International Journal of Applied Operational Research
Vol. 2, No. 1, pp. 41-53, Spring 2012

Journal homepage: www.ijorlu.ir

A Chance Constrained Multiple Objective Goal Programming Model of Fuzzy QFD and FMEA: Model Development

Y. Zare Mehrjerdi*

Received: September 21, 2011 ; **Accepted:** January 30, 2012

Abstract There are varieties of QFD combination forms available that can help management to choose the right model for his/her types of problem. The proposed MOCC-QFD-FMEA model is a right model to include variety of objectives as well as the risk factors into the model of the problem. Due to the fact that the model also takes into consideration the concept of Fuzzy set, it further allows management the flexibility in his/her modeling as well as decision making. The mathematical models presented in this article demonstrate the process of development of the equivalent deterministic form of chance constrained programming for the QFD and FMEA combined systems. The final model presented is a linear multi-objective goal programming problem that can be solved by a linear goal programming program.

Keywords QFD, FMEA, Multiple Objective Programming, Chance Constrained, Goal Programming Model, Fuzzy Set Theory.

1 Introduction

Rule of business is that any increase in customer expectation, growth in technology and real participation in international markets leads to the real competition requiring the management a true attention. Under such circumstances, the management tries to improve the quality of the products, reduce costs, enhance the service level, and eliminate any kind of deficiency/faults associated with the product. To make sure that the wanting results would be obtained as needed, companies use Failure Modes and Effects Analysis (FMEA) as a tool to make that possible. With the help of this tool it is possible to identify potential failure modes in the system, processes, products, and services.

Failure modes and effects analysis was first employed in studies conducted by NASA in 1963. It was eventually spread to other industries as well as car manufacturing where it served to identify and quantify possible potential defects at the design stage of a product [1]. Now, FMEA is a tool accepted by many large and small companies in variety of industries all around the world for identifying, prioritizing, and eliminating known potential failures, problems, and errors from systems under design before the product is released [2]. FMEA is often carried late in the design cycle after the design prototype has been built [3].

In the decade of 1970's, quality function deployment (QFD) started in Japan, and it was not until 1980's that the Western world began to appreciate that as a technique and using it as

* **Corresponding Author.** (✉)
E-mail: Yazm2000@yahoo.com (Y. Zare Mehrjerdi)

Y. Zare Mehrjerdi
Department of Industrial Engineering, Yazd University, Yazd, Iran.

a tool for decision making purposes. QFD has been successfully applied in many Japanese organizations to improve processes and to build competitive advantages. Today, companies are successfully using QFD as a powerful tool to address strategic and operational decisions in businesses. "QFD provides a means of translating customer requirements into appropriate technical requirements for each stage of product development and production (i.e., marketing strategy, planning, product design and engineering, prototype evaluation, production process development, production, sales)''[4]. In 1986, Kelsey Hayes used QFD for developing a coolant sensor, which fulfilled critical customer needs such as ''easy-to-add coolant'', ''easy-to-identify unit'', and ''provide cap removal instructions [5, 6].

Researchers [4, 7-10] have discussed on the benefits of QFD. However, these benefits as are pointed by researchers in the literature can be summarized as follows: (1) can help in making trade-offs between what the customer demands and what the company can afford to produce, (2) can enhance team work among the engineers in the department, (3) can increase customer satisfaction (this is done by taking customers' requirements into consideration and bring them into the product development process), (4) can shorten the time to market, (5) can cause employees to make sufficient documentation because of seeing the importance of information, and (6) can improve effective communication between company divisions.

The main purpose of this article is the development of multiple objective chance-constrained programming that can be used as a decision making tool in the fuzzy QFD and FMEA environment. The plan of this paper is as follows: section 2 gives an overview of the QFD methodology while House of Reliability (HOR) is the topic of section 3. Chance constrained programming is discussed in section 4, and QFD and FMEA combination is discussed in section 5. The chance constrained programming model of the problem is the topic of section 6. The multi-objective goal programming model of the problem is developed in section 7. The solution methodology is briefly discussed in section 8. Author's conclusion is the topic of section 9.

2 House of quality

The fact that the figure presented in 1 looks similar to a house it thus often referred to as the house of quality (HOQ). In QFD, customer requirements are usually shown by CR and the engineering design requirements are shown by DR. As it is shown in the fig, the i^{th} elements of CR and the j^{th} element of DR are shown by CR_i and DR_j, respectively. The matrix under consideration has two dimensions, i.e., customer wants and engineering design requirements. A triangular-shaped matrix placed over the engineering design requirements corresponds to the correlations between them. Using Fig. 1 we can say that $CR_1 \ldots CR_m$ are the m identified customer requirements while $DR_1 \ldots DR_n$ are the n identified engineering design requirements known as "WHATs", and "HOWS", respectively. The degrees of the importance of customer wants are shown by the vector of W1…Wm where m is the numbers of customer requirements. The relationship matrix between WHATs and HOWs are shown by R = (R_{ij}) and r = (r_{ij}) is the interrelationship matrix between HOWs such that $r_{ik} = r_{kj}$ for j, k =1,…,n.

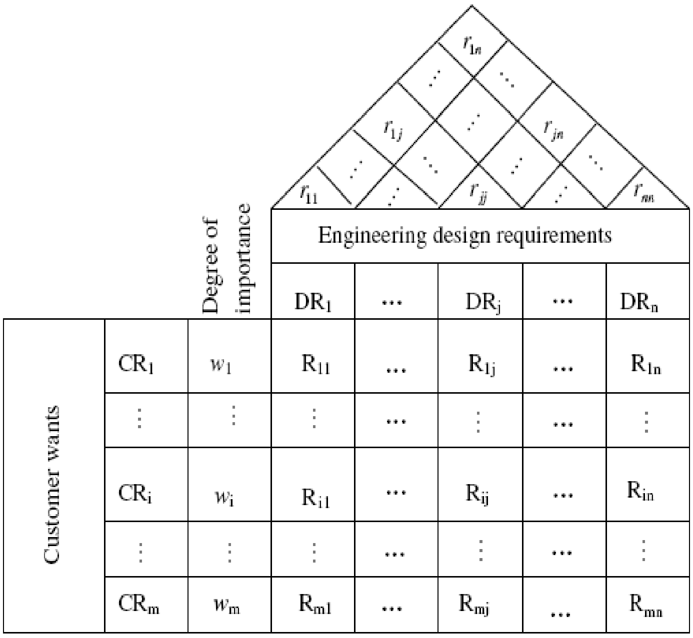

Fig. 1 The house of quality structure [36]

The typical approach to QFD is the four-phase process that is admired and widespread by the American Supplier Institute (ASI) in the United State of America [11]. The process is summarized in four phases below [12]:

Phase I. Qualitative customer requirements are translated into design independent, measurable, and quality characteristics of the product.

Phase II. This phase examines the relationship between the quality characteristics and the various components or parts of the design. The result of phase II is a prioritization of the component parts of the design in terms of their ability to meet the desired quality characteristic performance level.

Phase III. Phase III is a prioritization of manufacturing processes and specifications for key process parameters that are deployed to the fourth and final phase.

Phase IV. The key manufacturing processes and associated parameters are translated into work instructions, control and reaction plans, and training requirements necessary to ensure that the quality of key parts and processes is maintained.

Quality function deployment is a structured approach to seek out customers, understand their needs, and ensure that their needs are met. QFD is probably the most important management tool developed to assure quality in new or improved products and services [13]. Griffin and Hauser [14] believe that there are more than 100 major companies using QFD in the US. To find companies willing to use QFD technique in their decision making process refer to the annual United States quality function deployment symposium transactions.

Cindy Adiano, and Aleda V. Roth [15] have proposed a dynamic approach to QFD for translating customer wants and needs into relevant product and process parameters. Using feedback loops, this new approach incorporates updated customer satisfaction data and dynamically links evolving requirements directly back into manufacturing and related processes. After authors have introduced the concept and illustrated the mechanics of the approach, they described how it could benefit an IBM assembly plant. Boeing Airlift and

Tanker Programs (A&T) uses the criteria for performance excellence as its road-map to business excellence. A researcher has employed a house of quality to facilitate a detailed, quantitative analysis of how well the various strategic thrusts and initiatives at A&T address the individual items within the criteria. This unique application of QFD will demonstrate applicability to the design and development of a large organization [15].

To show that QFD is a tool that brings profit to the organization, [16] has designed various loops using system thinking perspectives. This article helps management to get a better understanding of the quality function deployment, its power of profit making and productivity enhancement, and the role that systems thinking can have in better describing the problem to the middle and top management.

Marvin et al. [17] proposed a modified approach to QFD, called “QFD strategy house”, as a systematic means of incorporating intelligence on markets, consumers and technologies in strategy development. It links marketing and manufacturing strategies by first developing a continuous improvement strategy. Both the marketing and manufacturing literatures have reported that an alignment between the two constituent strategies confers a competitive advantage in the marketplace.

The structure of the QFD models was strengthened by integrating different traditional techniques and approaches such as Total Quality Management (TQM), theory of solving inventive problems (TRIZ), Failure Mode and Effects Analysis (FMEA), Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and artificial intelligence.

Karsak and Ozogul [18] have developed a decision framework for ERP software selection based upon the quality function deployment (QFD), fuzzy linear regression, and zero–one goal programming tools. This framework allows the company to consider demand characteristics as well as the ERP system characteristics while providing the means for incorporating not only the relationships between company demands and ERP system characteristics, but also the interactions between ERP system characteristics through adopting the QFD principles. The potential use of the proposed decision framework is illustrated through an application.

3 House of reliability (HoR)

Braglia [19] purposed a structured methodology for performing build-in reliability (BIR) investigation during a new product development cycle. The methodology used in his article is an extension of the Quality Functional Deployment/House of Quality QFD/HoQ) concepts to reliability studies. This methodology is capable of translating the reliability requirements of customers into functional requirements for the product in a structured manner based on a Failure Mode and Effect Analysis (FMEA). Thereafter, it allows the building of a completely new operative tool named the House of Reliability (HoR) that enhances the standard analyses and introduces the most significant correlations among failure modes. Using the results from HoR, a cost-worth analysis can be easily performed, making it possible to analyze and to evaluate the economical consequences of a failure [19].

Failure modes and effects analysis (FMEA) is an important technique that is used to identify and eliminate known or potential failures to enhance reliability and safety of complex systems and is intended to provide information for making risk management decisions [2]. FMEA is a technique that identifies the potential failure modes of a product or a process, the effects of the failures, and assesses the criticality of these effects on the product functionality. The FMEA methodology is based on the study of the possible failure modes of plant components. Therefore, the first step of the work is to identify the complete list of the components to be analyzed, trying to trace a deeper breakdown of the systems, sub-systems, main components and sub-components as the possible failures need to be detailed because of differentiation of the failures and/or of the effects of the failures [20, 21, 22]. FMEA can be classified into (1) Design FMEA, and (2) Process FMEA.

FMEA, an early preventive action technique, used in system, design, process, or service, helps to prevent failures and errors from occurring in the product and, hence reaching the customer. The traditional FMEA calculation method determines the risk priorities of failure modes through the risk priority number (RPN = O * S * D), which is the product of the occurrence (O), severity (S) and detection (D) of a failure. Calculation of RPN using the crisp RPN has generated many critiques of various types by many different researchers all around the world.

There always is some possibility that a system, design, process, or service has multiple failure modes or causes and effects. In this situation, each failure mode or cause needs to be assessed and prioritized in terms of its risks, so high risky (or the most dangerous) failure modes can be corrected with top priority. Fuzzy linguistic terms such as very low, low, moderate, high and very high to evaluate O, S and D, and grey relational analysis to determine the risk priorities of potential causes are employed by Chang, Wei, and Lee [23]. Pillay and Wang [24] proposed a fuzzy rule base approach to avoid the use of traditional RPN. Braglia et al. [25] proposed a risk function allowing fuzzy if–then rules to be generated in an automatic way.

4 Chance constrained programming

Computer Aided Decision Making (CADM) has become a vital means and an important function in making valuable decisions in highly complex environments. The adaptation of microcomputers in medium- and large-sized organizations has reduced the expenses by simplifying the decision making process and enhancing the productivity. The presence of many objectives and undermined risk levels have encouraged the team of Decision Makers (DM) to combine their managerial intuition with the knowledge of CADM for consultation and practicing purposes. A valuable means for measuring the trade-offs among the objectives is known as Multiple Objective Goal Programming (MOGP). As a tool, MOGP is implemented in the development of CADM and Decision Support Systems. In this study, we use the MOGP technique to present an alternative procedure for solving a special class of NP problems discussed in the section that follows.

The event of a constraint violation must be regarded as a risk taking issue. The degree of constraint violation, shown by $(1-\alpha)$, is called the risk level with α referring to the constraint reliability. The input factors play a significant role in deteriorating systems' reliability by violating one or more constraints. For instance, the required work force level for the manufacturing of a product depends upon the sufficiency of raw materials, demand fluctuations, market saturation and inflation rates. One well defined methodology for treating such problems with probabilistic constraints is known as Chance Constraint Programming (CCP). The concept of chance constrained was introduced into the literature of stochastic programming mainly through the exposition of Charnes and Cooper [26] and since then developed and applied by Kataoka [27], Sengupta [28], and Seppala [29, 30], to mention a few.

5 QFD and FMEA integration: A management tool

A few models already exist in the literature of quality management that consider both QFD and FMEA as a tool for modeling a problem. These models are: (1) Fuzzy linear programming models of Chen and Ko [31]; (2) A DS tool based on QFD and FMEA for the selection of manufacturing automated technologies [32], and (3) Korayem and Iravani's [33, 34] model of applying QFD and FMEA . None of these models take the steps that this article follows to make a decision. This is a new approach that combines the concept of QFD, FMEA, CCP, GP and Fuzzy set theory to make a right and suitable decision.

5.1 Chen and Ko's model

Due to article researchers [31], the notations used in this model are as described below:
$\alpha = \alpha - cuts$
CR = customer requirement
DR = design requirement
PC = Part characteristics
R_{1ij} = the relation level in terms of score between the i^{th} CD and the j^{th} DR
$R_{1,jn}$= the correlation between the j^{th} and n^{th} DR in the first phase of QFD
r_{kj} = a factor as shown in Fig. 1.
W_{1j} = Fuzzy technical importance rating $\tilde{W_{1,j}}$ for the j^{th} DR
W_{2j} = weight
$K_{1,j}$ and $K_{2,j}$ = importance scores which is the importance rating Wij of the DRs in phase 1
$X_{1,j}$ = belongs to [0,1]. Zero means that DR has a basic design requirement, so no more efforts and resources are needed.
$X_{2,k}$ = it is the level of the fulfillment of the kth PC in the proposed model.
k= importance score such that $\sum k = 1$
W = rating
Subscript 1 = used in R, r, k, and W denotes the first phase of QFD
Subscript 2 = used in R, r, k, and W denotes the second phase of QFD
$R'_{1,ij}$ = normalized relationship value between CR_i and DR_j for all i=1,…,I and j=1,…,J such that $\sum_j R'_{1,ij} = 1$ for each i.
$\tilde{R_{1,i\tau}}$ = is described by linguistic terms and defined as the fuzzy subsets of [0, 1]
$\tilde{r_{1,\tau i}}$ =is described by linguistic terms and defined as the fuzzy subsets of [0, 1]
$(\tilde{R_{1,i\tau}})_\alpha^L$ = Lower α cut
$(\tilde{R_{1,i\tau}})_\alpha^U$ = Upper α cut
$\mu_{\tilde{R_{1,ir}}}$ (x) = membership degree of x belonging to $\tilde{R_{1,i\tau}}$

$m(R_{1,ij}^{\sim})_{\alpha}^{L}$ = Lower bound of the membership function at α cut

$m(R_{1,ij}^{\sim})_{\alpha}^{U}$ = Upper bound of the membership function at α cut

$(W_{1,j})_{\alpha}^{L}$ = Lower α cut

$(W_{1,j})_{\alpha}^{U}$ = Upper α cut

$(W_{1,j}^{\sim})_{\alpha} = [(W_{1,j})_{\alpha}^{L}, (W_{1,j})_{\alpha}^{U}]$

$(R_{1,j}^{\sim})_{\alpha} = [(R_{1,j\tau})_{\alpha}^{L}, (W_{1,j\tau})_{\alpha}^{U}]$

$(R_{1,j\tau})_{\alpha}^{L} = \inf_{x \in [0,1]} \{x \mid \mu_{R_{1,j\tau}^{\sim}}(x) \geq \alpha\}$

$(R_{1,j\tau})_{\alpha}^{U} = \sup_{x \in [0,1]} \{x \mid \mu_{R_{1,j\tau}^{\sim}}(x) \geq \alpha\}$

$x_{1,j}$ = Denotes the level of fulfillment percentage of DR_j for j=1,…, J

$x_{1,j} \in [0,1]$ where $x_{1,j} = 0$ implies that the DR has a basic design requirements, so no more efforts and resources are needed.

B1 = budget limitation

ε_j = Possible range of the fulfillment level of one DR (minimum required level due to the business competition)

$\eta_{1,j}$ = Possible range of the fulfillment level of one DR (maximum level due to technical difficulty)

$k_{2,j}$ = Normalized importance score of each DR

$m(R_{2,jk}^{'})_{\alpha}^{L}$ = Lower bound of the membership function at α cut

$m(R_{2,jk}^{'})_{\alpha}^{U}$ = Upper bound of the membership function at α cut

S = the severity of the potential failure

O=the frequency of potential failure

D=the detect ability index

RPN=risk priority number

$S_r^{\sim}$ = is a fuzzy subset of [0, 1]

$O_s^{\sim}$ = is a fuzzy subset of [0, 1]

$D_t^{\sim}$ = is a fuzzy subset of [0, 1]

$RPN_j^{\sim}$ = Fuzzified RPN of each DR

w_1, w_2, w_3 = Weight such that their sum value is equal to one that can be determined according to the QFD team member experience.

$C_{2k}^{\sim}$ = Increment unit cost to achieve the fulfillment level of the PCs

$\eta_{2k}^{\sim}$ = The technological difficulty of the PCs

$(Z_2)_{\alpha}^{L}$ = Lower bound of the objective value at α cut

$(Z_2)_{\alpha}^{U}$ = Upper bound of the objective value at α cut

$x_{2k}^{(L)}$ = Optimal fulfillment level for the lower bound model

$x_{2k}^{(U)}$ = Optimal fulfillment level for the upper bound model

$(W_{2,K})_\alpha^L$ = Lower bound of the PC's importance phase 2 of QFD at α cut

$(W_{2,K})_\alpha^U$ = Upper bound of the PCs importance phase 2 of QFD at α cut

$(R_{i,K})_\alpha^L$ = Lower bound of the PC's importance phase 2 of QFD at α cut

$(R_{i,K})_\alpha^U$ = Upper bound of the PCs importance phase 2 of QFD at α cut

$(C_{2,K})_\alpha^L$ = Lower bound of the increment unit cost at α cut

$(C_{2,K})_\alpha^U$ = Upper bound of the increment unit cost at α cut

Chen and Ko [31] proposed fuzzy linear programming models for new products' design using quality function deployment and failure mode and effect analysis. In this modeling, researchers took the fuzzy version of the QFD into consideration which is based upon the normalized relationship value between CRs and DRs as proposed by Wasserman, G.S., [35].

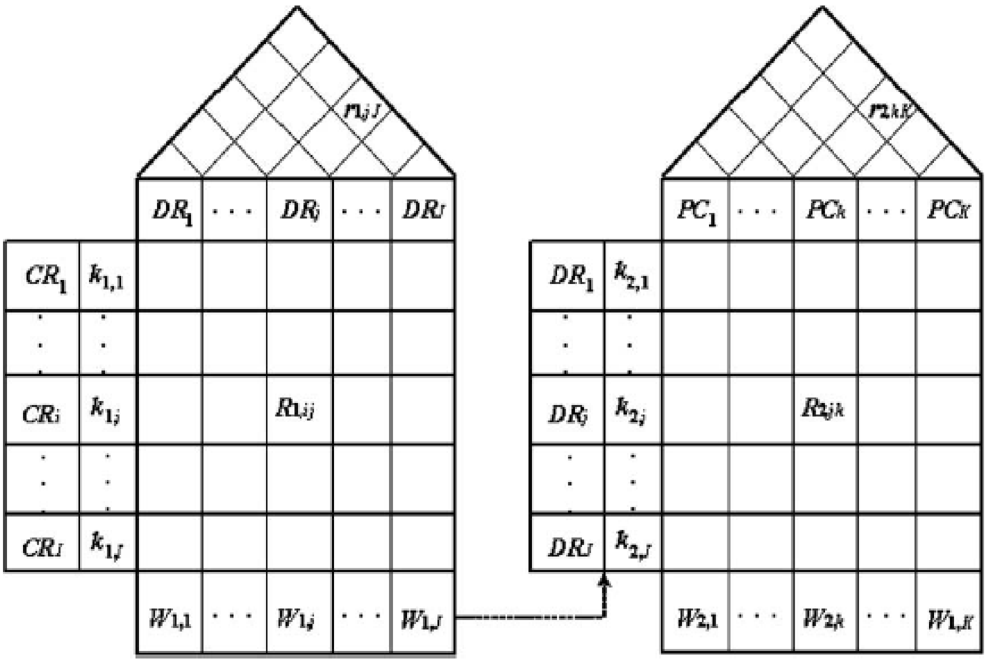

Fig. 2 Relating the first and second phases of QFD together

$$(Z_1)_\alpha^L = \text{Max} \sum_{j=1}^{J} (W_{1,j})_\alpha^L . x_{1,j}$$

s.t.

$$\sum_{j=1}^{J} (C_{1,j})_\alpha^U . x_{1,j} \le B_1,$$

$$(W_{1,s})_\alpha^L . x_{1,s} - (W_{1,p})_\alpha^U . x_{1,p} \ge 0,$$

$$0 \le \varepsilon_j \le x_{1,j} \le \eta_{1,j} \le 1,$$

$$\forall j, s, p \in \{1,2,3,\ldots,J\}.$$

and

$$
\begin{aligned}
(Z_1)_\alpha^U = \text{Max} \ & \sum_{j=1}^{J} (W_{1,j})_\alpha^U . x_{1,j} \\
\text{s.t.} \ & \\
& \sum_{j=1}^{J} (C_{1,j})_\alpha^L . x_{1,j} \le B_1, \\
& (W_{1,s})_\alpha^U . x_{1,s} - (W_{1,p})_\alpha^L . x_{1,p} \ge 0, \\
& 0 \le \varepsilon_j \le x_{1,j} \le \eta_{1,j} \le 1, \\
& \forall j,\ s, p \in \{1,2,3,...,J\}.
\end{aligned}
$$

To consider FMEA in the above model, the following LP model is proposed by Chen, L-H, Wen-Chang Ko, [31] taking that into account.

$$
\begin{aligned}
(Z_2)_\alpha^L = \text{Max} \ & \sum_{k=1}^{K} (W_{2,k})_\alpha^L . x_{2,k} \\
\text{s.t.} \ & \\
& k_{2,j} [\sum_{k=1}^{K} m(R'_{2,jk})_\alpha^L . x_{2,k}] \ge W_{1,j} . x_{1,j} \ \text{ for all j=1,…,J,} \\
& \sum_{k=1}^{K} (R_{i,k})_\alpha^U . x_{2,k} \le H, \\
& \sum_{k=1}^{K} (C_{2,k})_\alpha^U . x_{2,k} \le B_2, \\
& (W_{2,s})_\alpha^L . x_{2,s} - (W_{2,p})_\alpha^U . x_{2,p} \ge 0, \\
& 0 \le x_{2,k} \le \eta_{2,k} \le 1, \\
& \forall k,\ s, p \in \{1,2,3,...,K\}.
\end{aligned}
$$

and

$$
\begin{aligned}
(Z_2)_\alpha^U = \text{Max} \ & \sum_{k=1}^{K} (W_{2,k})_\alpha^U . x_{2,k} \\
\text{s.t.} \ & \\
& k_{2,j} [\sum_{k=1}^{K} m(R'_{2,jk})_\alpha^U . x_{2,k}] \ge W_{1,j} . x_{1,j} \ \text{ for all j=1,…, J,} \\
& \sum_{k=1}^{K} (R_{i,k})_\alpha^L . x_{2,k} \le H, \\
& \sum_{k=1}^{K} (C_{2,k})_\alpha^L . x_{2,k} \le B_2, \\
& (W_{2,s})_\alpha^U . x_{2,s} - (W_{2,p})_\alpha^L . x_{2,p} \ge 0, \\
& 0 \le x_{2,k} \le \eta_{2,k} \le 1, \\
& \forall k,\ s, p \in \{1,2,3,...,K\}.
\end{aligned}
$$

6 The CC programming model of the problem

Due to the fact that the risk level of H and the budget limitation of B2 can not be determined with certainty, the current author proposes the use of CC programming for modeling the problem as it is presented below:

$$
\begin{aligned}
(Z_2)_\alpha^L = \text{Max} \ & \sum_{k=1}^{K} (W_{2,k})_\alpha^L . x_{2,k} \\
\text{s.t.} \ & \\
& k_{2,j}[\sum_{k=1}^{K} m(R'_{2,jk})_\alpha^L . x_{2,k}] \geq W_{1,j} . x_{1,j} \quad \text{for all j=1,…,J,} \\
& P\{\sum_{k=1}^{K} (R_{i,k})_\alpha^U . x_{2,k} \leq H\} \geq (1-\beta), \\
& P\{\sum_{k=1}^{K} (C_{2,k})_\alpha^U . x_{2,k} \leq B_2\} \geq (1-\psi), \\
& (W_{2,s})_\alpha^L . x_{2,s} - (W_{2,p})_\alpha^U . x_{2,p} \geq 0, \\
& 0 \leq x_{2,k} \leq \eta_{2,k} \leq 1, \\
& \forall k,\ s, p \in \{1,2,3,...,K\}.
\end{aligned}
$$

and

$$
\begin{aligned}
(Z_2)_\alpha^U = \text{Max} \ & \sum_{k=1}^{K} (W_{2,k})_\alpha^U . x_{2,k} \\
\text{s.t.} \ & \\
& k_{2,j}[\sum_{k=1}^{K} m(R'_{2,jk})_\alpha^U . x_{2,k}] \geq W_{1,j} . x_{1,j} \quad \text{for all j=1,…,J,} \\
& P\{\sum_{k=1}^{K} (R_{i,k})_\alpha^L . x_{2,k} \leq H\} \geq (1-\beta), \\
& P\{\sum_{k=1}^{K} (C_{2,k})_\alpha^L . x_{2,k} \leq B_2\} \geq (1-\psi), \\
& (W_{2,s})_\alpha^U . x_{2,s} - (W_{2,p})_\alpha^L . x_{2,p} \geq 0, \\
& 0 \leq x_{2,k} \leq \eta_{2,k} \leq 1, \\
& \forall k,\ s, p \in \{1,2,3,...,K\}.
\end{aligned}
$$

7 A Multi objective goal programming model

$$
\begin{aligned}
&\text{Min P1 } \{d_1^-\}\\
&\text{Min P2 } \{d_2^+\}\\
&\text{Min P3 } \{d_3^+\}\\
&\text{s.t.}\\
&\qquad \sum_{k=1}^{K}(W_{2,k})_\alpha^L.x_{2,k} + d_1^- - d_1^+ = G^-{}_L + F^{-1}(1-\kappa)\sigma_G^{1/2},\\
&\qquad k_{2,j}[\sum_{k=1}^{K} m(R'_{2,jk})_\alpha^L.x_{2,k}] \geq W_{1,j}.x_{1,j} \quad \text{for all j=1,…,J,}\\
&\qquad \sum_{k=1}^{K}(R_{i,k})_\alpha^U.x_{2,k} + d_2^- - d_2^+ = \bar{H} + F^{-1}(1-\beta)\sigma_H^2,\\
&\qquad \sum_{k=1}^{K}(C_{2,k})_\alpha^U.x_{2,k} + d_3^- - d_3^+ = B_2^- + F^{-1}(1-\psi)\sigma_{B_2}^{1/2},\\
&\qquad (W_{2,s})_\alpha^L.x_{2,s} - (W_{2,p})_\alpha^U.x_{2,p} \geq 0,\\
&\qquad 0 \leq x_{2,k} \leq \eta_{2,k} \leq 1\\
&\qquad \forall k, s, p \in \{1,2,3,...,K\}.
\end{aligned}
$$

and the second problem is as formulated below:

$$
\begin{aligned}
&\text{Min P1 } \{d_1^-\}\\
&\text{Min P2 } \{d_2^+\}\\
&\text{Min P3 } \{d_3^+\}\\
&\text{s.t.}\\
&\qquad \sum_{k=1}^{K}(W_{2,k})_\alpha^U.x_{2,k} + d_1^- - d_1^+ = G^{-1}{}_U + F^{-1}(1-\kappa)\sigma_G^{1/2},\\
&\qquad k_{2,j}[\sum_{k=1}^{K} m(R'_{2,jk})_\alpha^U.x_{2,k}] \geq W_{1,j}.x_{1,j} \quad \text{for all j=1,…,J,}\\
&\qquad \sum_{k=1}^{K}(R_{i,k})_\alpha^L.x_{2,k} + d_2^- - d_2^+ = \bar{H} + F^{-1}(1-\beta)\sigma_H^{1/2},\\
&\qquad \sum_{k=1}^{K}(C_{2,k})_\alpha^L.x_{2,k} + d_3^- - d_3^+ = B_2^- + F^{-1}(1-\psi)\sigma_{B_2}^{1/2},\\
&\qquad (W_{2,s})_\alpha^U.x_{2,s} - (W_{2,p})_\alpha^L.x_{2,p} \geq 0,\\
&\qquad 0 \leq x_{2,k} \leq \eta_{2,k} \leq 1\\
&\qquad \forall k, s, p \in \{1,2,3,...,K\}.
\end{aligned}
$$

8 Solution methodology

The mathematical models presented in this article are the equivalent deterministic form of chance constrained programming for the QFD and FMEA combined systems. The final model presented is a linear multi-objective goal programming problem that can be solved by a linear goal programming program.

9 Conclusion

The primary functions of QFD are product development, quality management, and customer needs analysis. Today, QFD functions are expanded to various fields such as design, planning, decision-making, engineering, management, teamwork, timing, and costing. Obviously, there is no definite boundary for QFD potential fields of applications. Many companies have used quality function deployment to gain competitive advantages in business. The key managerial implications emerged from this research are.

1. There are varieties of QFD combination forms available that can help management to choose the right model for his/her types of problem.
2. Available cases from literature indicate that the results obtained by the decision maker and presented to top management are often acceptable and hence applicable.

However, the proposed MOCC-QFD-FMEA model is a right model to include the existence of variety of objectives as well as the risk factors into the model of the problem. Due to the fact that the model also takes into consideration the concept of Fuzzy set, it further allows management the flexibility in his/her modeling as well decision making.

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