Advanced Engineering Informatics 23 (2009) 222–228

Contents lists available at ScienceDirect

Advanced Engineering Informatics

journal homepage: www.elsevier.com/locate/aei

A rough set based QFD approach to the management of imprecise design information in product development

Lian-Yin Zhai, Li-Pheng Khoo *, Zhao-Wei Zhong

School of Mechanical and Aerospace Engineering, Nanyang Technological University, 50 Nanyang Avenue, Singapore 639798, Singapore

ARTICLE INFO

Article history:
Received 25 January 2008
Accepted 28 October 2008
Available online 16 December 2008

ABSTRACT

Intense competition and sophisticated customer needs have resulted in the development of more complex products with a shorter lead time to market. One of the key factors in product development concerns the understanding and management of complex relationships between customers' needs and technical requirements. Usually these complex relationships are expressed using imprecise descriptions in the form of natural linguistic terms. Frequently, quality function deployment (QFD) is employed to manage design information and assist decision-making in human centered product development. This work proposes a rough set based QFD approach to manage the aforementioned imprecise design information in product development. A novel concept known as rough number*, which is derived from the basic notions of rough sets, is proposed to manage the imprecise design information in QFD analysis. A case study on a bicycle design is used to illustrate the approach proposed. The result shows that the new approach proposed can effectively manage the imprecise design information and facilitate decision-making in product development.

1. Introduction

Product design is a knowledge intensive multi-disciplinary development process which requires the acquisition, representation, management, and application of various design knowledge. In this respect, techniques that are able to treat and manipulate raw design information for product development become important. Intense competition and sophisticated customer needs have resulted in the development of more complex products with a shorter lead time to market. One of the key factors in product development concerns the understanding and management of complex relationships between customers' needs and technical requirements (TRs). In this regard, quality function deployment (QFD), which is widely accepted as a systematic methodology for product development, is frequently used as an effective tool to manage design information [1].

The first stage of QFD, which is known as the house of quality (HOQ), manages the initial design information related to various customer needs (called 'WHATs' in the HOQ) and the necessary technical requirements (called 'HOWs' in the HOQ) that can fulfill these needs. In developing a HOQ, customers' perceptions/expectations about a product are usually solicited through survey and are organized into a number of key customer needs. Subsequently, a set of technical requirements that are able to fulfill these needs are established by a team of experts in design and their relationships with each customer need are determined by these experts. As a result, QFD analysis ineluctably involves much imprecise information, i.e. linguistic vague descriptions, which are frequently expressed using such statements as 'low importance', 'high importance', 'strong relationship' and 'weak relationship'. Usually such imprecise design information cannot be effectively handled by crisp values in the traditional way. In this respect, many studies focusing on techniques to manage the vague and uncertain design information in QFD have been carried out. Among them, fuzzy set theory is one of the widely used techniques. Using fuzzy set theory, linguistic descriptions can be translated into fuzzy numbers, which can be manipulated by the mathematical operators provided by fuzzy set theory. For example, Khoo and Ho [2] proposed a framework of fuzzy QFD using symmetrical triangular fuzzy numbers (STFNs) to describe the linguistic variables. Chan et al. [3] employed STFNs to analyze the voice of customers and rate the importance of customer needs in QFD. More recently, Chen et al. [4] rated technical attributes in fuzzy QFD by integrating fuzzy weighted average method with fuzzy expected value operators. Some other fuzzy approaches which were based on fuzzy arithmetic and/or fuzzy defuzzification [5–8], had also been developed to manage imprecise and vague design information in product development.

Although fuzzy set theory has been widely used in QFD analysis, the issues concerning the impact of fuzzy interval enlargement after fuzzy arithmetic operations on the result of QFD analysis and the subjectivity involved in the selection of fuzzy membership functions to quantify vague design information have not been thoroughly investigated. Fuzzy arithmetic operations [9], which were

* Corresponding author.
E-mail address: mlpkhoo@ntu.edu.sg (L.-P. Khoo).

1474-0346/$ - see front matter © 2008 Elsevier Ltd. All rights reserved.
doi:10.1016/j.aei.2008.10.010

extended from interval analysis [10], such as the addition and multiplication operations used in QFD analysis, may lead to the enlargement of the resultant fuzzy intervals [11]. Accordingly, the enlargement of fuzzy intervals may have an impact on QFD analysis. On the other hand, as suggested by Jin [12], selection of membership functions is critical for the performance of a fuzzy system. Thus, it has been one of the challenging research topics in the field of fuzzy set applications. More specifically, in the applications of subjective evaluations and heuristics, where fuzzy sets are used to model the cognitive process of human beings, the determination of membership functions is usually based on experience and intuition [12,13]. In practice, certain types of functions such as triangular, trapezoidal, Gaussian or bell-shaped functions are often used. Although some more sophisticated and objective methods such as neural networks can be employed to tune the membership functions through learning/training process [14,15], in the early stages of product development, such learning/training process may not be realistic or even feasible because the available data are very limited [16].

This work attempts to address these issues by using a different approach and proposes a novel concept known as rough number* to manage the imprecise design information in product development. The concept of rough number* is directly derived from the basic notion of approximations in rough set theory. The rest of the paper is organized as follows. Section two reviews the basic concepts of rough set theory and highlights its advantages in dealing with imprecise information. Section 3 proposes a novel concept known as rough number*, which is derived using the basic notion of rough approximations. Similar to fuzzy arithmetic, a set of arithmetic operations enabling the manipulation of rough number*s for QFD analysis, based on the interval analysis [10], are proposed. Section four describes a QFD case study on a bicycle design to illustrate the approach developed. Finally, the major conclusions achieved in this work are summarized in Section 5.

2. Basic notions of rough sets

Conventional mathematical logic is incapable of manipulating data representing subjective or vague human ideas such as 'very important' or 'strong relationship', which are very frequently encountered in QFD analysis for example. In this respect, rough set theory and its related techniques can be employed to determine the distinctions among data with the concept of approximations and generate reasonable solutions from vague or imprecise information. Basically, a rough set is a formal approximation of a crisp set (conventional set). It uses a pair of sets which give the lower and upper approximations of the target set. The lower and upper approximation sets themselves are crisp sets in the standard version of rough set theory [17,18]. The lower approximation of a target set is a conservative approximation consisting of only those elements which can positively and certainly (probability = 1) be identified as members of the set. The upper approximation is a liberal approximation which includes all elements that can possibly (with nonzero probability) be identified as members of the target set. The difference between the upper and lower approximations is the boundary region of a rough set, consisting of the elements that can neither be ruled in nor ruled out as members of the target set. Fig. 1 depicts the basic notions of rough set theory.

Obviously, a non-empty boundary region of a set implies that the knowledge about the set is not sufficient to define it precisely. In this respect, rough set theory expresses vagueness by means of the boundary region of a set instead of using membership function [17]. This is indeed the unique advantage of rough set theory in dealing with vagueness and uncertainty. Unlike other methods such as fuzzy set theory, Dempster–Shafer theory and statistical methods, rough set theory does not require any external information or additional subjective adjustment for data analysis. It uses only the information presented in the given data and remains the objectivity of information [17,19]. Furthermore, rough set theory excels in handling imprecise information especially when the data set is small in size and other tools like statistics are not suitable [20]. In fact, in product development activities, especially in new product design, it is very difficult to obtain large amount of design information such as customer ratings and designer evaluations in QFD analysis, and thus, the data size is usually very small. Hence, rough set theory appears to be a more suitable tool to handle the imprecise information for product development.

3. Rough number* enabled QFD

As mentioned earlier, QFD analysis usually has to deal with imprecise descriptions of both customer needs and technical requirements, which include subjective perceptions of customers and judgments of technologists. Such information is usually in the form of importance ratings based on an evaluation scale. Traditional standard rough set theory has to be modified so as to handle such data in the ordered manner. In the following sub-section, a novel concept of rough number* is proposed based on the basic notions of rough sets, and integrated with fuzzy arithmetic operations to represent and analyze vague design information in QFD.

3.1. Rough number and rough boundary interval*

As known, classical rough set theory was suggested by Pawlak [17] to solve inconsistencies in classification problems such as importance ratings in QFD analysis. For example, when evaluating the importance of a customer need, the distinct importance ratings perceived by the customers can be viewed as 'classes' associated with the customer need (also known as 'object' in classification problems). Due to the diversity in customer opinions when assessing the importance of a customer need, inconsistencies may exist in the classes. Thus, the concept of approximations in rough set theory can be extended to deal with such inconsistent or imprecise information, as elaborated below.

Let U be a universe containing all the objects registered in an information table, Y is an arbitrary object of U, and there is a set of n classes, $R = \{C_1, C_2, \cdots, C_n\}$, defined in the universe. If these classes are ordered in the manner of $C_1 < C_2 < \ldots < C_n$, then for any class, $C_i \in R$, $1 \leqslant i \leqslant n$, the lower approximation of C_i can be defined as

$$\underline{Apr}(C_i) = \cup\{Y \in U/R(Y) \leqslant C_i\}; \tag{1}$$

the upper approximation of C_i can be expressed as

$$\overline{Apr}(C_i) = \cup\{Y \in U/R(Y) \geqslant C_i\} \tag{2}$$

and the boundary region of C_i is given by

$$\begin{aligned} Bnd(C_i) &= \cup\{Y \in U/R(Y) \neq C_i\} \\ &= \{Y \in U/R(Y) > C_i\} \cup \{Y \in U/R(Y) < C_i\} \end{aligned} \tag{3}$$

Thus the class, C_i, can be represented by a rough number* (RN) which is defined by its lower limit ($\underline{Lim}(Ci)$) and upper limit ($\underline{Lim}(Ci)$), where

$$\underline{Lim}(C_i) = \frac{1}{M_L}\sum R(Y)\Big| Y \in \underline{Apr}(C_i); \tag{4}$$

where M_L is the number of objects contained in the lower approximation of C_i; and

$$\overline{Lim}(C_i) = \frac{1}{M_U}\sum R(Y)\Big| Y \in \overline{Apr}(C_i) \tag{5}$$