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An innovative DFSS approach for multivariate production process

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ABSTRACT

Design for Six Sigma (DFSS) is a popular design concept and systematic methodology aiming at quality and reliability improvements based on customer requirements and market competitiveness; however, now, there is no unified model and tools for DFSS activities and the conventional DFSS easily overlook the complexity in production processes. In this article, an innovative DFSS for multivariate production process is divided into four main phases, namely, identify, design, optimize and verify (IDOV), with methodologies and tools analyzed thoroughly.

Key words: Design for six sigma; fuzzy sets; quality function deploy; failure mode and effects analysis; principal component analysis; robust parameter design

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INTRODUCTION

SixSigma has been considered as a philosophy that employs a well-structured continuous improvement methodology to reduce process variability and drive out waste within the business processes using statistical tools and techniques [1, 2]. Today, Six Sigma focuses on systematic defect reduction and cost optimization by using either a continuous improvement methodology of five procedures, viz, define, measure, analyze and control (DMAIC), or a design approach known as Design for Six Sigma in early design stage which integrates the Current Engineering (CE), Robust Design, Design for X (DFX), Reliability Engineering (RE) etc. to achieve defect-free products and processes design and six sigma quality level.

However, as existing processes-oriented six sigma overlooked the inherent quality of product, five sigma quality levels is difficult to surpass except that products processes and services redesign by means of DFSS. Thus, researchers are devoting themselves to find appropriate procedures and tools for DFSS. For example, Yousef Amer et al presented Design for Six Sigma, which focuses on customer requirements from the onset, as an effective methodology for monitoring and controlling variables, optimizing processes and meeting customer's requirements [3]; LI Bei-zhi suggested an adaptive design for six sigma (ADFSS) incorporating the traits of artificial intelligence and statistical techniques with four major phases [4]; Sebastian Koziołek presented a methodology for assessing the process of designing and constructing vehicles and machines, which implements Design for Six Sigma tools [5].

DFSS is a rigorous approach rather than a fixed methodology. Despite various patterns researchers and enterprises proposed, there is no a unified model with specific tools for DFSS. Also, taking the systematic complexity into consideration, multivariate should be integral parts of a DFSS system. Thus, in this article, at the premise of a well-structured plan under current engineering, an innovative DFSS for multivariate production process with four main phases, namely, identify, design, optimize and verify (IDOV), is analyzed thoroughly.

AN OVERVIEW OF DFSS INTEGRATION FRAMEWORK

Starting with customer requirements and ending with it as well, design for Six Sigma (DFSS) can be accomplished using any kind of methodologies during the processing procedure. An innovative DFSS for multivariate production process is a methodology with specific process steps to be followed rather than a single method.

An innovative DFSS for multivariate production process integration framework combined common design tools and methods is illustrated on the behalf of most typical enterprises. As shown in the Fig. 1

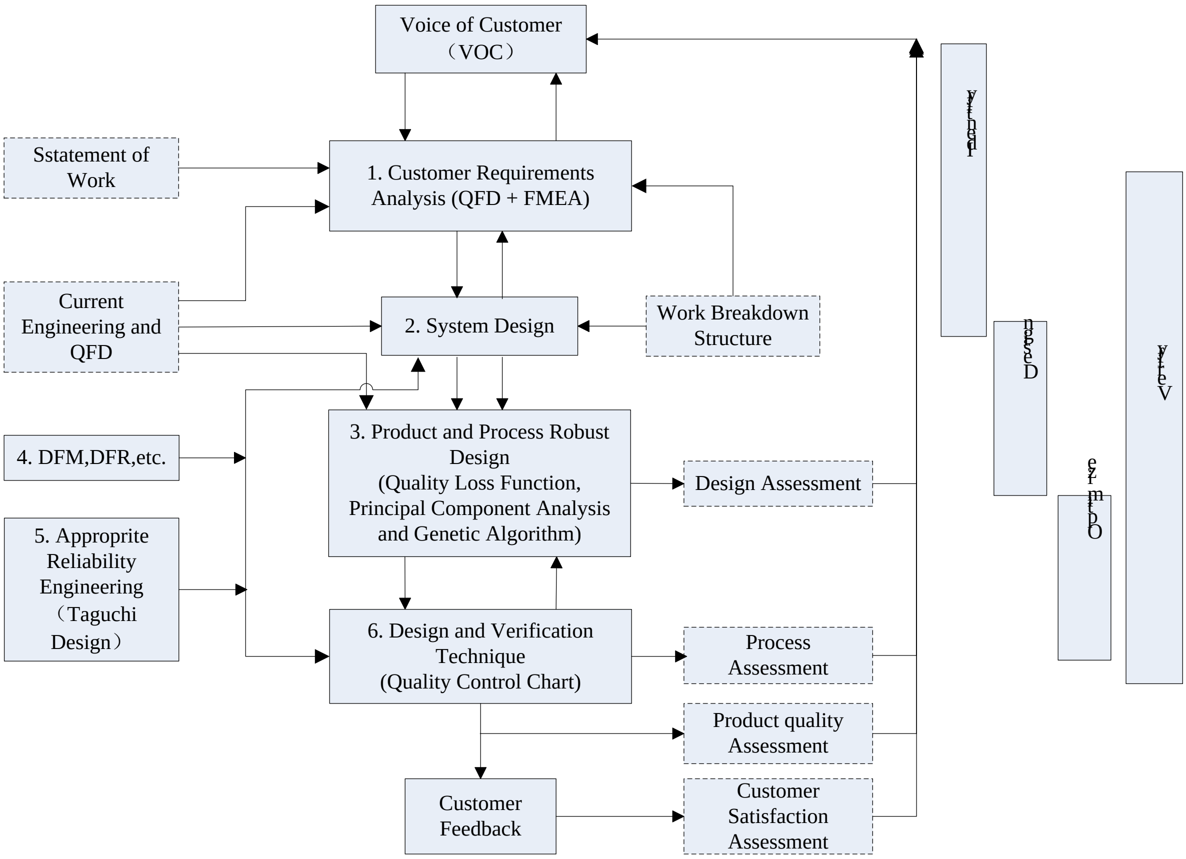

Fig.1: Block diagram of design for Six Sigma

In this toolkits and block diagram showed in figure 1, DFSS starts with collecting voice of customer (VOC) which is broken down to design requirements by using quality function deployment (QFD) integrating with failure mode and effects analysis (FMEA) in the subsequent step. After that, system design is taken to set technique targets by QFD based on customer requirements, competitors and their competitiveness in order to provide potential market opportunities for the company. Then start the product and process robust design for critical quality characteristics, obtain the best parameter matching and design output with the help of quality loss function, principal component analysis (PCA) and genetic algorithm (GA). Finally, multivariate or univariate quality control chart is established to assess whether the multivariate production process is under the control, following by assess of customer satisfaction.

THE PHASES FOR THE INNOVATIVE DFSS T

DFSS procedures are broadly divided into four mutually overlapping phases, identify, design, optimize and verify with particular tools and methods in each.

The identify phase based on IDOV model focuses on looking for market opportunities, identifying customer requirements (CRs) and engineering requirements(ERs) to define critical to quality (CTQ) and or critical to process (CTP).

QFD, as a customer-driven approach, is employed to maximize customer satisfaction and translate them into the fulfillment levels of ECs. Yahia Zare Mehrjerdi discussed the key elements of QFD and built it on the principles taking CRs into consideration and relating CRs to DRs[6]. But because the classical QFD is lack of capabilities of handling the design risk, FMEA dealing with identifying and eliminating known or potential failures to enhance reliability and safety is integrated. HE Zhen et al realized QFD and FMEA is familiar in principal and is mutual benefit; QFD results are helpful for the cross-functional design team to identify the following during FMEA while FMEA results can be useful for re-evaluating the house of quality (HOQ) [7]; Liang-Hsuan Chen incorporates failure modes and effect analysis (FMEA) into QFD processes, which is treated as the constraint in the fuzzy linear programming models [8]. According to this study, the vague nature of product development processes which can be solved by fuzzy theory surfaces as the next barrier bothering scholars.

In conclusion, an incorporation model of QFD and FMEA based on fuzzy theory is established in identify stage. The specific steps can be described as follows:
① Modeling the variables related to the rules in fuzzy sets;
② Fuzzy reasoning to evaluate original importance of DRs;
③ Obtaining the scrip value by α-cut method for defuzzification and normalizing them;
④ Fuzzy reasoning to evaluate Risk Priority Number (RPN) of FMEA;
⑤ Expressing contribution of each DRs by RPN and normalizing the result;
⑥ Normalizing cost;
⑦ Multiplying normalized original importance of DRs, contribution of each DRs and cost to acquire the final importance of DRs.

The process explained above is enabling the integration of QFD and FMEA results to satisfy customer requirements and reduce risks in product design. Besides, the contribution of each DRs facilitates accuracy of RPN in FMEA. Also, with the financial budget analysis, cost is able to be well controlled.

Product design is a start point for product type, market positioning and potential opportunities and production resources. Based on IDOV model, the design phase devotes itself to evaluate techniques regarding to competitors and their competitiveness on the basis of market and customers for the sake of providing a specific, measurable, attainable, realistic and timely market opportunity.

Conventional DFSS tool in design step significantly rely on general concept design, manufacturing parameters design and support resources design to conduct initial design work. ZOU Feng, HE Zhen et al, after translating CRs to DRs by Axiomatic Design (AD), system design, QFD, FMEA, DFX, parameter design, tolerance design and CAD/CAM are suggested for design stage in design of digital platform oriented to six sigma for design [9]. On the contrary, a growing number of people pay their attention to target setting using QFD prior to the product design in case of being taken off the market. X.F. Liu et al presented an innovative quantitative method of setting technical targets in software quality function deployment (SQFD) to analyze impact of unachieved target values on customer satisfaction based on CRs, DRs and its linear or nonlinear relationship, including both linear and nonlinear regression techniques are utilized in this method [10]. Also a new method for technical target setting in QFD, based on an artificial neural network, is also presented by him [11]. In spite of successfully taking into nonlinear relationships between CRs and DRs, this kind of intelligent algorithm companied with a shortcoming of long learning time and historical data access.

Taking into what mentioned above, a target setting of design requirements based on their impact and trade-off analysis by QFD is demonstrated as follows:
① Market competitive evaluation;
② Customer satisfaction evaluation;
③ Setting the quality goal of customer satisfaction for each CR by market research
④ Calculating the percentage of impact of DRs on each CR;
⑤ The proportion of the quality goal for each DR is the product of customer satisfaction quality goal for each CR and the percent of impact;
⑥ The relationship between the proportion of the quality goal for each DR and the target for each DR is established in a linear or nonlinear regression model;
⑦ Using the functional relationship and the quality goal for each DR to have an access to the DRs' targets.

Target setting in design phase is an instructive method to assist enterprise to adapt itself to market and customer requirement changes rapidly and correctly.

The Optimize phase aims at strive the balance between quality, cost and lead time with statistical approaches and models to conduct the optimum quality level. In the view of IDOV, Robust Design comprised of Design of Experiments (DOE), parameter design, tolerance design and DFX etc. is enable stabilization of product quality characteristics around the target value, via, small variation, and is decreasing the quality loss simultaneously [12].

In most production processes, however, interactional multivariate quality traits lead to the disability of optimization of one single quality characteristic at a time. Hence, Jing-Shiang Shih et al employed principal component analysis coupled with Taguchi methods in the study for multiple quality characteristics optimization [13]. It turns out that

PCA is an effective way to transfer multivariate quality characteristics to a single quality characteristic; meanwhile, with the help of Taguchi quality loss function, the quality loss is minimized. Regardless of the establishment of objective function, a novel approach based on artificial algorithm to simultaneously optimize multiple responses including both qualitative and quantitative quality characteristics is presented [14]. Lake of precise functional relationship, it does not show its merits in higher executing speed, higher reliability, faster convergence rate and high precision.

Therefore, robust parameter design-based Atiles-leon[15] multivariate quality loss function incorporating principal component analysis method used for data dimension reduction raises and is solved by genetic algorithm (GA) as follows:

① Determining the type of each quality characteristic: larger the best, smaller the better and nominal the better;

② Deciding the controllable factors, error factors and appropriate trials for robust parameter design;

③Calculating quality loss in each test according to Atiles-leon multivariate quality loss function;

④ Performing PCA analysis for the normalized data attained in step 3 and getting multivariate quality loss function in the terms of minimizing quality loss;

⑤ Implementing GA with multivariate quality loss function as objective function to gain the optimal quality target sets.

In short, developing detailed design elements, predicting performance, and optimizing design, take place within this phase.

Product optimization stage is designed to verify the product or service levels of customer requirements fulfillment in order to ensure CTQ's effectiveness. The verify stage based on IDOV consists of small sample statistic process control (SPC) and acceptance test procedures (ATP) to control the manufacturing quality when simulation tests, V&V test, reliability test etc. to examine the level of product quality. Finally, the outcomes reached the six sigma goal are documented for the subsequent production processes.

Recently, monitoring the process mean and variability simultaneously for multivariate processes by using a single control chart has drawn some attention. However, due to the complexity of multivariate distributions, existing methods in univariate processes cannot be readily extended to multivariate processes [16]. Various methods are proposed for a common purpose of quality consistency. For example, multivariate control chart, such as Hotelling T^2, MCUSUM and Multivariate Exponentially Weighted Moving Average (MEWMA) are popular in monitoring quality characteristics of the mass production process [17]. Among them, MEWMA control charts have the best performance both in independent and autocorrelation process, especially for the smaller values of smoothing constant; MCUSUM control charts outperform Hotelling T^2 control charts in detecting small shifts, but Hotelling T^2 control charts outperform MCUSUM control charts for monitoring big shifts.

This paper studies verify phase in a non-controlled for different products and processes, selects multivariate T^2 control chart when the process mean shift is large and chooses Z statistic MEWMA control chart when the process mean shift is small. Establishment of multi-variable control charts MEWMA application procedure is as follows:

①Calculating the mean vector of n samples;

② Calculating the mean vector of n samples' mean vector;

③ Calculating statistics of n samples;

④Calculating the mean of k samples' covariance matrix;

⑤ Calculating the T2-statistics for each sample;

⑥ Calculating the upper control limit to achieve specified average run length (ARL)

⑦ Plotting MEWMA multivariate control charts.

This chart is proposed as a solution to the detection of small shifts in a multivariate process and is utilized to monitor the process mean, keeping the six sigma system in a continuous improvement.

CONCLUSION

In this research an innovative DFSS for multivariate production process has been proposed. Aiming at identifying DRs by integrating fuzzy QFD and FMEA, plus target setting with respect to customer satisfaction rate and market competitiveness, the proposed methodology is capable of exploiting profits for products in maximum. Also, Taguchi Design minimizes quality loss and takes full account of the relationship between quality characteristics while data dimension reduction is performed by PCA The objective function is optimized by utilizing GA and the results obtained are statistically validated via conducting Z statistic MEWMA control chart.

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