.001	r = 0.218
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 services	Availability of spare parts	p = 0.027	r = -0.129

Further analysis was conducted on the patterns that were successfully trained and the correlation results with respect to the Type of Customer are exhibited in Table 2.

To correlation between the attributes and type of customers on the whole dataset is also computed and the results are summarized in Table 3.

Note that for both tables, the machine performance has significant correlation with the Type of Customers ($p < 0.05$). The training patterns that do not learn have significant correlation with only Machine Standard Specification, in particular the Pneumatics Clamp Type (see Table 4). This may be due to the fact that not many respondents use machines with Pneumatics clamp type since the maintenance cost is high.

Table 4. Correlation summary for the patterns that do not learn

Type of customer with respect to Machine Characteristics (N=35)			Significant Values	Correlation Coefficient
Type of Customer	Machine Standard Specification	Clamp Type: Pneumatics	.048	.139(*)

The highest average test percentage obtained by NN is **87.696%.** 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. The highest average test percentage obtained from the experiment is **87.621%.**

Based on the results, the datasets with individual value achieves higher percentage accuracy (87.696%) or lowest misclassification accuracy (12.304%). Therefore, NN model that represents the QFD model based on voice of customer with architecture of 97-11-4.

4.2 Statistical results on Quality Function Deployment (QFD)

The dataset used for NN modelling was also used for regression model. Nagelkerke obtained 91.6% and Cox & Snell obtained 84.6%. This result indicates that NN model is able to produce accuracy within the regression ranges of result. Hence, NN has potential to be used as classification or for forecasting QFD with respect to customers' choice. To support NN findings, further explanation on the dataset used is described in the following paragraphs. Closer inspection on the type of work piece material with respect to voice of customer (see Table 5 and Figure 8) reveals that the Professional group prefers to use wood. However, when patterns that are learnt by NN were analyzed, there is no significant correlation between the Type of Piece Material Used/ Processed and the Type of Customer.

During the interview with the Professional group, the respondents indicate that when dealing with wood work piece material, the use of lubrication oil is very minimal. For management group, the preference is on mixed and product assembly work piece. In general, this group may not have sufficient *knowledge know how* with regard to the machine operation.

The maintenance group preferred types of work piece material used are mixed and composite. The correlation between items in the questionnaire with respect to type of customer indicates that the most significant type of work piece is plastic (*r = 0.218 and p< 0.001*).

Table 5. Type of Piece Material Used/Processed

		Type Of Customer
Spearman's rho	**Correlation Coefficient (N = 223)**	
Material Used		.
Wood	**0.023**	**0.152***
Plastic	**0.001**	**0.218****
Metal	0.334	0.065
Composite	0.977	0.002
Mixed	**0.050**	**0.132***
Product assembly	**0.002**	**-0.205****

*	Correlation is significant at the 0.05 level (2-tailed).
**	Correlation is significant at the 0.01 level (2-tailed).

With regard to the machine manufacturer, the only significant machine made is from Japan (*r = 0.188 and p< 0.005*). The most significant drive type preferred by the customer is pneumatic (*r = 0.261 and p< 0.001* versus *r = 0.178 and p< 0.008*).

Both horizontal/vertical and flexible clamp configuration are significant. However, horizontal scores higher correlation value than flexible (*r = 0.297 and p< 0.00*). For clamp type, both pneumatic and hydraulic are most preferable by the customer. Machine with high pressure (*r = 0.266 and p< 0.00*) is more preferable to the ones with low and medium pressure. Machine with low torque has the highest correlation with (*r = 0.275 and p< 0.00*). This maybe due to the fact that machine with low torque last longer since this type of machine has low stress and strain.

Dimension machine standard specification decision is an important category to locate whether the machine is 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, the findings indicate that the dimension of the machine that has more than 1000 mm^3 has the strongest significant correlation at *r = 0.414* and *p<0.000*. The findings also reveal that the significant weight of the machine is more than 2000 kg (*r = 0.414 and p<0.00*).

The correlations coefficient presented in Table 2, 3, 4 and 5 help to explain the relationship between attributes used in the study. To complete the study, NN forecasting model has been established with 12.304% misclassification 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.

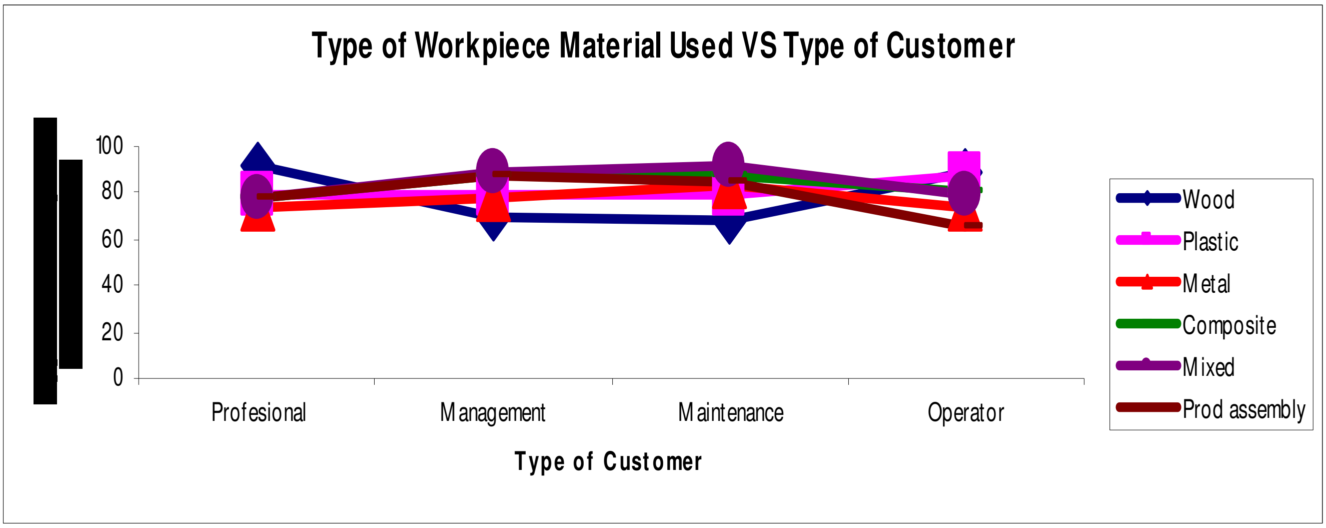

Figure 8 Type of work piece material used VS type of customer

5. CONCLUSION

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 to find the best machine specifications.

- QFD forecasting model gives the customer to give a response 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 will be easier to understand and analyze.

The findings presented in this paper may benefit 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.

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