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A methodology of generating customer satisfaction models for new product development using a neuro-fuzzy approach

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ABSTRACT

When developing new products it is important for design teams to understand customer perceptions of consumer products because the success of such products is heavily dependent upon the associated customer satisfaction level. The chance of a new product's success in a marketplace is higher if users are satisfied with it. In this study, a new methodology of generating customer satisfaction models using a neuro-fuzzy approach is proposed. In contrast to previous research, non-linear and explicit customer satisfaction models can be developed with the use of the proposed methodology. An example of notebook computer design is used to illustrate the methodology. The proposed methodology was measured against the benchmark of statistical regression to determine its effectiveness. Experimental results suggested that the proposed approach outperformed the statistical regression method in terms of mean absolute errors and variance of errors.

1. Introduction

Over the past few decades, there has been an increasing emphasis on a company's ability to produce high-quality consumer products. Such products can be identified by measuring the associated customer satisfaction level. Therefore, this emphasis has gradually transformed most industries from production-centralized to customer-driven ones. Market analysis is an effective means to understand customer perception towards new consumer products. Data collection tools such as questionnaires and users' interviews, can be used in this regard. Based on the survey data, customer satisfaction models developed can be used to identify customer perceptions towards new products and the associated customer satisfaction level. Customer satisfaction has a direct influence on customer retention (Choi, Cho, Lee, Lee, & Kim, 2004; Hansemark & Albinsson, 2004) and company's profitability (Johnson, Nader, & Fornell, 1996; Zeithaml, 2000). In this regard, it is crucial to improve customer satisfaction and identify the associated design attributes that would ensure sustained customer loyalty and competitiveness for the firm (Deng & Pei, in press).

Previous studies have attempted to develop customer satisfaction models with statistical regression, fuzzy regression, neural networks, quantification analysis I, and fuzzy rule-based modeling. Chen, Khoo, and Yan (2006) developed a prototype system for affective design in which Kohonen's self-organizing map neural network was employed to consolidate the relationship between design attributes and customer satisfaction. Hsiao and Tsai (2005) proposed a method that enables an automatic product form search or product image evaluation by means of a neural network-based fuzzy reasoning genetic algorithm. The neural network-based fuzzy reasoning algorithm was applied to establish relationships between the input form parameters and a series of adjectival image words. Fung, Popplewell, and Xie (1998) proposed fuzzy rule-based models to relate design attributes to customer satisfaction. Han, Yun, Kim, and Kwahk (2000) developed a variety of usability dimensions, including both subjective and objective aspects, and evaluated product usability based on statistically regressed models. These models were then used to identify functional relationships between design attributes and customer satisfaction. At the same time, various techniques have been attempted to model the fuzzy relationships between design attributes and customer satisfaction. Kim and Park (1998) suggested a fuzzy regression approach to estimate functional relationships. Chen, Tang, Fung, and Ren (2004) proposed another fuzzy regression approach, based on asymmetric triangular fuzzy coefficients, to model the functional relationships. The use of non-linear programming to develop fuzzy regression models for the functional relationships was proposed by Chen and Chen (2005). However, the above approaches are only applicable to developing linear models, and ignore non-linear terms of models. Multiple linear regression, which considers non-linear coefficients, was attempted to model the relationships between customer requirements and

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engineering characteristics (Dawson & Askin, 1999). However, an optimal model could not be generated because the model is in a polynomial form, and the order of the polynomials generated is user defined. Liu, Zeng, Xu, and Koehl (2008) proposed a fuzzy model to examine the customer satisfaction index in e-commerce. They considered a method that would calculate the index based on a 5-level quantity table using fuzzy logic. However, the developed model is implicit, in other words, a black-box model. Grigoroudis and Siskos (2002) developed the MUlticriteria Satisfaction Analysis (MUSA) method for measuring and analyzing customer satisfaction. MUSA is a preference disaggregation model based on the working principles of ordinal regression analysis. Using the survey data, MUSA aggregated individual judgments into a collective value function for quantifying customer satisfaction. The model assumed that the overall customer satisfaction was measured solely with respect to several customer attributes, and ignored the customer satisfaction model towards each customer attribute. Grigoroudis, Litos, Moustakis, Politis, and Tsironis (2008) further applied the MUSA method to measure the user-perceived web quality. Park and Han (2004) proposed a fuzzy rule-based approach to examine customer satisfaction levels towards office chair designs. They reported that the fuzzy rule-based approach outperformed the multiple linear regression approach in terms of the number of variables used. Similarly, Lin, Lai, and Yeh (2007) proposed a fuzzy logic model to determine the consumer-oriented mobile phone form design. The experimental results suggest that the fuzzy model outperformed two neural network-based models in terms of the root of mean square errors. You, Ryu, Oh, Yun, and Kim (2006) developed the customer satisfaction models for automotive interior material using quantification I analysis, which examined the relatively important design variables and preferred design features. Hence, significant design variables and their values affecting customer satisfaction were identified. However, the models developed are implicit.

Before endeavouring to develop customer satisfaction models, the vague affiliation between customer attributes and design attributes must be thoroughly investigated (Kim, Moskowitz, Dhingra, & Evans, 2000; Kwong, Chen, Bai, & Chan, 2007). The literature review indicates that most of the existing models assume a linear relationship between customer attributes and design attributes. In fact, they could be highly non-linear. Although neural networks are capable of modeling the non-linear relationships between them, the customer satisfaction models generated are implicit. Thus, it is difficult to analyze the behaviour of the relationships. In this paper, a new methodology for developing customer satisfaction models using a neuro-fuzzy approach is proposed, whereby non-linear and explicit customer satisfaction models can be generated.

The organization of this paper is as follows: Section 2 describes the main steps of the proposed methodology. Section 3 presents an illustrative example to demonstrate the usefulness of the methodology. Two validation tests are depicted in Section 4. Conclusions are given, together with future research work, in Section 5.

2. The proposed methodology

Recently, an Adaptive Neuro-Fuzzy Inference System (ANFIS) has been applied to, but not limited to different areas such as the assignment problem (Kelemen, Kozma, & Liang, 2002), knowledge recovery (Huang, Tsou, & Lee, 2006), and process prediction (Bateni, Borghei, & Jeng, 2007; Chang & Chang, 2006; Kwong, Chan, & Wong, 2008; Wang & Elhag, 2008). According to Wang and Elhag (2008), an ANFIS can be a multi-layer feed-forward network in which neural network is regarded as the learning mechanism and fuzzy reasoning is used for the mapping of inputs into an output. In this research, the ANFIS was investigated to generate customer satisfaction models. Usually, ANFIS-based models are the black-box type. In order to generate non-linear and explicit customer satisfaction models, a new ANFIS-based methodology is proposed. The major steps of the methodology involve (a) data collection using market surveys; (b) generation of fuzzy rules based on market survey data using an ANFIS; (c) extraction of significant fuzzy rules and the corresponding internal models using a proposed rule extraction method; and (d) formulation of customer satisfaction models by aggregating internal models of significant fuzzy rules. The first step concerns the design of market surveys and collection of survey results. Details will not be given here as there are plenty of publications on this step (e.g. Malhotra, 2004). Descriptions of the remaining steps are presented in the following sub-sections.

2.1. Generation of fuzzy rules based on the market survey data using an ANFIS

Suppose that market survey data have been successfully collected. The data can be input to an ANFIS for generating some fuzzy rules. An example of an ANFIS with four layers and two inputs is presented in Fig. 1. If both inputs, x_1 and x_2, have two linguistic descriptions (e.g. low and high) respectively, a membership function is used to represent each description. So, $\mu_i(x_1)$ denotes the membership function for ith linguistic description of x_1 and $\lambda_j(x_2)$ denotes the membership function of jth linguistic description of x_2 where $i = 1,\ldots,2$ and $j = 1,\ldots,2$. So, there is a total of four membership functions for all inputs as defined by four nodes in Layer 1 (L1). At L2, one rule is used to denote the outcome for each combination of x_1 and x_2, hence, the total number of rules required is $2^* 2 = 4$. The fuzzy rules can be generally expressed as follows:

$$R_{ij} : IF\ x_1\ is\ \mu_i\ AND\ x_2\ is\ \lambda_j, THEN\ f_{ij} = p_{ij}x_1 + q_{ij}x_2 + r_{ij},$$

where μ_i and λ_j are the membership functions of ith and jth linguistic descriptions of x_1 and x_2 respectively, p_{ij}, q_{ij}, and r_{ij} are the parameters of the internal models (f_{ij}) of the fuzzy rules (R_{ij}). For each R_{ij}, the firing strength is defined by (1).

$$w_{ij} = \mu_i(x_1) \cdot \lambda_j(x_2) \quad (\forall\ i = 1,\ldots,2,\ j = 1,\ldots,2), \tag{1}$$

$$\bar{w}_{ij} = \frac{w_{ij}}{W} \quad \text{where } W = \sum_i \sum_j w_{ij} \quad (\forall\ i = 1,\ldots,2,\ j = 1,\ldots,2). \tag{2}$$

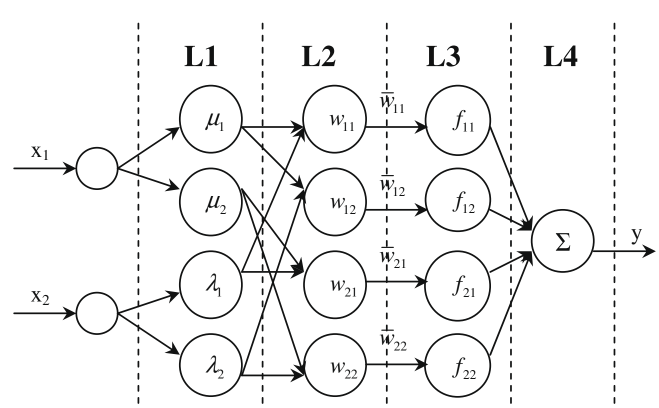

Fig. 1. An example of an ANFIS with four layers and two inputs.