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A hybrid fuzzy quality function deployment framework using cognitive network process and aggregative grading clustering: An application to cloud software product development

Kevin Kam Fung Yuen *

Department of Computer Science and Software Engineering, Xi'an Jiaotong-Liverpool University, Suzhou, China

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ABSTRACT

Quality function deployment (QFD) is an essential decision tool for product development in various domains. QFD enables the cross-functional team to translate the customer requirements into engineering characteristics during product development. Whilst there are some limitations for criteria evaluation and analysis in QFD, this study proposes a hybrid framework of Fuzzy Cognitive Network Process, Aggregative Grading Clustering, and Quality Function Deployment (F-CNP – AGC – QFD) for the criteria evaluation and analysis in QFD. The fuzzy number applied to the QFD, i.e. FQFD, enables rating flexibility for the expert judgment to handle uncertainty. The Fuzzy Cognitive Network Process (FCNP) is used for the criteria weights/priorities evaluation. The Fuzzy Aggregative Grading Clustering (FAGC) classifies the weights/priorities as ordinal grades. The proposed hybrid QFD approach applied to the cloud software product development is demonstrated to show the validity and applicability.

1. Introduction

When designing a new product or improving a current product, the product development team should work closely with the customers. Quality Function Deployment (QFD) is the popular tool to incorporate the customer requirements to the final products in the product development life cycle. The concept of QFD was firstly introduced in Japan in late 1960s, rapidly spread to the US in the 1980s [1–3], and the vast applications and literatures of the QFD are evolving in various domains.

Since customer requirements elicitation is the essential initial process in software development life cycle, QFD could be the useful tool for the software requirement engineering. A number of related studies using QFD for the software development are identified. Erikkson and McFadden [4] combined QFD and ISO standard for software quality measurement. [5] described some ideas about software quality function deployment (SQFD). Haag et al. [6] utilized QFD for object-oriented software design. Karlsson [7] described QFD as a framework for managing software requirements from the experiences of telecommunications project at Ericsson radio systems. Herzwurm et al. [8] applied QFD for the rapid user-focused software development. Erder and Pureur [9] leveraged QFD to design architectures that fully support requirements. Sun and Liu [10] combined QFD and CMMI for the Business-oriented software process improvement. Lianzang and Liu [11] combined QFD and Artificial Neural Network (ANN) for developing web service systems. Şen and Baraçlı [12] presented a fuzzy QFD for enterprise software selection. Sener and Karsak [13] applied the fuzzy regression to software quality function deployment for setting target levels. However, it seems that a lack of study presents applying QFD to cloud application development. This research demonstrates how the proposed hybrid QFD is applied to application development of Software as a Service (SaaS) for an online order system in a textile company.

To enhance QFD due to its functional limitations of assessment and analysis, various hybrid QFD approaches have been proposed. Fuzzy theory, Analytic Hierarchy/Network Process (AHP/ANP), or/and clustering are the useful methods enhancing QFD. Authors of [12–27] utilized fuzzy linguistic variables to QFD applications. The linguistic terms in fuzzy number enable rating flexibility for the expert judgment to handle uncertainty. Authors of [28–31] integrated AHP/ANP to QFD. Güngor et al. [32] and Kwong and Bai [33] integrated fuzzy AHP/ANP using Extent Analysis Method [34] into QFD. Chan et al. [35] used fuzzy data compression and clustering methods for market segmentation in new product development process. Liu and Wang [36] integrated fuzzy analytic network process (FANP) and fuzzy k-means clustering into QFD, but description of the fuzzy k-means clustering lacks details.

* Tel.: +86 512 88161517.
E-mail addresses: kevinkf.yuen@gmail.com, kevin.yuen@xjtlu.edu.cn

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Analytic Hierarchy Process (AHP) [37] and Analytic Network Process (ANP) [38] based on the pairwise comparison method typically are useful for rating interface and assessment. The fuzzy AHP (FAHP) extents the fuzzy number for the judgment scales of pairwise comparisons in AHP. Extent Analysis Method [34], the most popular FAHP approach, has been progressively applied in various areas. However, Wang et al. [39] and Yuen [40] recently showed the incorrectness of the EAM and proposed their better FAHPs respectively.

The core idea of AHP relies on the paired ratio scale $a_{ij} = w_i/w_j$. Yuen [41–45] indicated that the basic numerical definition of the paired ratio scale does not always appropriately represents the human perception or cognition of paired difference. The inappropriate definition of paired ratio scale for AHP follows the inappropriate FAHP, as the FAHP applies fuzzy number, instead of the crisp number in the AHP, to the paired ratio scale to compare two different objects. Yuen [41,43–45] proposed the Primitive Cognitive Network Process (PCNP) using paired interval (or differential) scale to replace AHP's paired ratio scale which potentially produces misapplications. The Fuzzy Cognitive Network Process (FCNP) [42,44] is the extension of PCNP by applying fuzzy number to the cognitive rating scale, pairwise opposite matrix, cognitive prioritization operator and aggregation.

The rest of this article is organized as follows. Section 2 presents the concept of Fuzzy Cognitive Network Process (FCNP) with little modifications for the rating assessment in FQFD. Section 3 proposes the novel Fuzzy Aggregative Grading Clustering (FAGC) method for evaluation result analysis in FQFD. Section 4 proposes the hybrid FQFD framework combining FCNP and FAGC. Section 5 demonstrates the applicability of the proposed hybrid method. Section 6 discusses the limitations of established methods and merits of the proposed methods. Section 7 concludes the notion of the proposed method.

2. Fuzzy Cognitive Network Process

The proposed Fuzzy Cognitive Network Process (FCNP) with some minor modifications of [42,44] is used for the FQFD. The Triangular Fuzzy Number (TFN) is used to represent the verbal linguistic scales. The details of FCNP are as below.

2.1. Fuzzy Cognitive Assessment Process

In the Fuzzy Cognitive Assessment Process, the survey is conducted. An example of a survey question used in Section 5 is presented in Fig. 1. A list of the Fuzzy Pairwise Opposite Matrices (FPOMs) is formed according to the rating scores in the questionnaire completed by the raters. The Fuzzy Accordance Index (FAI) is used to check the validity of each FPOM.

The fuzzy pairwise opposite matrix (FPOM) is proposed to interpret the individual utilities (weights or priorities) of the candidates. A Fuzzy triangular number is chosen as a fuzzy set due to its popularity in fuzzy applications. Let an ideal fuzzy utility set be $\widehat{V} = \{\widehat{v}_1, \ldots, \widehat{v}_n\}$, where an utility in fuzzy triangular number has the form $\widehat{v}_i = (v_i^l, v_i^\pi, v_i^u)$, and the comparison score in fuzzy number is $\widehat{b}_{ij} \cong \widehat{v}_i - \widehat{v}_j$. The ideal FPOM is $\widehat{B} = [\widehat{v}_i - \widehat{v}_j]$, whilst a subjective judgmental FPOM using fuzzy paired interval scale is $\widehat{B} = [\widehat{b}_{ij}]$. $\widehat{B}$ is determined by $\widehat{B}$ as follows:

$$\tilde{\widehat{B}} = [\tilde{\widehat{b}}_{ij}] = \begin{bmatrix} \widehat{v}_1 - \widehat{v}_1 & \widehat{v}_1 - \widehat{v}_2 & \ldots & \widehat{v}_1 - \widehat{v}_n \\ \widehat{v}_2 - \widehat{v}_1 & \widehat{v}_2 - \widehat{v}_2 & \ldots & \widehat{v}_2 - \widehat{v}_n \\ \vdots & \vdots & \ddots & \vdots \\ \widehat{v}_n - \widehat{v}_1 & \widehat{v}_n - \widehat{v}_2 & \cdots & \widehat{v}_n - \widehat{v}_n \end{bmatrix}$$

$$\cong \begin{bmatrix} \widehat{b}_{11} & \widehat{b}_{12} & \ldots & \widehat{b}_{1n} \\ \widehat{b}_{21} & \widehat{b}_{22} & \ldots & \widehat{b}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \widehat{b}_{n1} & \widehat{b}_{n2} & \cdots & \widehat{b}_{nn} \end{bmatrix} = [\widehat{b}_{ij}] = \widehat{B} \tag{1}$$

$\widehat{b}_{ij} = (b_{ij}^l, b_{ij}^\pi, b_{ij}^u) = -\widehat{b}_{ji} = (-b_{ji}^u, -b_{ji}^\pi, -b_{ji}^l)$, and for $i,j = 1, \ldots, n$ and $i \neq j$. If $i = j$, then $\widehat{b}_{ij} = \widehat{v}_i - \widehat{v}_j = (0,0,0)$. Thus the above matrix has the form.

$$\tilde{\widehat{B}} = \begin{bmatrix} (0,0,0) & \widehat{v}_1 - \widehat{v}_2 & \ldots & \widehat{v}_1 - \widehat{v}_n \\ \widehat{v}_2 - \widehat{v}_1 & (0,0,0) & \ldots & \widehat{v}_2 - \widehat{v}_n \\ \vdots & \vdots & \ddots & \vdots \\ \widehat{v}_n - \widehat{v}_1 & \widehat{v}_n - \widehat{v}_2 & \cdots & (0,0,0) \end{bmatrix}$$

$$\cong \begin{bmatrix} (0,0,0) & (b_{12}^l, b_{12}^\pi, b_{12}^u) & \ldots & (b_{1n}^l, b_{1n}^\pi, b_{1n}^u) \\ (-b_{12}^u, -b_{12}^\pi, -b_{12}^l) & (0,0,0) & \ldots & (b_{2n}^l, b_{2n}^\pi, b_{2n}^u) \\ \vdots & \vdots & \ddots & \vdots \\ (-b_{1n}^u, -b_{1n}^\pi, -b_{1n}^l) & (-b_{2n}^u, -b_{2n}^\pi, -b_{2n}^l) & \cdots & (0,0,0) \end{bmatrix}$$

$$= \widehat{B} \tag{2}$$

The indices i and j are local indices subject to their attached variable symbol. Usually, $\widehat{b}_{ij} \in \widehat{B}$ is given during the rating process of the expert using the rating scale schema shown in Table 1. The crisp normal utility κ is used to determine a vector of scales in fuzzy triangular number.

The expert only fills the elements of a fuzzy upper triangular matrix, and the lower triangular matrix is given by the opposite of the upper triangular matrix. The complete comparisons for a FPOM need $(n(n-1)/2), n \geq 2$, ratings. $\widehat{B}$ is validated by the Fuzzy Accordance Index AI or FAI of the below form:

$$\widehat{AI} = (AI^l)^{1/4} \times (AI^\pi)^{1/2} \times (AI^u)^{1/4},$$

The objective of this question is to evaluate the priorities of three attributes proposed as follows.

$\widehat{\beta}_{31}$: Response time ,

$\widehat{\beta}_{32}$: Page generation speed ,

$\widehat{\beta}_{33}$: User volume ,

Compare the relative preference for each pair, and circle the mark accordingly.

	Absolutely		Significantly		Highly		Moderately		Equally		Moderately		Highly		Significantly		Absolutely	
$\widehat{\beta}_{31}$	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	$\widehat{\beta}_{32}$
$\widehat{\beta}_{31}$	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	$\widehat{\beta}_{33}$
$\widehat{\beta}_{32}$	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	$\widehat{\beta}_{33}$

Fig. 1. Example of a survey question using pairwise comparisons.