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# Evolution of Quality Function Deployment (QFD)via Fuzzy concepts and Neural networks

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***Abstract*—**Quality Function Deployment (QFD) is an expounded, multi-step planning method for delivering commodity, services, and processes to customers, both external and internal to an organization. It is a way to convert between the diverse customer languages expressing demands (Voice of the Customer), and the organization's languages expressing results that sate those demands. The policy is to establish one or more matrices that inter-relate producer and consumer reciprocal expectations. Due to its visual presence is called the "House of Quality" (HOQ). In this paper, we assumed HOQ in multi attribute decision making (MADM) pattern and through a proposed MADM method, rank technical specifications. Thereafter compute satisfaction degree of customer requirements and for it, we apply vagueness and uncertainty conditions in decision making by fuzzy set theory. This approach would propound supervised neural network (perceptron) for MADM problem solving.

***Keywords*—**MADM, Fuzzy set, QFD, supervised neural network (perceptron).

## I. Introduction

QFD is methodology which concentrates on taking account of quality and its different dimensions during the product design process and integrate quality to a product from the beginning [1], [2] ,[3]. Unlike customary quality systems which focus at minimizing contrary quality in a product, QFD adds values to the product by maximizing the confident quality. Insistence is on customers wants. It can be defined as an organized planning and decision making methodology for catching customer wants and translating those requirements into product requirements, part characteristics, process plans and quality/production plans through a series of matrices. Customary QFD, which is chiefly used in manufacturing industry, includes four phases:

1. House of Quality
2. Part deployment
3. Process planning
4. Production planning

During the product planning phase a matrix called House of Quality (HOQ) is made [4] . In this paper, we assumed HOQ in multi attribute decision making (MADM) pattern [4]-[8]. and through a proposed MADM method, rank technical specifications [9], [10], [11].

Thereafter compute satisfaction degree of customer requirements. This approach propound supervised neural network (perceptron) for MADM problem solving. The customer requirements are analyzed and prioritized. Customers are asked to determine the importance of various requirements. So, attained results are in linguistic terms form, such as "approximately notable". During the correlation of requirements each combination of customer requirement and a technical requirement, the QFD team must assign a weighting based on the question: "How important is technical requirement A is satisfying customer requirement B?"[1], [3]. As well as, reply of this question is in linguistic term form, such as "very related". For applying these vagueness and ambiguous, we implement fuzzy set theory.To insert images in *Word,* position the cursor at the insertion point and either use Insert | Picture | From File or copy the image to the Windows clipboard and then Edit | Paste Special | Picture (with "Float over text" unchecked).

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## II. Fuzzy sets background information

The fuzzy sets theory, introduced by Zadeh (1968) to deal with vague, imprecise and uncertain problems, has been applied as a modeling tool for complex systems that are hard to define precisely. Some basic definitions of fuzzy sets, fuzzy numbers and linguistic variables are reviewed are presented from Buckley (1985) and Kaufmann and Gupta (1991).

*Definition 1:* A fuzzy set $\tilde{N}$ in a universe of discourse *X* is characterized by a membership function $\mu_{\tilde{N}}(x)$ which associates with each element *x* in *X*, a real number in the interval $[0,1]$. The function value $\mu_{\tilde{N}}(x)$ is termed the grade of membership of *x* in $\tilde{N}$. (Bellman and Zadeh (1970)

*Definition 2:*A fuzzy number is a fuzzy subset of the universe of discourse X that is both convex and normal.

Figure (1) shows A fuzzy number $\tilde{N}$. In the universe of discourse X that conforms to this definition (Zadeh (1965)).

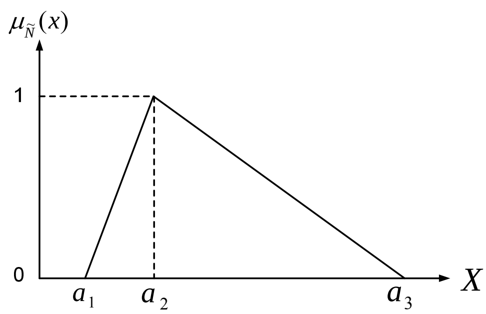


Fig. 1 a triangular fuzzy number $\tilde{N}$

We use triangular fuzzy numbers. A triangular fuzzy number $\tilde{N}$ can be defined by a triplet $(a_1 a_2, a_3)$. Its conceptual schema and mathematical form is shown by equation (1).

$$\mu_{\tilde{N}}(x) = \begin{cases} 0 & x \le a_1; \\ \frac{x-a_1}{a_2-a_1} & a_1 < x \le a_2; \\ \frac{a_3-x}{a_3-a_2} & a_2 < x \le a_3; \\ 0 & x > a_3; \end{cases} \quad (1)$$

Where $(a_1, a_2, a_3)$ denote as left hand number, middle number and right hand number of $\tilde{N}$ respectively.

*Definition 3:*

Assuming that both $\tilde{N} = (a_1, a_2, a_3)$ and $\tilde{M} = (b_1, b_2, b_3)$ are fuzzy number and $c$ is positive real numbers, then the basic operations such as multiplication, addition, distance, maximum and minimum on fuzzy triangular numbers are defined as follows respectively (Zadeh (1965)).

$$c \times \tilde{N} = (c \times a_1, c \times a_2, c \times a_3)$$

$$\tilde{N} + \tilde{M} = (a_1 + b_1, a_2 + b_2, a_3 + b_3)$$

$$d(\tilde{N}, \tilde{M}) = \frac{a_1 + 2a_2 + a_3}{4} - \frac{b_1 + 2b_2 + b_3}{4}$$

$$Max\{(a_i, b_i, c_i)_{i=1,\dots,n}\} = (max(a_i), max(b_i), max(c_i))$$

$$Min\{(a_i, b_i, c_i)_{i=1,\dots,n}\} = (min(a_i), min(b_i), min(c_i)) \quad (2)$$

*Definition 4:*

when we consider a variable, in general, it takes numbers as its value. If the variable takes linguistic terms, it is called linguistic variable (Zadeh (1975)). The concept of a linguistic variable is very useful to describe situations that are too complex or not well defined in conventional quantitative expressions. For example, "temperature" is a linguistic variable which it is contain the values as freeze, cold, cool, hot, very hot, etc where it is defined as linguistic terms.

## III. Perception Neural Network

An artificial neural network (ANN), usually called "neural network" (NN), is a mathematical model or computational model that tries to simulate the structure and/or functional aspects of biological neural networks[17]-[19].

It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. Neural networks are non-linear statistical *data modeling* tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data. Perceptron is one of NN models that is supervised, that mean for training process, must give a sample output and input set. Follow shape is perceptron structure:

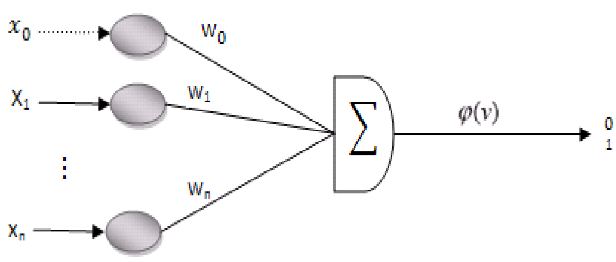


Fig. 2 perceptron structure

Perceptron has external input ($x_i$), an internal input that called bias ($x_0 = 1$), a threshold point ($\theta$) and output values. Peceptron outputs are 1 (true) and 0 (false). If output of perceptron is 1, then it is called active perceptron. One of most important components of any neuron is activate function. This function delivers output due to its input. Function after multiply all weights at inputs, sum them. If attained value ($v(t)$) be more than threshold point, perceptron will be active else no. So if follow relation be satisfy, perceptron will be active:

$$w_0x_0 + w_1x_1 + \dots + w_nx_n \ge \theta$$

Perceptron training is according to following steps:

1. First, make an output
2. Compare attained output by real output
3. Adapt weights such that converge by real output

This training method called Delta rule, in this method variation of weights calculate as bottom relation:

$$w_i = x_i . \delta$$

Which $\delta$ is difference of real output and attained output. $x_i$ is input value , too .

In this paper, we put value of threshold equal 0, ( $\theta = 0$ ).

## IV. HoQ in Fuzzy MADM Pattern

Let $A_i$ ($i = 1, 2, \dots, m$) be the alternatives (customer requirement) to be evaluated against criteria $C_j$ ($j = 1, 2, \dots, n$). Some of the criteria (technical specifications) have positive concepts, mean DMs will to increase it (for example: productivity), and some other have negative concept (for example: cost). All numbers (parts) of decision matrix are fuzzificated and state correlation measure between customer requirement and technical specifications. Correlation measure indicate by fixed linguistic term with QFD team [4]. As well as, QFD team fix linguistic term for measure importance customer requirement.

TABLE I
HOQ AS A FUZZY MADM

| HOQ | $C_1$ | ⋯ | $C_n$ |
|---|---|---|---|
| $A_1$ | $(\ddot{y}_{11l}, \ddot{y}_{11m}, \ddot{y}_{11r})$ | ⋯ | $(\ddot{y}_{1nl}, \ddot{y}_{1nm}, \ddot{y}_{1nr})$ |
| ⋮ | ⋮ | | ⋮ |
| $A_m$ | $(\ddot{y}_{m1l}, \ddot{y}_{m1m}, \ddot{y}_{m1r})$ | ⋯ | $(\ddot{y}_{mnl}, \ddot{y}_{mnm}, \ddot{y}_{mnr})$ |

This model implementing is dependent of following steps doing:
Step 1) initial step is for influence measure importance customer requirement on table 1. For this influence, we multiply measure importance customer requirement in any part of its row. Attained result is follow matrix:

TABLE II
CUSTOMER REQUIREMENTS INFLUENCING

| HOQ | $C_1$ | ⋯ | $C_n$ |
|---|---|---|---|
| $A_1$ | $(y_{11l}, y_{11m}, y_{11r})$ | ⋯ | $(y_{1nl}, y_{1nm}, y_{1nr})$ |
| ⋮ | ⋮ | | ⋮ |
| $A_m$ | $(y_{m1l}, y_{m1m}, y_{m1r})$ | ⋯ | $(y_{mnl}, y_{mnm}, y_{mnr})$ |

Step 2) Normalization: we normalized any columns separately. If j$^{th}$ column (technical specifications) have be positive concept, then d$^{th}$ line and j$^{th}$ column part of decision matrix normalized by following relation:

$$\left(\frac{y_{djl}}{\max_{i\in(1,..,m)} y_{ijr}}, \frac{y_{djm}}{\max_{i\in(1,..,m)} y_{ijr}}, \frac{y_{djr}}{\max_{i\in(1,..,m)} y_{ijr}}\right) \quad (3)$$

And if j$^{th}$ column (technical specifications) has be negative concept, then d$^{th}$ line and j$^{th}$ column part of decision matrix normalized by following relation:

$$\left(\frac{\min_{i\in(1,..,m)} y_{ijl}}{y_{djl}}, \frac{\min_{i\in(1,..,m)} y_{ijl}}{y_{djm}}, \frac{\min_{i\in(1,..,m)} y_{ijl}}{y_{djr}}\right) \quad (4)$$

Step 3 ) this step tries to give a new weight determination approach to retain the merits of both subjective and objective approaches: to determine weights by solving mathematical models automatically and at the same time take into consideration the decision maker's preferences :
Step 3.1)) subjective weights ($w_j^s$) : Weights determined by subjective approaches can reflect the subjective judgments of decision makers, thus makes the rankings of alternatives in Fuzzy MADM problem have more arbitrary factors. First, formation a structure similar following matrix:

TABLE III
RECIPROCAL COMPARISON OF TECHNICAL SPECIFICATIONS

| Reciprocal comparison | $C_1$ | ⋯ | $C_n$ |
|---|---|---|---|
| $C_1$ | | | |
| ⋮ | | ⋮ | |
| $C_n$ | | | |

This is a reciprocal pairwise criterion comparison matrix; this comparison is with linguistic terms. Later, it is necessary transform these linguistic terms to fuzzy numbers. Notice that if i$^{th}$ line and j$^{th}$ column part be $(a, b, c)$ then j$^{th}$ line and i$^{th}$ column part will be $(\frac{1}{c}, \frac{1}{b}, \frac{1}{a})$ . After framing above matrix, we normalize it and calculated any line mean. These n-times mean are fuzzy numbers, obviously .in this stage, we defuzzified these n-times mean to obtain crisp numbers those are $w_j^s$ .
Step 3.2)) objective weights ($w_j^o$): The objective approaches select weights through mathematical calculation, which neglects subjective judgment information of decision makers. Entropy theory is another important theory to study the problem of uncertainty. Entropy weight is a parameter that describes how much different alternatives approach one another in respect to a certain attribute. The greater the value of the entropy, the smaller the entropy weight, then the smaller the differences of different alternatives in this specific attribute, and the less information the specific attribute provides, and the less important this attribute becomes in the decision making process. In this paper we give a Fuzzy Entropy Weight. While for fuzzy numbers, we could not use the above formula to calculate the entropies of fuzzy numbers directly. Generally, we would first transform the fuzzy numbers into crisp numbers, and then calculate their respective entropies. So, we defuzzified all numbers of normalized matrix to obtained $x_{ij}$ . Next, normalize $x_{ij}$ according to the following equation:

$$f_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (5)$$

Then, the fuzzy entropies of the technical specifications can be calculated with the following:

$$\bar{E}_j = -K.\sum_{i=1}^{m} f_{ij} \times Ln(f_{ij}) = -\frac{1}{Ln(m)}\sum_{i=1}^{m} f_{ij} \times Ln(f_{ij}) \quad (6)$$

Now, calculate the objective weight with the following equation:

$$W_j^o = \frac{1-\bar{E}_j}{\sum_{j=1}^{n}(1-\bar{E}_j)} \quad (7)$$

Step 2.3)) Calculation of the combined weights of technical specifications: Derive the combined weight according to:

$$w_j - (w_j^o)^{\alpha} \times (w_j^s)^{\gamma} \tag{8}$$

Where $\alpha$, $\gamma$ and represents the relative importance of the subjective weights and the objective weights to decision makers respectively, $+\gamma = 1$ . Combined fuzzy weight is such an indicator that not only shows how much important a technical specification is to the decision-maker, but also shows how much different the values of the technical specification in different alternatives are. These weights are as total score of any technical specification. For technical specifications ranking, we must rank these scores.

Now, we compute satisfaction degree of customer requirements through perceptron neural network [17].

Training set must contain all possible cases. Each output is related by an ordered customer requirement list. Neuron number of output layer is equal by all possible case number, so, network has $m!$ - times output and $mn$ - times input. Output function is competency, this mean which maximum value of output neuron get 1 value and other output neuron get 0 values. Output function $\varphi(v(t))$ is as following relation:

$$\varphi(v(t)) = \begin{cases} 1 : & \max(v(t)) \\ 0 : & otherwise \end{cases} \tag{9}$$

Initial weights of network assume 0. In continue, we multiply technical specifications weights at normalized matrix. Result of it will be $[a_{ij}{}^{fuzzy}]_{m\times n}$ matrix. All parts of this matrix are triangular fuzzy numbers, obviously. For easiness, we defuzzfy those and then normalize it. Attained matrix is $[a_{ij}]_{m\times n}$ . Training set calculates by following relations:

$$\Pi_j = max_i(\, a_{ij})$$

$$\pi_j = min_i(\, a_{ij})$$

$$\tau_i^{jk} = \frac{\Pi_j - \pi_j}{m-1}(j-1) + \pi_j$$

$$\Gamma_i = \begin{bmatrix} \tau_i^{11} & \tau_i^{12} & \cdots & \tau_i^{1n} \\ \tau_i^{21} & \tau_i^{22} & \cdots & \tau_i^{2n} \\ \vdots & \vdots & \ddots & \vdots \\ t_i^{m1} & \tau_i^{m2} & \cdots & \tau_i^{mn} \end{bmatrix} \tag{10}$$

$\Gamma_i$ is a training set that show $A_1 \leq A_2 \leq \cdots \leq A_m$ case . For other cases getting must interchange among all rows. After training, must give decision matrix to neural network to attain order of customer requirements.

## V. Conclusion

The preferred practice of the quality management method QFD is to acquire high-quality products by means of methodical processes already in the early points of the product begetting process; whereby quality in these circumstances is understood to mean a high scale of customer satisfaction which in turn is a critical factor for the long-term triumph of an enterprise. For this purpose, we apply vagueness and uncertainty conditions in QFD decision making by fuzzy set theory. This approach would propound supervised neural network (perceptron) for MADM problem solving.

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