Fuzzy Logic Approach for the Design of Six Sigma

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This paper presents a Fuzzy logic based Design for Six Sigma (FLBDFSS) incorporating the traits of artificial intelligence and statistical techniques. In the identify phase of FLBDFSS, fuzzy relation measures between Customer Attributes and Engineering Characteristics as well as fuzzy correlation measures among ECs are determined with the aid of two Fuzzy Logic Controllers. These two measures are then used to establish the cumulative impact factor for ECs. In design phase, a transfer function is developed and optimized with the simulated annealing algorithm. In the validate phase, t-test is conducted for the validation of the design resulted in earlier phase.

1. Introduction

More than a decade, Six Sigma has been known to be one of the most successful breakthrough business strategies to achieve quality excellence through systematic defect reduction and cost optimization (Catherwood, 2002; Bisgaard and De Mast, 2006). One of the most practiced methodologies to accomplish six sigma objectives is the DMAIC (Define, Measure Analysis, Improve and Control) approach. The strategic implementation of DMAIC ensures to find and eliminate causes of defects in business processes by focusing on process outcomes. However, the entire Six Sigma efforts will be of no value if the fundamental design is inaccurate, and consequently manufacutring a product that does not sell (Banuelas and Antony, 2004; Lee, 2001). In view of this, the Design for Six Sigma (DFSS) offers a better alternative as to focus on the early design stage so that the company may obtain six sigma products and services from the very beginning (Tenant, 2002; Antony and Banuelas, 2002; Kwak and Anbari, 2006). In the recent years, there is a remarkable trend of the proliferation of DFSS methodology which is indicated by the increasing academic interests (Hoerl, 2001; Brady and Allen, 2006) and the exponential growth of books in the market (Goh, 2002). Basically, DFSS is a dynamic problem-solving process focusing on preventing and removing defects before and during design, resulting in improved product/service performance and profitability. Pertaining to several ways in which DFSS is applied to various organizations, it can be broadly classified in two groups (Ferryanlo, 2005). The first group comprises the organizations that implement DFSS by creating a six sigma infrastructure (e.g. General electric, Bank of America, and Ford). This group consists of Green Belt (GB), Black Belt (BB), and a Master Black Belt (MBB). The second group embraces the organizations that exercise DFSS without six sigma infrastructure (e.g. IBM, Dell, Sony and Microsoft). In this group, neither BBs nor MBBs exist, and yet DFSS tools and techniques are employed to design the products or products supporting six sigma tools or software.

In general, DFSS activities are classified into four major phases viz. Identify, Design, Optimize and Validate (IDOV) (Yousef *et al.*, 2008). In identify phase, Customer Attributes (CAs) are collected and translated into relevant Engineering Characteristics (ECs) with the aid of Quality Function Deployment (QFD). The design phase emphasizes on proposing and evaluating conceptual solutions to address the previously identified critical customer requirements. In the optimize phase, optimization of the resource allocation and levels of design parameters are carried out in given environmental and manufacturing variations. The final phase (i.e. validate phase) consists of validation of the optimal design obtained in the penultimate phase.

In the design of new products/services, various vague and abstract conditions arise. This inherent ambiguity generally arises due to the following reasons: (1) CAs may be in the form of linguistic data based on human perception, judgment, and evolution, which are highly subjective and vague (Chan and Wu, 2002); (2) There are normally many CAs for a product, each CA can be translated into multiple ECs, and conversely a certain EC may affect multiple CAs. In general, these CAs tend to be translated into ECs in a subjective, qualitative and non-technical way, which should be expressed in more quantitative and technical terms. Hence, the relationships between CAs and ECs are often vague or imprecise (Kim *et al.*, 2000); (3) Owing to the uncertainties in the design process, the data available for product design is often limited and may be inaccurate, especially when an entirely new product is developed, and a certain degree of vagueness in correlation measures among ECs is often inevitable (Fung *et al.*, 2006). In this context, research on fuzzy QFD has received much attention (Temponi *et al.*, 1999; Harding *et al.*, 2001), and made substantial progress. In an attempt to adequately deal with the above mentioned uncertainties and vagueness, this research proposes a Fuzzy Logic Based Design for Six Sigma (FLBDFSS). This approach incorporates fuzzy logic in the identify phase. In the FLBDFSS, fuzzy relation measures between CAs and ECs as well as fuzzy correlation measures among ECs are determined by fuzzy logic controllers. Further, these two measures are used to determine cumulative impact factor of ECs. In the next phase (i.e. Design phase) of FLBDFSS, a transfer function is developed with the aid of robust multiple nonlinear regression analysis identifying the functional relationship between key ECs and the system's performance. Further, this design is optimized with the aid of Simulated Annealing Algorithm in the optimize phase.

Proposed by Kirkpatrik *et al*. (1983), SA is suitable for complicated problems where global optimum is hidden among many local optima. The idea of the SA approach is an analogy with the way molten metals cool and anneal. In the last phase (i.e., validate phase), a *t*-test is conducted to verify the design. In order to test the efficacy of the proposed FLBDFSS it is deployed on a simulated case study of a hypothetical writing instrument. Part of the attributes of writing instrument are taken from Wasserman (1993), where *easy to hold*, *does not smear*, *point lasts* and *does not roll* are the four identified important customer wants based on a market survey. And the length of pencil, time between sharpening, lead dust generated, hexagonality and minimal erasure residue are the five important engineering characteristics.

The remainder of paper is organized as follows. In section 2, the framework of the proposed FLBDFSS is presented. Section 3 concludes the paper.

2. A Fuzzy Logic Based Design for Six Sigma

The recent technological advancements have drastically increased the product variety, thereby, providing the end users more options to select and customize their products. Hence, it becomes vital for the manufacturer to acknowledge the importance of the customer requirements for maintaining a permanent goodwill among them. In this respect, Design for Six Sigma (DFSS) methodology is one of the prominent techniques for integrating the voice of customer (VOC) with the design characteristics. The generic activities involved in the DFSS methodology include the following four major phases: Identify, Define/Design, Optimize and Validate which are also referred to as IDOV.

2.1 The Identify Phase

As discussed above, DFSS is broadly divided into four distinct phases and each phase has its own significant role in the product development. The DFSS methodology starts by collecting the basic customer requirements (CRs) via various market techniques. In the identification phase, a planning and problem solving tool, quality function design (QFD) is employed to translate the CRs into specific engineering characteristics (ECs). QFD is a cross functional efficient planning methodology utilized for developing new products or for modifying existing products. It is a systematic method used by the product development team for deploying the VOC into the ECs. Due to its inherent characteristic of efficiently identifying the key ECs, QFD has been an area of significance importance among the researchers (Chan and Wu 2002, Prasad 1998, Ghahramani Houshyar 1996). It is a tool for quality assurance and simultaneously for successfully amalgamating the customer satisfaction into the product development even before designing is accomplished. Therefore, it is also known as a customer driven product development tool (Kwong *et al.* 2007).

In QFD, the CAs with respect to the product performance are analyzed by constructing a house of quality (HOQ). The HOQ classifies CAs by reorganizing them into several categories, like design needs of the product and process, component specifications, quality control of the production etc. (Akao 1990). Thereafter, a relationship matrix between the CAs and ECs and an interrelationship matrix among ECs are developed and finally the ECs are prioritized.

The classical QFD has lack of capabilities of handling qualitative and fuzzy information, and this limitation is becoming increasingly serious with its deep-going application. To deal with these situations, FLBDFSS makes use of a Fuzzy Logic Controller (FLC) embedded quality function deployment. A Fuzzy Logic Controller (FLC) is a conceptual input-output machine, capable of making certain decisions based on the input linguistic variables fed to it. It works on the principals of fuzzy logic as suggested by Zadeh (1965) in his revolutionary work which stresses on the significance of fuzzy membership functions instead of crisp values. Numerous researchers like Gen *et al.* (1996), Mierswa (2005), and Anand *et al.* (2007) applied fuzzy set theory to represent non-statistical uncertainty and approximate reasoning in real life situations.

Incorporating fuzziness into the QFD methodology becomes significantly important with the realization that CAs are essentially linguistic in nature, which may be later on quantified according to the needs. The primary motivation behind employing the Fuzzy Logic Controller (FLC) is to adequately deal with the inherent vagueness associated with the CAs. The proposed methodology includes following two separate FLCs.

1. Between CAs and ECs (F_{ce}): The first FLC is utilized to study the relations between CAs and ECs which calculates the significance factor (f_s) for each EC.
2. Between two ECs (F_{ee}): Correlations existing between two ECs are obtained via this FLC which provides the decision maker with the importance factor (γ_x) for each EC

Finally, a cumulative impact factor (δx) for each EC has been calculated. The obtained δx value provides the decision maker with the guidelines for passing only the relevant ECs into the designing phase.

In general, a fuzzy set is an extension of classical set. Given X as the universe of discourse and x as its elements, a fuzzy set A in X is defined as follows:

$$A = \left\{ x,\ \mu_A(x) \middle| \ x \in X \right\} \qquad \dots (1)$$

$\mu_A(x)$ is called the membership function of *x* in *A*. The membership function can take any form (piecewise, triangular, Gaussian, etc) and maps each element of *X* to a membership value between 0 and 1. In this research, a smooth Gaussian curve has been selected as the membership function for defining the input and output fuzzy sets. These membership functions are also employed for fuzzification of the crisp data. Thereafter, a rule base inference engine consisting of several if-then rules are generated in accordance with *if-then* format. Since only two input variables and one output variable is being utilized in both the FLCs (F_{ce} and F_{ee}), the format of *if-then* rule, in this research, is as below:

R_i : *If* (A_{i1} is a_{i1} and A_{i2} is a_{i2}) *Then* C_i is c_i

In the antecedent part of the rule (containing the '*If*' statement), a_{i1} and a_{i2} are fuzzy sets corresponding to the input linguistic variables A_{i1} and A_{i2} are in the consequent part of the rule (containing the '*Then*' statement), c_i is the fuzzy set corresponding to the output linguistic variable C_i . After rule evaluation, all the sub-outputs are amalgamated and transformed into a complete fuzzy output which is ready for defuzzification.

Defuzzification is an inverse process of fuzzification, where an aggregated fuzzy output value is transformed into a crisp value which can be easily interpreted thereafter. Several defuzzification procedures have been proposed in literature, and choice of an appropriate one depends upon the nature of the analysis being carried out, ease of application and on the personal preference of the decision maker (Ross, 1995). In this research, the authors have utilized the centroid methodology where the outputs can be defuzzified using the algebraic function as given in the following equation:

$$Z^* = \frac{\sum m_c(\tilde{z}).\tilde{z}}{\sum m_c(\tilde{z})} \quad \ldots (2)$$

Here, $m_c(\tilde{z})$ is the output membership value of the fuzzified quantity $\tilde{z}$ and Z^* being the output defuzzified value. This methodology weighs each membership function in the output by its respective membership value. This approach of defuzzification is applied only to the symmetric output membership functions and thus suits our case.

2.1.1 The Cumulative Impact Factor (δ_x):

The primary objective of employing the QFD methodology is to identify the relevant ECs that could be passed on to the design team for further processing. Therefore, cumulative impact factor *(* δ_x *)* for each EC has been calculated which directly reflects the significance of a EC. As a general rule, larger the value of δ_x , greater is its impact.

As discussed above, the two FLCs (F_{ce} and F_{ee}) generate f_s and γ_x . After γ_x values are computed, they are utilized to calculate the δ_x . Let ξ be a set defined completely by collecting all the individual γ_x values. If N be the total number of ECs,

$$\xi = \{\gamma_1, \gamma_2, \ldots, \gamma_N\} \quad \ldots (3)$$

The boundary value (τ_x) for the importance factor is calculated in accordance with the following equation:

$$\tau_x = \frac{\sum_{x=1}^{N} \gamma_x}{N}, \ x = 1, 2, \ldots, N \quad \ldots (4)$$

If γ_{xy} is the correlation value between γ_x and γ_y , Influence Factor (λ_x) for EC_x is defined as,

$$\lambda_x = \sqrt{\sum_{\substack{y=1 \\ y \neq x}}^{N} (\gamma_{xy} - \tau_x)^2}, \qquad x = 1, 2, \ldots, N \text{ and } y = 1, 2, \ldots, N \quad \ldots (5)$$

Influence Factor (λ_x) is then normalized to obtain the following Normalized Influence Factor ($\lambda_x^{'}$),

$$\lambda_x^{'} = \frac{\lambda_x}{\sum_{x=1}^{N} \lambda_x}, \ x = 1, 2 \ldots N \quad \ldots (6)$$

This Normalized Influence Factor ($\lambda_x^{'}$) is amalgamated with Normalized Importance ($\mu_x^{'}$) to obtain a Cumulative Impact Factor (δ_x)

$$\delta_x = \lambda_x^{'} \times \mu_x^{'}, \ x = 1, 2, \ldots, N \quad \ldots (7)$$

2.2 The Design Phase

After translating the VOC into engineering characteristics (ECs) and gathering sufficient amount of data, the next task is to develop a transfer function to identify the functional relationships among important ECs and customer utility (y). Customer utility is defined as ratio of satisfied customer with the total number of customers purchasing the same product variant. The transfer function can be established by deploying various statistical and artificial intelligence techniques. In this paper, robust multiple nonlinear regression analysis is employed to accomplish the same. Before establishing the transfer function, for the sake of simplicity, all design parameters are coded in an interval of (-1, 1) by using the fallowing coding schema:

Where,

$$\left.\begin{aligned} x_i &= \frac{\text{Actual value of } i^{th} \text{ parameter} - \chi_i}{\gamma_i} \\ \chi_i &= \frac{(Upper\ bound)_i + (Lower\ bound)_i}{2} \\ \gamma_i &= \frac{(\text{Upper bound})_i - (\text{Lower bound})_i}{2} \end{aligned}\right\} \quad ..(8)$$

The second order regression equation is expressed as (Park, 1996; Montgomery, 2000):

$$\hat{y} = \hat{\beta}_0 + \sum_{i=1}^{k} \hat{\beta}_i x_i + \sum_{i=1}^{k} \hat{\beta}_{ii} x_i^2 + \sum_{i<} \sum_{j}^{k} \hat{\beta}_{ij} x_i x_j \quad \ldots (9)$$

$$= \hat{\beta}_0 + x'b + x'Bx$$

Where *x* is EC, *b* is the regression coefficient, *y* is the customer utility and *B* is regression coefficient for square effect and interaction between ECs.

$$x = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ \vdots \\ x_k \end{pmatrix}, \quad \ldots (10)$$

$$b = \begin{pmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ : \\ : \\ \hat{\beta}_k \end{pmatrix} \quad \ldots (11)$$

$$B = \begin{pmatrix} \hat{\beta}_{11} & \hat{\beta}_{12}/2 & .. & .. & \hat{\beta}_{1k}/2 \\ \hat{\beta}_{12}/2 & \hat{\beta}_{22} & .. & .. & \hat{\beta}_{2k}/2 \\ : & : & : & : & : \\ : & : & : & : & : \\ \hat{\beta}_{1k}/2 & \hat{\beta}_{2k}/2 & .. & .. & \hat{\beta}_{kk} \end{pmatrix} \quad (12)$$

Thereafter, least square estimate method is used to compute the regression coefficients in following manner:

$$\hat{\beta} = \begin{pmatrix} \hat{\beta}_0 \\ \hat{\beta}_i \\ : \\ : \\ \hat{\beta}_k \\ : \\ : \\ \hat{\beta}_{kk} \end{pmatrix} = (X'X)^{-1} X'y \quad \ldots (13)$$

Where X is the matrix of ECs (design parameters) and can be represented as:

$$X = \begin{pmatrix} 1 & x_{11} & x_{21} & \cdots & \cdots & x_{k1} \\ 1 & x_{12} & x_{22} & \cdots & \cdots & x_{k2} \\ \vdots & \vdots & \vdots & \cdots & \cdots & \vdots \\ \vdots & \vdots & \vdots & \cdots & \cdots & \vdots \\ \vdots & \vdots & \vdots & \cdots & \cdots & \vdots \\ 1 & x_{1n} & x_{2n} & \cdots & \cdots & x_{kn} \end{pmatrix} \qquad \ldots(14)$$

And Y is the customer utility matrix which is expressed as:

$$Y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ \vdots \\ \vdots \\ y_n \end{pmatrix} \qquad \ldots(15)$$

With the help of Equations 8-15 a transfer function is to be developed to map the functional relationship between design parameters and the customer utility.

2.3 The Optimize Phase

FLBDFSS explores the search capability of simulated annealing (SA) for the optimization of design obtained from the earlier phase. Originally proposed by Kirkpatrick *et al.* (1983), SA is a random search technique that derives its inspiration from physical annealing of solids, where a metal is brought to its lowest energy state by first heating it to a very high temperature (usually re-crystallization temperature of metal) and then cooling at a very slow rate, to a very low temperature (Metropolis *et al*., 1953). If the cooling is not slow enough, it may result in quenching, which is not desirable. Based on the iterative improvement concept, the SA algorithm is in fact heuristic method with the basic idea of generating random displacement from any feasible solution. This process accepts not only the generated solutions, which improve the objective function but also those which do not improve it with the probability exp (-ΔF/T), a parameter depending on the objective function and decreasing temperature. Following is the pseudo code of SA.

The cooling schedule plays a key role in guiding the solutions towards the optima. Hajek (1998) had proposed the following cooling schedule.

$$T_k = \frac{C}{\ln(1+k)} \qquad \ldots(16)$$

This annealing schedule asymptotically approaches to the global minimum as $k \to \infty$. In practice, above cooling schedule requires too much computational time. Therefore, several other non-optimal schedules that work well in practice are commonly used, such as (Shukla *et al*., 2008):

$$T_{h+1} \leftarrow \alpha T_h \qquad \ldots(17)$$

Where α is called the cooling coefficient with $0.8 \leq \alpha \leq 1.0$.

Occasionally accepting the comparatively worse points in the neighborhood with some non-zero probability that gradually decreases. This probability is expressed in terms of the acceptance function. In general, the performance of SA search technique is marked by 4 parameters i.e., choice of initial temperature, the epoch length or number of transitions made before the temperature is reduced, a proper cooling schedule for temperature reduction and some terminating criteria.

Once the optimal design is achieved next task is to validate it. In the proposed approach, *t*-test is employed for the validation of design obtained from the optimize phase. The following section delineates an illustrative example for implementation of FLBDFSS on a simulated case study of a hypothetical writing instrument.

3. Conclusion

In this paper, a Simulated Annealing Embedded Fuzzy Logic Based Design for Six Sigma (FLBDFSS) has been proposed. The proposed methodology aims to calculate an accurate product design, capable of providing maximum customer satisfaction. The methodology utilizes customer inputs in terms of linguistic variables and incorporates two FLCs to adequately map these variables. The outputs of these FLCs have been utilized to compute the actual design parameters. Thereafter, a transfer function is developed with the aid of robust multiple nonlinear regression analysis identifying the functional relationship between key ECs and the system performance. The transfer function is optimized by utilizing SA and the results obtained are statistically validated by conducting the t-test. As an example, a case study of a hypothetical writing instrument is simulated. The results for the underlying case study were found to be highly encouraging with 99.83% customer satisfaction. The future research focus should be to enhance the applicability and efficiency of the proposed FLBDFSS to various product development scenarios. The drawback of the proposed methodology is that a slight increase in design parameters may cause a polynomial increase in the complexity of the regression analysis. Therefore, the future research should be guided to develop more robust methodologies for computing the transfer function.

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This paper presents a Fuzzy logic based Design for Six Sigma (FLBDFSS) incorporating the traits of artificial intelligence and statistical techniques. In the identify phase of FLBDFSS, fuzzy relation measures between Customer Attributes and Engineering Characteristics as well as fuzzy correlation measures among ECs are determined with the aid of two Fuzzy Logic Controllers. These two measures are then used to establish the cumulative impact factor for ECs. In design phase, a transfer function is developed and optimized with the simulated annealing algorithm. In the validate phase, t-test is co Fuzzy logic approach dealt well with such problems. Linguistic variables were used for selection of the critical factors of breakdowns. These were further converted into fuzzy numbers as shown in Table 2 for the current study.Â Conveyor malfunction, slide not working, and CWD unit fault, coolant pump malfunction and hydraulic oil leakage are found to be the critical factors of breakdowns in CLG section. This study explores the feasibility of fuzzy VIKOR and fuzzy TOPSIS methods in Six Sigma analysis phase for selection of the breakdown/failure parameters. Briefly, the main features of this study are summarized as follows: (a). The study helps to highlight the importance of â€˜Analysis Phaseâ€™ for successful implementation of Six Sigma project. (b). Six Sigma is considered as a logical business strategy that attempts to identify and eliminate the defects or failures for improving the quality of product and processes. A decision on project selection in Six Sigma is always very critical; it plays a key role in successful implementation of Six Sigma. Selection of a right Six Sigma project is essentially important for an automotive company because it greatly influences the manufacturing costs. This paper discusses an approach for right Six Sigma project selection at an automotive industry using fuzzy logic based TOPSIS method. The fuzzy TOPSI This paper presents a Fuzzy logic based Design for Six Sigma (FLBDFSS) incorporating the traits of artificial intelligence and statistical techniques. In the identify phase of FLBDFSS, fuzzy relation measures between Customer Attributes and Engineering Characteristics as well as fuzzy correlation measures among ECs are determined with the aid of two Fuzzy Logic Controllers. These two measures are then used to establish the cumulative impact factor for ECs. In design phase, a transfer functionâ€¦ CONTINUE READING. aims-international.org. Optimizing order fulllment using design for six sigma and fuzzy logic. âˆ—. Yousef Amer1â€ , Lee Luong1, Sang-Heon Lee1, M. Azeem Ashraf2 1 School of Advanced Manufacturing and Mechanical Engineering.Â Six sigma is a highly disciplined, data-oriented, top-down approach which explicitly links the tactical and the strategic. Statistical techniques are used in a systematic way to reduce variation and improve processes, with a strong focus on results [22]. Today the design of services within the supply chain in many industries exhibit deciencies like modest levels of quality, ignorance of customer wants, and too much complexity.