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A methodology of integrating affective design with defining engineering specifications for product design

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Affective design and the determination of engineering specifications are commonly conducted separately in early product design stage. Generally, designers and engineers are required to determine the settings of design attributes (for affective design) and engineering requirements (for engineering design), respectively, for new products. Some design attributes and some engineering requirements could be common. However, the settings of the design attributes and engineering requirements could be different because of the separation of the two processes. In previous studies, a methodology that considers the determination of the settings of the design attributes and engineering requirements simultaneously was not found. To bridge this gap, a methodology for considering affective design and the determination of engineering specifications of a new product simultaneously is proposed. The proposed methodology mainly involves generation of customer satisfaction models, formulation of a multi-objective optimisation model and its solving using a chaos-based NSGA-II. To illustrate and validate the proposed methodology, a case study of mobile phone design was conducted. A validation test was conducted and the test results showed that the customer satisfaction values obtained based on the proposed methodology were higher than those obtained based on the combined standalone quality function deployment and standalone affective design approach.

Keywords: product design; affective design; determination of engineering specifications; chaos optimisation algorithm; NSGA-II

1. Introduction

In the early product design stage, the two processes, affective design and the determination of engineering specifications, are always involved, especially for consumer product design. Affective design has been shown to excite customers' psychological feelings and can help improve customer satisfaction in terms of emotional aspects. Affective design involves the processes of identifying, measuring, analysing and understanding the relationship between the affective needs of the customer domain and the perceptual design attributes in the design domain (Lai, Chang, and Chang 2005). Design attributes, such as shape and colour, evoke the affective responses of customers to products. Products with good affective design can attract customers and influence their choices and preferences, such as loyalty to the company and joy of use (Noble and Kumar 2008). A product usually is associated with a number of engineering requirements, such as weight, size, processing speed, and power consumption that could affect customer satisfaction. Therefore, it is crucial for product development teams to identify appropriate or even optimal engineering specifications for improving or maximising customer satisfaction (Deng and Pei 2009). To determine engineering specifications for new products, quality function deployment (QFD) is commonly used to translate the collected customer requirements to various engineering requirements for product design. New product design with QFD can enhance organisational learning and improve customer satisfaction. It can also enable a company to reduce product costs, simplify manufacturing processes and shorten development time of new products (Vonderembse and Raghunathan 1997).

In new product development projects, it is noted that some design attributes considered in affective design could be identical to some engineering requirements considered in the determination of engineering specifications. For example, setting the thickness of a new notebook computer may need to be considered in both affective design and the determination of engineering specifications. However, affective design and the determination of engineering specifications are always conducted separately. Thus, the settings of engineering requirements and design attributes of a new product based on existing practice could be different and may not lead to the maximum customer satisfaction to be obtained for

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the new product. Therefore, it is desirable to have a framework or a methodology that considers affective design and the determination of engineering specifications simultaneously in determining the settings of engineering requirements and design attributes. However, no such framework or methodology has been found thus far in previous studies.

To fill the existing research gap, a methodology of simultaneous consideration of affective design and the determination of engineering specifications is proposed to determine design attribute settings and engineering requirement settings for a new product. In the proposed methodology, a chaos-based fuzzy regression (FR) approach is proposed to develop customer satisfaction models based on QFD. The generated fuzzy polynomial models can contain second- and/or higher-order terms and interaction terms such that nonlinearity of the modelling can be better captured. For affective design, rough set and particle swarm optimisation (PSO)-based adaptive neural fuzzy inference system (ANFIS) approaches are proposed to model the affective relationships in order to make up the deficiency of ANFIS and further improve the modelling accuracy. The two types of customer satisfaction models are then used to formulate an optimisation model. The model is solved using a chaos-based non-dominated sorting genetic algorithm-II (NSGA-II) and the optimal settings of the engineering requirements and design attributes of a new product can be determined. The proposed methodology can yield higher customer satisfaction values to be obtained compared with the combined standalone QFD and standalone affective design method. We organise the rest of this paper as follows: first, a review of the related research is presented in Section 2. The proposed methodology is described in Section 3. Section 4 describes the application of the proposed methodology in the design of mobile phone products. The validation of the proposed methodology and its results is presented in Section 5. Finally, discussion and conclusion are given in Section 6 and 7, respectively.

2. Literature review

In the following, literature review of affective design, modelling customer satisfaction and defining engineering specifications, as well as combining Kansei engineering with QFD is provided in Sections 2.1–2.3 respectively.

2.1 *Previous studies on affective design*

Affective design is a systematic approach to the analysis of customer reactions to candidate designs (Barnes and Lillford 2009). It aims to quantify such reactions and integrate them into physical product design parameters to maximise customer affective satisfaction with a product. Nagamachi (1995) proposed Kansei engineering or named affective engineering (Nagamachi 2008), which is a product development methodology for acquiring and transforming customer affections into design attribute settings using quantitative methods. Surveys are always required in Kansei engineering which study the affective meanings related to a product domain based on the semantic differential method (Chuang and Ma 2001). Kansei engineering has been applied in various affective product designs, such as interior design of automobiles (Jindo and Hirasago 1997) and drink bottles (Barnes and Lillford 2009). The framework of Kansei engineering encompasses four tasks (Nagamachi 1995; Barnes and Lillford 2007) which are the definition of the product domain, determination of dimensions of customer affections, determination of design attributes and attribute options and evaluation of relationships between customer affections and design attributes. One important task of the Kansei engineering framework is the evaluation of relationships between the defined affective dimensions and the design attributes. Various approaches have been attempted in previous studies on modelling the affective relationships such as quantification theory I (Chang 2008), ordinal logistic regression (Barone, Lombardo, and Tarantino 2007), partial least-squares analysis (Nagamachi 2008), artificial neural network (Lai, Lin, and Yeh 2005; Chen, Khoo, and Yan 2006), fuzzy logic approach (Lau et al. 2006; Lin, Lai, and Yeh 2007), FR (Sekkeli et al. 2010), genetic programming-based FR (Chan, Kwong, et al. 2011), support vector regression model (Yang and Shieh 2010) and ANFIS (Kwong, Wong, and Chan 2009). Orsborn, Cagan, and Boatwright (2009) quantified aesthetic form preference using utility functions. In addition, some previous studies attempted to discover the interactions between customer affections and design attributes. Park and Han (2004) developed fuzzy rule-based models for explaining the relationship between affective user satisfaction and product design attributes. Jiao, Zhang, and Helander (2006) developed a Kansei mining system for generating Kansei mapping patterns using associated rule mining. Zhai, Khoo, and Zhong (2009) proposed a rough set-based decision support approach to study the interactions between customer affective needs and product attributes. Fung et al. (2012) employed a multi-objective genetic algorithm approach to generate approximate rules that can be used to determine the lower and upper limits of the affective effect of design patterns. The mined rules were then introduced to guide genetic algorithm for searching optimal affective design (Fung et al. 2014).

In the early product design stage, one of the key tasks of undertaking affective design is to determine the optimal settings of the design attributes for affective aspects of products to achieve maximum customer satisfaction. Some studies have been attempted to determine the optimal settings. Conjoint analysis was introduced to determine the optimal setting of design attributes in product design (Shi, Olafsson, and Chen 2001). Hong, Han, and Kim (2008) proposed a variant of multiple response surfaces methodology for optimally balancing affective dimensions. A setting of design attributes which optimally balance the luxuriousness, attractiveness and overall satisfaction was obtained. Aktar Demirtas, Anagun, and Koksal (2009) adopted an ordinal logistical regression to determine an optimal design attribute settings by maximising the overall preference scores. Hsiao and Tsai (2005) employed genetic algorithms to search for a near optimal design which would satisfy the required product image using a trained neural network as a fitness function.

2.2 *Previous studies on modelling customer satisfaction and defining engineering specifications*

Numerous studies of modelling customer satisfaction based on QFD have been conducted. To address the fuzziness of the modelling, quite a few previous studies have adopted fuzzy set theory to model customer satisfaction in QFD such as fuzzy rule-based systems (Fung, Popplewell, and Xie 1998), FR-based mathematical programming approach (Chen et al. 2004) and generalised fuzzy least-squares regression approach (Kwong et al. 2010). Some other artificial intelligence techniques have been introduced to address the nonlinearities of the modelling. Zhang, Bode, and Ren (1996) proposed a neural network approach to model the functional relationships between customer satisfaction and engineering requirements. Fung et al. (2002) proposed a parametric optimisation method to develop nonlinear fuzzy models in QFD. Chan, Kwong, and Wong (2011) proposed a method based on genetic programming (GP) to generate models for relating customer satisfaction to engineering requirements. The projections to latent structures technique and the partial least-squares path modelling algorithm were introduced to develop revealed value models that relate customer satisfaction to engineering requirements (Withanage, Park, and Choi 2010; Withanage et al. 2012).

Some previous research has attempted to develop systematic procedures and methods for setting optimal target values of engineering requirements in QFD. Wasserman (1993) formulated the QFD planning process as a linear programming model to select a mix of engineering requirements under a limitation of a given target cost. Kim and Park (1998) developed an integer programming model to determine the target value setting of engineering requirements in order to maximise customer satisfaction. A mixed-integer linear programming model was proposed by Zhou (1998) to optimise the improvement of the target values setting and to prioritise engineering requirements through a fuzzy ranking method. Fung, Law, and Ip (1999) proposed a fuzzy customer requirements inference system to determine design targets by amalgamating the principles and techniques of the analytic hierarchy process, fuzzy sets theory and bisection method. Kusiak (1999) presented an approach which allows one to analyse the impact of changing the value of a variable on the values of engineering requirements by deriving quantitative relationships. Dawson and Askin (1999) developed a nonlinear mathematical programme to determine optimal value settings of the engineering requirements and formulated a customer value function which took into account development time constraints and production costs. Kim et al. (2000) developed a prescriptive fuzzy optimisation model to determine the optimal target values of engineering requirements by defining parameters, objectives and constraints in a crisp or fuzzy way. Bai and Kwong (2003) introduced an inexact genetic algorithm approach to solve a fuzzy optimisation model for the determination of target values for engineering requirements in QFD. Instead of obtaining one set of exact optimal target values, the approach can generate a family of inexact optimal target values setting within an acceptable satisfaction degree. Kahraman, Ertay, and Buyukozkan (2006) proposed an integrated framework based on fuzzy-QFD and a fuzzy optimisation model to determine target value settings of the engineering requirements. Chen and Ko (2009) proposed a fuzzy nonlinear programming model based on Kano's concept to determine the fulfilment levels of the engineering requirements. Sun, Mei, and Zhang (2009) applied a fuzzy conversion matrix in a simplified systematic method to acquire a tight limited target range for engineering requirements. A mathematical programming model was developed by Sener and Karsak (2010) to determine target levels of technical attributes using the customer satisfaction models developed based on FR. Sener and Karsak (2011) later proposed a combined fuzzy linear regression and fuzzy multiple objective programming approach for setting target values of engineering requirements.

2.3 *Combining Kansei engineering with QFD*

Some previous studies have attempted to combine Kansei engineering with QFD for service and product design. Schütte (2002) discussed three possible ways to combine Kansei engineering with QFD. Hartono et al. (2012) employed Kano model, Markov chain modelling, QFD and Kansei engineering in service design. In their study, the Kano model and Kansei engineering were used to determine the significance of Kansei responses. Then, Markov chain modelling was introduced to determine the future importance of service attributes. Finally, a house of quality (HoQ) was developed using the future importance weights for hotel service design. Previous studies have shown that the concept of the combination of QFD and Kansei engineering is possible. However, research on simultaneous consideration of Kansei engineering and QFD in determining design attribute settings and engineering specifications has not been found.

3. A methodology for integrating affective design with defining engineering specifications

In this paper, a methodology of simultaneous consideration of affective design and the determination of engineering specifications is proposed to determine design attribute settings and engineering requirement settings for a new product. In the proposed methodology, a chaos-based FR approach is introduced to model customer satisfaction based on QFD, while PSO-based ANFIS approach is proposed to model the relationships between affective responses of customers and design attributes. The generated customer satisfaction models are used to formulate a multi-objective optimisation model. A chaos-based NSGA-II is proposed in this research to solve the optimisation model from which optimal settings of the engineering requirements and design attributes for new products can be determined. Figure 1 shows a flowchart of the proposed methodology.

3.1 *Modelling customer satisfaction based on QFD*

To determine engineering specifications for new products, QFD is introduced in this research. After developing a HoQ, modelling the relationships between customer satisfaction and engineering requirements based on the HoQ can be performed. Normally, only a small number of data-sets can be obtained from HoQ for the modelling. On the other hand, development of HoQ always involves human subjective judgement that would lead to the existence of a high degree of fuzziness in modelling the relationships. Of the approaches used in previous studies for modelling the relationships, FR was found to be the most suitable one for the modelling, as FR is the only one of those previously attempted approaches which is able to capture the fuzziness of modelling data and requires only a small number of data-sets for developing explicit customer satisfaction models. However, FR can only yield a linear type model but the relationships

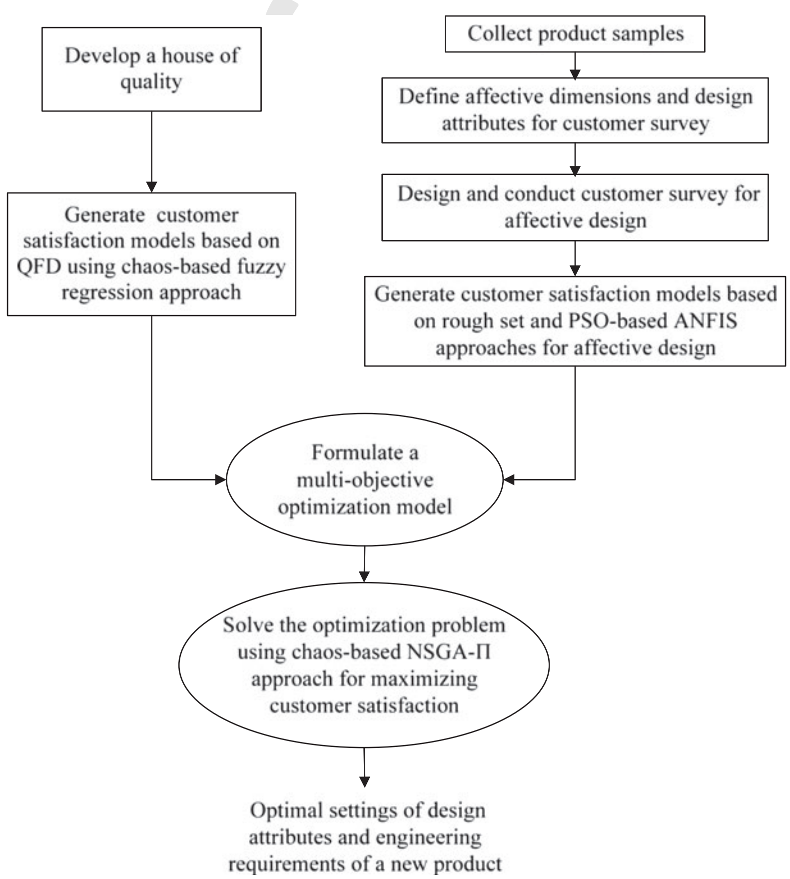

Figure 1. A proposed methodology.

can be highly nonlinear. To address both the fuzziness and the nonlinear issues in modelling the relationships, in this research, a chaos-based FR approach is proposed to develop models for relating customer satisfaction and engineering requirements based on QFD. In the proposed approach, a chaos optimisation algorithm (COA) is introduced to generate the nonlinear polynomial structures of customer satisfaction models which could contain second- and/or higher order terms and interaction terms. The FR method is employed to determine the fuzzy coefficients for all the terms of the customer satisfaction models. Details of the chaos-based FR approach to modelling customer satisfaction based on QFD can be referred to the authors' publication (Jiang et al. 2013).

3.2 *Conducting a survey for affective design*

In this research, product samples need to be identified and collected first for conducting a survey. Then, affective dimensions and design attributes are defined. Design attributes commonly involve categorical and quantitative types. For categorical attributes, morphological analysis is adopted to create numerical data by emulating the possible options of attributes. For example, the side shape can be trapezoidal, a parallelogram or polygonal. A market survey is then conducted for gathering affective responses of customers on the product samples. In the survey, images of the product samples are shown to respondents and they are required to rate various affective dimensions of the product samples. The semantic differential (SD) method (Chuang and Ma 2001) is adopted in this research to design a SD questionnaire for collecting affective responses of customers on products. The SD scale can be a five- or seven-point scale with a pair of affective words.

3.3 *Modelling customer satisfaction for affective design*

Based on the survey data, PSO-based ANFIS approach is proposed to model the relationships between the affective responses of customers and design attributes. Since the number of fuzzy rules increases exponentially when the number of ANFIS inputs increases, rough set theory is first employed to determine the indispensable design attributes and reduce the number of fuzzy rules for simplifying the structure of ANFIS. Then, PSO-based ANFIS approach is introduced to generate explicit non-linear customer satisfaction models for affective design in which PSO is used to determine the optimal values of antecedent parameters in membership functions, such that the errors between the predictive customer satisfaction values and the actual customer satisfaction values can be minimised. Details of the PSO-based ANFIS approach to modelling customer satisfaction for affective design can be referred to the authors' publication (Jiang et al. 2012).

3.4 *Formulation of an optimisation model for determining design specifications*

Once the customer satisfaction models are developed, they can be used to formulate a multi-objective optimisation model for determining optimal settings of the design attributes and engineering requirements. The two types of generated customer satisfaction models respectively based on chaos-based FR and PSO-based ANFIS approaches are used to formulate objective functions of the optimisation model. Constraints of the optimisation model are mainly about the ranges of design variables and the correlations among the design variables. In this research, chaos-based NSGA-II is proposed to solve the optimisation problem for the determination of optimal settings of the engineering requirements and design attributes for new products. The optimisation model can be expressed as follows.

AQ1

Objectives:

$$\begin{gathered}
\textit{Maximise customer satisfaction value of affective dimension } 1, \hat{y}_1 \\
\vdots \\
\textit{Maximise customer satisfaction value of affective dimension } k, \hat{y}_k \\
\textit{Maximise customer satisfaction value of customer requirement}, \hat{y}_m
\end{gathered}$$

Subject to:

$$\hat{y}_k = f_k(x) \tag{1}$$

$$\hat{y}_m = f_m(x) \tag{2}$$

$$\hat{y}_k,\ \hat{y}_m \geq \lambda \tag{3}$$

$$x_{j\,\min} \leq x_j \leq x_{j\,\max} \tag{4}$$

$$x_j = g(x_i),\ where\ i \neq j \tag{5}$$

where x denotes design variables of new products, which involves design attributes in affective design and engineering requirements in QFD; (1) is the nonlinear customer satisfaction model of the kth affective dimension for affective design, which is generated based on PSO-based ANFIS approach; (2) is the fuzzy polynomial model generated based on chaos-based FR approach in QFD. λ is the minimum value of customer satisfaction, which is set as 3 when a five-point scale is used in the market survey. (4) are the ranges of settings of the design variables. (5) is the correlation model generated based on the technical correlation matrix of HoQ for relating the jth design variable and some other design variables. For example, in mobile phone design, screen size has technical correlation with the weight and width.

3.5 *Solving the optimisation model using a chaos-based NSGA-II approach*

NSGA-II is an elitist genetic algorithm and commonly used to solve multi-objective optimisation problems. The major features of NSGA-II include low computational complexity, parameter-less diversity preservation, elitism and real-valued representation (Deb et al. 2002). NSGA-II uses a real-coded simulated binary crossover (SBX) operator and a real-coded polynomial mutation operator to support crossover and mutation operations directly for real-valued decision variables. Deb et al. (2002) found that NSGA-II was able to maintain better spread of solutions and had better convergence than other multi-objective genetic algorithms, such as Pareto-archived evolution strategy and strength Pareto evolutionary algorithm. A flowchart of NSGA-II is shown in Appendix 1. However, NSGA-II may not provide a good diversity of Pareto optimal solutions and its searching solutions are easy to be trapped into a local optimum. In this paper, a chaos-based NSGA-II approach is proposed to solve the multi-objective optimisation problem by which optimal settings of the engineering requirements and design attributes for product design can be determined. In the proposed approach, a COA is incorporated into the process of NSGA-II to refine the search range in order to achieve a good diversity of its Pareto optimal solutions and avoid trapping into a local optimum. Details of the chaos-based NSGA-II are shown in Appendix 2.

4. Case study

A case study of mobile phone design was conducted based on the proposed methodology to evaluate the effectiveness of the methodology. With reference to the HoQ for mobile phones developed by Abu-Assab and Baier (2010), six representative customer satisfaction dimensions and the related 16 design variables for mobile phone design were identified. A HoQ for mobile phone design was developed as shown in Figure 2. Ten major competitive mobile phones were identified and denoted as brands A-J. Four lead users were invited to assess the 10 mobile phones in terms of the six dimensions of customer satisfaction: ‘easy to use’, ‘easy to read display’, ‘good sound quality’, ‘long operation time’, ‘good functionality’ and ‘comfortable to hold’.

Customer satisfaction models based on the HoQ were generated using a chaos-based FR approach (Jiang et al. 2013). The following shows the generated customer satisfaction models, respectively, for ‘comfortable to hold’ and ‘easy to use’.

$$\begin{aligned}\tilde{y}_1 = {}& \left(14.9991, 2.8422 \times 10^{-14}\right) + \left(-1.5036, 2.8422 \times 10^{-14}\right)x_3 + (-0.2890, 0)x_4 + \left(-0.3634, 5.6843 \times 10^{-14}\right)x_1 \\ & + (0.0045, 0.0077)x_1x_2\end{aligned} \tag{6}$$

$$\tilde{y}_2 = (-9.2351, 0) + (-1.1582, 0.2120)x_6^2 + (-0.1594, 0.0437)x_5x_6 + (8.3566, 0)x_6 \tag{7}$$

where $\tilde{y}_1$ and $\tilde{y}_2$ are the predicted customer satisfaction values of ‘comfortable to hold’ and ‘easy to use’, respectively; and x_1, x_2, x_3, x_4, x_5 and x_6 are the engineering requirements, weight, height, width, thickness, menu layers and screen size, respectively.

For affective design of mobile phones, a total of 32 mobile phones of various brands were selected. By consulting four product designers, nine representative design attributes for mobile phones: top shape, bottom shape, side shape,

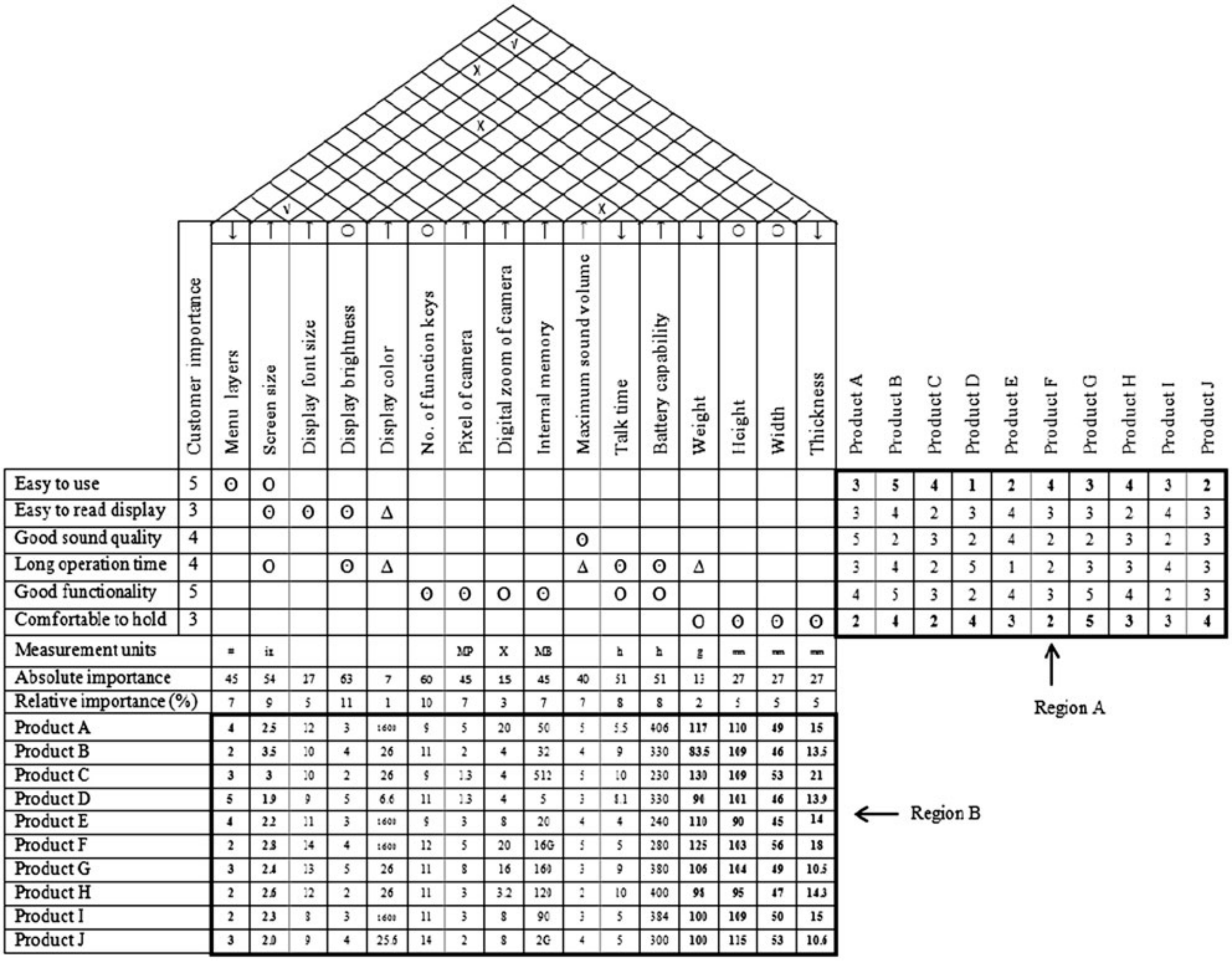

Figure 2. The HoQ for mobile phone products (Jiang et al. 2013).

function button shape, number buttons style, screen size, thickness, layout and weight, were identified. Four affective dimensions were used to evaluate the affective design of the mobile phones. They are simple–complex (S–C), unique–general (U-G), high-tech–classic (H–C) and handy–bulky (H–B). A morphological matrix based on the nine design attributes of the 32 mobile phones was generated as shown in Table 1.

A survey was conducted using a questionnaire, in which a five-point scale was used. A total of 34 design students and designers were involved in the survey for the assessment of the mobile phone appearance corresponding to the four affective dimensions. A part of the questionnaire is shown in Figure 3.

A PSO-based ANFIS approach was introduced to generate customer satisfaction models for the affective dimensions (Jiang et al. 2012). The following shows the generated customer satisfaction models, respectively, for H–B and S–C.

$$F_2 = \frac{0.6798(x_4)^2x_1 - 0.0891x_4(x_1)^2 - 58.9181(x_4)^2 + 1.0502(x_1)^2 - 0.4287x_4x_1 + 659.2281x_4 - 84.5350x_1 + 40.2534}{0.0362x_4x_1 - 2.8100x_4 - 0.3523x_1 + 27.3809} \quad (8)$$

$$F_3 = \frac{40.1216(x_7)^2x_6 - 2.6635x_7(x_6)^2 - 83.3900(x_7)^2 - 39.3286(x_6)^2 - 150.5709x_7x_6 + 345.1479x_7 + 444.8509x_6 - 797.9387}{6.3155x_7x_6 - 12.2878x_7 - 5.4294x_6 + 10.5638} \quad (9)$$

where F_2 and F_3 are the predicted customer satisfaction values of H–B and S–C, respectively; and x_7 is the side shape.

For illustrative purpose, two affective dimensions, H–B and S–C, and two customer satisfaction dimensions, 'comfortable to hold' and 'easy to use', are considered in the optimisation. Thus, four customer satisfaction models, respectively, for H–B, S–C, 'comfortable to hold' and 'easy to use' are used to formulate the objective functions of the

Table 1. Morphological matrix of the 32 mobile phone samples.

Design Attributes \ Alternative	1	2	3	4	5	6
Top Shape	Line and no fillet	Arc and no fillet	Line and small fillet	Arc and small fillet	Irregular	Curve
Bottom Shape	Line and no fillet	Arc and no fillet	Line and small fillet	Arc and small fillet	Irregular	Curve
Side Shape (x_7)	Trapezoidal rear	Rounded end	Parallelogram	Bowed	Trapezoid fore	Polygonal
Function Button Shape	Round	Square and round inner	Small squares	Large square	Wide large	Other Shape
Number Buttons Style	Regular grid	Shaped grid	Bars	One piece	Other style	No Number buttons
Screen size (x_6)	≦2.2 in	2.4-2.8 in	≧ 3 in			
Thickness (x_4)	≦10 mm	11-14 mm	15-18 mm	≧19 mm		
Layout	Bar	Slide	Large screen	Other Layout		
Weight (x_1)	≦80g	83-100 g	101-120 g	125-140 g	141-149 g	≧ 150 g

optimisation model. The first objective function is to maximise customer satisfaction in QFD. Considering the importance of customer requirements as shown in Figure 2, the objective function is formulated by linearly combining the two customer satisfaction models (6) and (7), respectively, for 'comfortable to hold' and 'easy to use'. Since the importance weights of 'comfortable to hold' and 'easy to use' are 3 and 5, respectively, the first objective function can be formulated as follows:

$$\begin{aligned} F_1 = 3 \times \{ & \left(14.9991, 2.8422 \times 10^{-14}\right) + \left(-1.5036, 2.8422 \times 10^{-14}\right)x_3 + (-0.2890, 0)x_4 \\ & + \left(-0.3634, 5.6843 \times 10^{-14}\right)x_1 + (0.0045, 0.0077)x_1x_2\} + 5 \\ & \times \{(-9.2351, 0) + (-1.1582, 0.2120)x_6^2 + (-0.1594, 0.0437)x_5x_6 + (8.3566, 0)x_6\} \end{aligned} \quad (10)$$

The second and the third objective functions are the generated customer satisfaction models of H–B and S–C, respectively, which are expressed as (8) and (9), respectively.

Three constraints are involved in the formulation of the multi-objective optimisation model. The first constraint is the data type of the design variables. Among the seven design variables, x_1, x_2, x_3, x_4 and x_6 are quantitative variables, which are real numbers. x_5 and x_7 are categorical variables, which are integers. The second constraint is the ranges of the design variables, which are [78, 165], [90, 120], [43.5, 62.1], [9.9, 16], [2, 5], [1.8, 3.5], and [1, 6] for x_1, x_2, x_3, x_4, x_5, x_6 and x_7, respectively. The third constraint is the technical correlation among the design variables. As shown in the

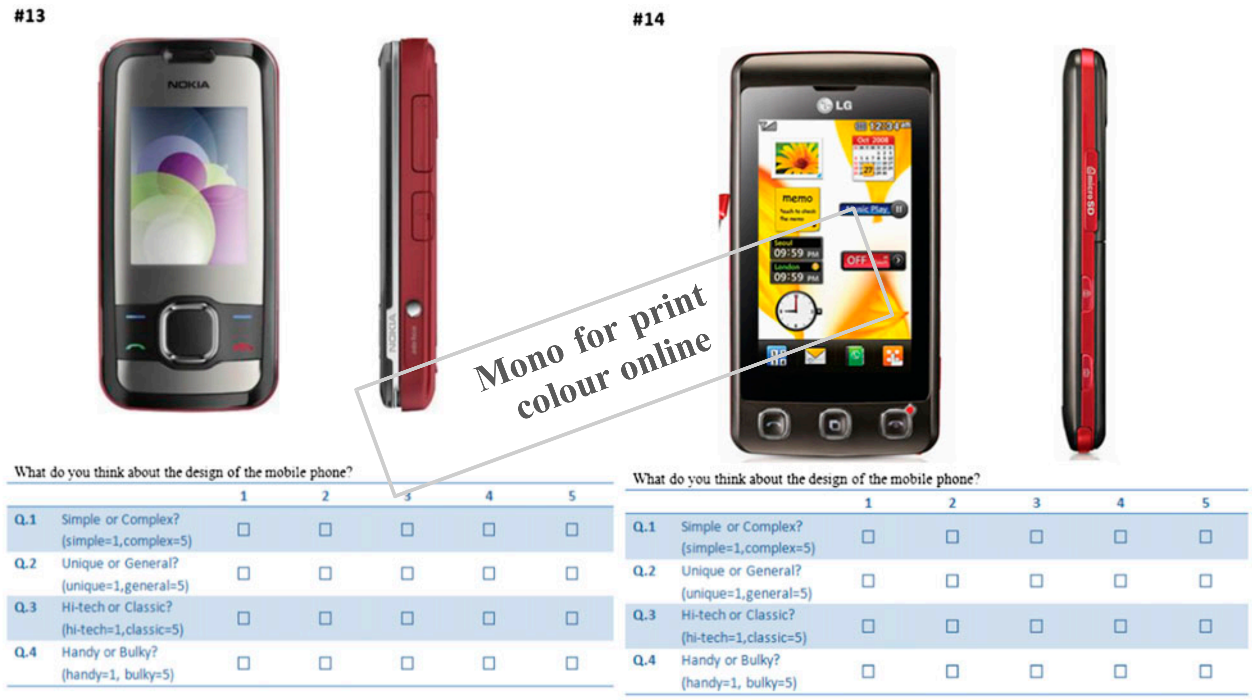

Figure 3. A part of survey questionnaire.

HoQ of Figure 2, screen size x_6 has technical correlations with the weight x_1 and width x_3. Statistical regression (SR) was applied to model the relationship between x_6 and x_1, x_3. The confidence interval in SR was set as 95%. The generated correlation model is shown below.

$$x_6 = -1.5090 + 0.0048x_1 + 0.0670x_3 \tag{11}$$

After formulating the multi-objective optimisation model, a chaos-based NSGA-II approach was introduced to determine the optimal settings of the engineering requirements and design attributes for mobile phone design. In this study, the population size N was set as 100. The distribution index for crossover η_c and mutation η_m was both set as 20. The crossover probability and mutation probability were set as 0.9 and 0.1, respectively. The above parameter settings, suggested by Deb et al. (2002), have been adopted widely by other researchers. The tournament size and the size of the mating pool are commonly set as 2 and one half of the population size, respectively. The number of generations was set as 100 and the iteration number of COA was set as 200 through the repeated operations to ensure that the least running time and optimal solutions are obtained. The proposed chaos-based NSGA-II approach was implemented using Matlab software. Figure 4 shows the Pareto optimal solutions of the multi-objective optimisation problem solved by the chaos-based NSGA-II approach.

The Pareto front contains a total number of 100 non-dominated solutions, namely all individuals in the population. Each optimal solution contains settings of the engineering requirements and design attributes. Decision-makers can choose their optimal solutions according to various scenarios. In this research, the solution with the largest sum of the values of the four dimensions of customer satisfaction, namely the largest total customer satisfaction value, is recommended to be the optimal solution. The optimal settings of the design attributes and engineering requirements of a new mobile phone, as well as the customer satisfaction values, can be obtained as shown in Table 2.

6. Validation

In order to evaluate the effectiveness of the proposed methodology, a validation test was conducted. In the test, two optimisation models were formulated based on the standalone QFD and the standalone affective design, respectively. Then, the two optimisation models were solved using chaos-based NSGA-II approach, from which optimal settings of the engineering requirements and design attributes can be obtained. The parameter settings of the chaos-based NSGA-II used in the three optimisation models, respectively, based on the proposed methodology, the standalone QFD and the

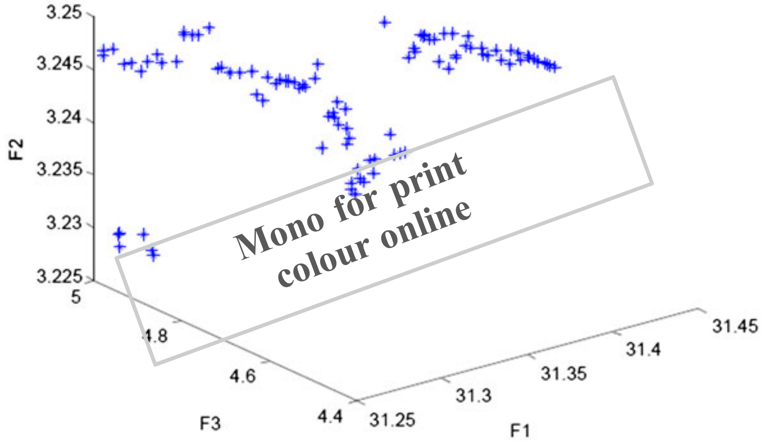

Figure 4. Pareto solutions based on chaos-based NSGA-II.

Table 2. Optimisation results based on the proposed methodology.

Design variables (units)	Settings
Weight x_1 (g)	78
Height x_2 (mm)	119.99
Width x_3 (mm)	57.62
Thickness x_4 (mm)	9.9
Menu layers x_5	2
Screen size x_6 (in)	2.73
Side shape x_7	3rd alternative
Customer satisfaction	
Comfortable to hold	3.64
Easy to use	4.08
Handy–bulky (H–B)	3.25
Simple–complex (S–C)	4.99

standalone affective design are all the same. The customer satisfaction values obtained based on the proposed methodology were then compared with those based on the standalone QFD and the standalone affective design.

5.1 *Design optimisation based on the standalone QFD and the standalone affective design*

To formulate an optimisation model based on the standalone QFD, Equations (10) and (11) were set as the objective function and a constraint, respectively. The optimisation problem is a single objective one. Figure 5 shows the searching values of the objective function based on 100 generations.

From the figure, it can be observed that the value of the objective function reaches a maximum value at the 54th generation and remains the same in the following generations. After solving, an optimal setting of the engineering requirements for maximising total customer satisfaction value based on the standalone QFD is obtained. The setting and the customer satisfaction values of 'comfortable to hold' and 'easy to use' are shown in the second column of Table 3.

To formulate an optimisation model for the standalone affective design, Equations (8) and (9) were adopted as objective functions. The optimisation model is a multi-objective one. The third column of Table 3 shows the optimal setting of the design attributes for maximising the total customer satisfaction value.

From Table 3, it can be observed that the customer satisfaction value of 'easy to use' based on the standalone QFD is higher than that based on the proposed methodology, while the value of 'comfortable to hold' based on the standalone QFD is smaller. The sum of the customer satisfaction values of 'comfortable to hold' and 'easy to use' based on the proposed methodology is slightly higher than that based on the standalone QFD, which are 7.72 and 7.55, respectively. By comparing the optimisation results based on the standalone affective design with those based on the proposed methodology, it can be seen that the customer satisfaction value of H–B based on the standalone affective design is higher

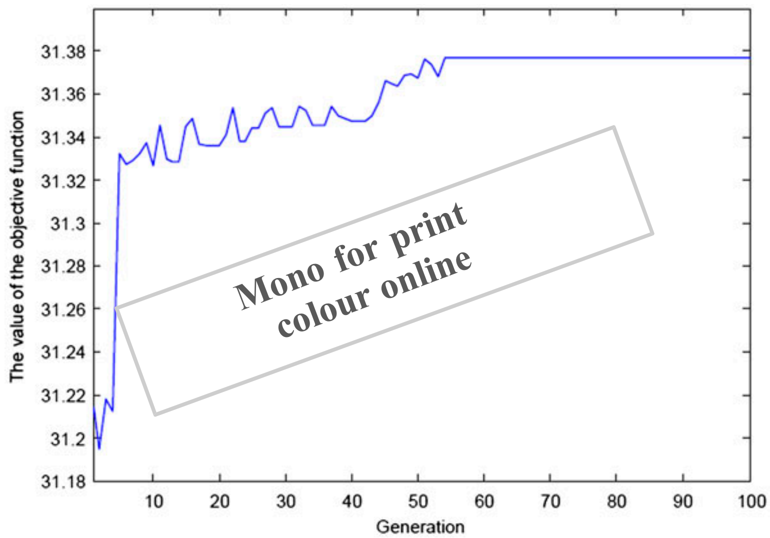

Figure 5. The searching results for the standalone QFD.

Table 3. Comparison of optimisation results based on the standalone QFD, the standalone affective design and the proposed methodology.

		The standalone QFD	The standalone affective design	The proposed methodology
Design variables (units)	Weight x_1 (g)	78.33	79.2	78
	Height x_2 (mm)	119.64	N/A	119.99
	Width x_3 (mm)	60.48	N/A	57.62
	Thickness x_4 (mm)	9.91	15.44	9.9
	Menu layers x_5	2	N/A	2
	Screen size x_6 (in)	2.92	2.13	2.73
	Side shape x_7	N/A	5th alternative	3rd alternative
Customer satisfaction	Comfortable to hold	3.19	N/A	3.64
	Easy to use	4.36	N/A	4.08
	Handy–bulky (H–B)	N/A	4.97	3.25
	Simple–complex (S–C)	N/A	3.5	4.99

than that based on the proposed methodology, while the customer satisfaction value of S–C based on the standalone affective design is smaller than that based on the proposed methodology. The sum of the customer satisfaction values of H–B and S–C based on the standalone affective design is higher than that based on the proposed methodology, which are 8.47 and 8.24, respectively.

5.2 *Validation test*

From Table 3, it can be noted that there are two different settings of x_1, x_4 and x_6 based on the standalone QFD and the standalone affective design. Engineers and designers, who are responsible for defining engineering specifications and affective design, respectively, need to compromise the differences of the settings. In this case study, different scenarios of the compromise in terms of ratios of the settings based on the standalone QFD and the settings based on the standalone affective design were studied, which are 0.3:0.7, 0.7:0.3, 0.5:0.5, 0.4:0.6, and 0.6:0.4. Taking the ratio 0.3:0.7 as an example, the compromised settings of x_1, x_4 and x_6 are calculated as follows:

$$x_1' = 0.3 \times 78.33 + 0.7 \times 79.2 = 78.94g \tag{12}$$

$$x'_4 = 0.3 \times 9.91 + 0.7 \times 15.44 = 13.78mm \quad (13)$$

$$x'_6 = 0.3 \times 2.92 + 0.7 \times 2.13 = 2.37in \quad (14)$$

where x'_1, x'_4, and x'_6 refer to the compromised settings of x_1, x_4, and x_6 respectively.

Similarly, the compromised settings of x'_1, x'_4, and x'_6 for the other ratios can be calculated as shown in Table 4. Based on the compromised settings, the customer satisfaction values for ‘comfortable to hold’, ‘easy to use’, H–B, and S–C are calculated again using (6), (7), (8) and (9), respectively. The customer satisfaction values obtained based on the combined standalone QFD and standalone affective design with compromised settings, and the proposed methodology are compared in Table 4.

From the table, it can be observed that the customer satisfaction values of ‘comfortable to hold’, ‘easy to use’, H–B, and S–C based on the proposed methodology are higher than those based on the combined standalone QFD and standalone affective design method. The total customer satisfaction value based on the proposed methodology is 35.6, 11.92, 30.29, 34.23 and 24.4%, respectively higher than that based on the combined method with the ratios of 0.3:0.7, 0.7:0.3, 0.5:0.5, 0.4:0.6, and 0.6:0.4.

6. Discussion

The proposed methodology provides a scientific and systematic way to determine the optimal settings of the design attributes and engineering requirements with simultaneous consideration of affective design and the determination of engineering specifications. The Pareto optimal solutions can be generated based on the proposed methodology. Thus, product development teams can select solutions in view of different scenarios, such as high simplicity and high quality. The methodology can help reduce product development time, improve the attractiveness of new products and reduce possible conflicts between engineers and designers in determining the settings of particular design variables. Although, in this paper, a case study of mobile phone design was used to demonstrate the proposed methodology, the methodology is generic and can be applied to the design of different kinds of products, such as household appliance and furniture, where affective design of products plays an important role in influencing decisions on choice by consumers. However, the proposed methodology has some limitations. The predefined number of generations was adopted as the stopping criterion for the chaos-based NSGA-II approach. Single objective optimisation can be terminated when its convergence remains stable over several generations and a satisfactory solution is obtained. However, the determination of proper trade-off solutions among multi-objective functions is difficult. A higher maximum number of generations can be adopted to ensure the convergence, but it requires a longer computational time. On the other hand, the proposed

Table 4. Comparison of results.

	Ratios for compromised settings	The combined standalone QFD and standalone affective design 0.3:0.7	0.7:0.3	0.5:0.5	0.4:0.6	0.6:0.4	The proposed methodology of simultaneous consideration of affective design and engineering specifications
Design variables (units)	Weight x_1 (g)	78.94	78.59	78.77	78.85	78.68	78
	Height x_2 (mm)	119.64	119.64	119.64	119.64	119.64	119.99
	Width x_3 (mm)	60.48	60.48	60.48	60.48	60.48	57.62
	Thicknessx_4(mm)	13.78	11.57	12.68	13.23	12.12	9.9
	Menu layers x_5	2	2	2	2	2	2
	Screen sizex_6 (in)	2.37	2.68	2.53	2.45	2.6	2.73
	Side shape x_7	5th alternative	5th alternative	5th alternative	5th alternative	5th alternative	3rd alternative
Customer satisfaction	Comfortable to hold	3.06	3.14	3.1	3.08	3.12	3.64
	Easy to use	3.31	3.99	3.69	3.51	3.83	4.08
	Handy–bulky	2.97	2.31	2.38	2.61	2.28	3.25
	Simple–complex	2.43	4.82	3.08	2.69	3.6	4.99
	Total customer satisfaction value	11.77	14.26	12.25	11.89	12.83	15.96

methodology may not be suitable for the design of breakthrough new products as very few or even no competitive products can be identified.

7. Conclusion

This paper proposes and describes a methodology of simultaneous consideration of affective design and the determination of engineering specifications to determine design attribute settings and engineering requirement settings for a new product. The proposed methodology mainly involves the generation of two types of customer satisfaction models, respectively, based on QFD and affective design, as well as formulation of a multi-objective optimisation model. A chaos-based NSGA-II approach is proposed to solve the optimisation problem by which optimal settings of engineering requirements and design attributes for a new product can be determined.

A case study of mobile phone design was conducted to evaluate the proposed methodology. A multi-objective optimisation model was formulated based on the four customer satisfaction models, which are for ‘comfortable to hold’, ‘easy to use’, H–B and S–C, respectively. Optimal settings of the engineering requirements and design attributes were determined based a chaos-based NSGA-II approach. Validation test was conducted to evaluate the effectiveness of the proposed methodology. Determination of optimal settings of the engineering requirements based on the standalone QFD and determination of optimal settings of the design attributes based on the standalone affective design are described. The customer satisfaction values obtained from the proposed methodology are compared with those based on the combined standalone QFD and standalone affective design method. The validation results indicate that higher customer satisfaction values can be obtained based on the proposed methodology.

In the development of the proposed methodology, it is assumed that the perceptions, needs and desires of customers regarding particular products are static. In reality, they could be quite dynamic. Future work could consider dynamic effects in the simultaneous consideration of affective design and the determination of engineering specifications. Furthermore, the methodology can be further extended to perform product line design, which involves the design of various product variants in a product line to satisfy the needs of various market segments.

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References

Abu-Assab, S., and D. Baier. 2010. “Designing Products Using Quality Function Deployment and Conjoint Analysis: A Comparison in a Market for Elderly People.” In *Advances in Data Analysis, Data Handling and Business Intelligence Studies in Classification, Data Analysis, and Knowledge Organization*, edited by A. Fink, B. Lausen, W. Seidel, and A. Ultsch, 515–526. Berlin: Springer.

Aktar Demirtas, E., A. S. Anagun, and G. Koksal. 2009. “Determination of Optimal Product Styles by Ordinal Logistic Regression Versus Conjoint Analysis for Kitchen Faucets.” *International Journal of Industrial Ergonomics* 39 (5): 866–875.

Bai, H., and C. K. Kwong. 2003. “Inexact Genetic Algorithm Approach to Target Values Setting of Engineering Requirements in QFD.” *International Journal of Production Research* 41 (16): 3861–3881.

Barnes, C., and S. P. Lillford. 2007. “Affective Design Decision-Making – Issues and Opportunities.” *CoDesign* 3 (sup1): 135–146.

Barnes, C., and S. P. Lillford. 2009. “Decision Support for the Design of Affective Products.” *Journal of Engineering Design* 20 (5): 477–492.

Barone, S., A. Lombardo, and P. Tarantino. 2007. “A Weighted Logistic Regression for Conjoint Analysis and Kansei Engineering.” *Quality and Reliability Engineering International* 23 (6): 689–706.

Chan, K. Y., C. K. Kwong, T. S. Dillon, and K. Y. Fung. 2011. “An Intelligent Fuzzy Regression Approach for Affective Product Design That Captures Nonlinearity and Fuzziness.” *Journal of Engineering Design* 22 (8): 523–542.

Chan, K. Y., C. K. Kwong, and T. C. Wong. 2011. “Modelling Customer Satisfaction for Product Development Using Genetic Programming.” *Journal of Engineering Design* 22 (1): 55–68.

Chang, C. C. 2008. “Factors Influencing Visual Comfort Appreciation of the Product Form of Digital Cameras.” *International Journal of Industrial Ergonomics* 38 (11–12): 1007–1016.

Chen, L. H., and W. C. Ko. 2009. “Fuzzy Approaches to Quality Function Deployment for New Product Design.” *Fuzzy Sets and Systems* 160 (18): 2620–2639.

Chen, C. H., L. P. Khoo, and W. Yan. 2006. “An Investigation into Affective Design Using Sorting Technique and Kohonen Self-Organising Map.” *Advances in Engineering Software* 37 (5): 334–349.

Chen, Y., J. Tang, R. Y. K. Fung, and Z. Ren. 2004. “Fuzzy Regression-Based Mathematical Programming Model for Quality Function Deployment.” *International Journal of Production Research* 42 (5): 1009–1027.

Chuang, M. C., and Y. C. Ma. 2001. “Expressing the Expected Product Images in Product Design of Micro-Electronic Products.” *International Journal of Industrial Ergonomics* 27 (4): 233–245.

Cong, S., G. Li, and X. Feng. 2010. “An Improved Algorithm of Chaos Optimization..” Proceedings of the 8th IEEE International Conference on Control and Automation, Xiamen, June 9–11.

Dawson, D., and R. G. Askin. 1999. “Optimal New Product Design Using Quality Function Deployment with Empirical Value Functions.” *Quality and Reliability Engineering International* 15 (1): 17–32.

Deb, K., A. Pratap, S. Agarwal, and T. Meyarivan. 2002. “A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II.” *IEEE Transactions on Evolutionary Computation* 6 (2): 182–197.

Deng, W. J., and W. Pei. 2009. “Fuzzy Neural Based Importance-Performance Analysis for Determining Critical Service Attributes.” *Expert Systems with Applications* 36 (2): 3774–3784.

Fung, C. K. Y., C. K. Kwong, K. Y. Chan, and H. Jiang. 2014. “A Guided Search Genetic Algorithm Using Mined Rules for Optimal Affective Product Design.” *Engineering Optimization* 46 (8): 1094–1108.

Fung, K. Y., C. K. Kwong, K. W. M. Siu, and K. M. Yu. 2012. “A Multi-Objective Genetic Algorithm Approach to Rule Mining for Affective Product Design.” *Expert Systems with Applications* 39 (8): 7411–7419.

Fung, R., D. Law, and W. Ip. 1999. “Design Targets Determination for Inter-Dependent Product Attributes in QFD Using Fuzzy Inference.” *Integrated Manufacturing System* 10 (6): 376–383.

Fung, R. Y. K., K. Popplewell, and J. Xie. 1998. “An Intelligent Hybrid System for Customer Requirements Analysis and Product Attribute Targets Determination.” *International Journal of Production Research* 36 (1): 13–34.

Fung, R. Y. K., J. Tang, Y. Tu, and D. Wang. 2002. “Product Design Resources Optimization Using a Non-Linear Fuzzy Quality Function Deployment Model.” *International Journal of Production Research* 40 (3): 585–599.

Hartono, M., T. K. Chuan, S. Ishihara, and J. B. Peacock. 2012. “Incorporating Markov Chain Modelling and QFD into Kansei Engineering Applied to Services.” *International Journal of Human Factors and Ergonomics* 1 (1): 74–97.

Hong, S. W., S. H. Han, and K. J. Kim. 2008. “Optimal Balancing of Multiple Affective Satisfaction Dimensions: A Case Study on Mobile Phones.” *International Journal of Industrial Ergonomics* 38 (3–4): 272–279.

Hsiao, S. W., and H. C. Tsai. 2005. “Applying a Hybrid Approach Based on Fuzzy Neural Network and Genetic Algorithm to Product from Design.” *International Journal of Industrial Ergonomics* 35 (5): 411–428.

Jiang, H. M., C. K. Kwong, W. H. Ip, and T. C. Wong. 2012. “Modeling Customer Satisfaction for New Product Development Using a PSO-Based ANFIS Approach.” *Applied Soft Computing* 12 (2): 726–734.

Jiang, Huimin, C. K. Kwong, W. H. Ip, and Zengqiang Chen. 2013. “Chaos-Based Fuzzy Regression Approach to Modeling Customer Satisfaction for Product Design.” *IEEE Transactions on Fuzzy Systems* 21 (5): 926–936. AQ2

Jiao, J. R., Y. Zhang, and M. Helander. 2006. “A Kansei Mining System for Affective Design.” *Expert Systems with Applications* 30 (4): 658–673.

Jindo, T., and K. Hirasago. 1997. “Application Studies to Car Interior of Kansei Engineering.” *International Journal of Industrial Ergonomics* 19 (2): 105–114.

Kahraman, C., T. Ertay, and G. Buyukozkan. 2006. “A Fuzzy Optimization Model for QFD Planning Process Using Analytic Network Approach.” *European Journal of Operational Research* 171 (2): 390–411.

Kim, K. J., H. Moskowitz, A. Dhingra, and G. Evans. 2000. “Fuzzy Multicriteria Models for Quality Function Deployment.” *European Journal of Operational Research* 121 (3): 504–518.

Kim, K., and T. Park. 1998. “Determination of an Optimal Set of Design Requirements Using House of Quality.” *Journal of Operations Management* 16 (5): 569–581.

AQ3 Kusiak, A. 1999. *Engineering Design: Products, Processes and Systems*. FL: Academic Press.

Kwong, C. K., Y. Chen, K. Y. Chan, and X. Luo. 2010. “A Generalized Fuzzy Least- Squares Regression Approach to Modeling Functional Relationships in QFD.” *Journal of Engineering Design* 21 (5): 601–613.

Kwong, C. K., T. C. Wong, and K. Y. Chan. 2009. “A Methodology of Generating Customer Satisfaction Models for New Product Development Using a Neuro-Fuzzy Approach.” *Expert Systems with Applications* 36 (8): 11262–11270.

Lai, H. H., Y. M. Chang, and H. C. Chang. 2005. “A Robust Design Approach for Enhancing the Feeling Quality of a Product: A Car Profile Case Study.” *International Journal of Industrial Ergonomics* 35 (5): 445–460.

Lai, H. H., Y. C. Lin, and C. H. Yeh. 2005. “Form Design of Product Image Using Grey Relational Analysis and Neural Network Models.” *Computers & Operations Research* 32 (10): 2689–2711.

Lau, T. W., P. C. L. Hui, F. S. F. Ng, and K. C. C. Chan. 2006. “A New Fuzzy Approach to Improve Fashion Product Development.” *Computers in Industry* 57 (1): 82–92.

Lin, Y. C., H. H. Lai, and C. H. Yeh. 2007. “Consumer-Oriented Product Form Design Based on Fuzzy Logic: A Case Study of Mobile Phones.” *International Journal of Industrial Ergonomics* 37 (6): 531–543.

Nagamachi, M. 1995. “Kansei Engineering: A New Ergonomic Consumer-Oriented Technology for Product Development.” *International Journal of Industrial Ergonomics* 15 (1): 3–11.

Nagamachi, M. 2008. "Perspectives and the New Trend of Kansei/Affective Engineering." *The TQM Journal* 20 (4): 290–298.

Noble, C. H., and M. Kumar. 2008. "Using Product Design Strategically to Create Deeper Consumer Connections." *Business Horizons* 51 (5): 441–450.

Orsborn, S., J. Cagan, and P. Boatwright. 2009. "Quantifying Aesthetic Form Preference in a Utility Function." *Journal of Mechanical Design* 131 (6): 061001-1–061001-10.

Park, J., and S. H. Han. 2004. "A Fuzzy Rule-Based Approach to Modeling Affective User Satisfaction towards Office Chair Design." *International Journal of Industrial Ergonomics* 34 (1): 31–47.

Schütte, S. 2002. "Design Feelings into Products: Integrating Kansei Engineering Methodology in Product Development." PhD diss., Linkopings universitet.

Sekkeli, G., G. Koksal, I. Batmaz, and O. T. Bayrak. 2010. "Classification Models Based on Tanaka's Fuzzy Linear Regression Approach: The Case of Customer Satisfaction Modeling." *Journal of Intelligent & Fuzzy Systems* 21 (5): 341–351.

Sener, Z., and E. E. Karsak. 2010. "A Fuzzy Regression and Optimization Approach for Setting Target Levels in Software Quality Function Deployment." *Software Quality Journal* 18 (3): 323–339.

Sener, Z., and E. E. Karsak. 2011. "A Combined Fuzzy Linear Regression and Fuzzy Multiple Objective Programming Approach for Setting Target Levels in Quality Function Deployment." *Expert Systems with Applications* 38 (4): 3015–3022.

Shi, L., S. Olafsson, and Q. Chen. 2001. "An Optimization Framework for Product Design." *Management Science* 47 (12): 1681–1692.

Sun, N., X. Mei, and Y. Zhang. 2009. "A Simplified Systematic Method of Acquiring Design Specifications from Customer Requirements." *Journal of Computing and Information Science in Engineering* 9 (3): 031004-1–031004-10.

Vonderembse, M. A., and T. S. Raghunathan. 1997. "Quality Function Deployment's Impact on Product Development." *International Journal of Quality Science* 2 (4): 253–271.

Wasserman, G. S. 1993. "On How to Prioritize Design Requirements During the QFD Planning Process." *IIE Transactions* 25 (3): 59–65.

Withanage, C., T. Park, and H. J. Choi. 2010. "A Concept Evaluation Method for Strategic Product Design with Concurrent Consideration of Future Customer Requirements." *Concurrent Engineering* 18 (4): 275–289.

Withanage, C., T. Park, T. T. H. Duc, and H. J. Choi. 2012. "Dynamic Partial Least Square Path Modeling for the Front-End Product Design and Development." *Journal of Mechanical Design* 134 (10): 100907-1–100907-14.

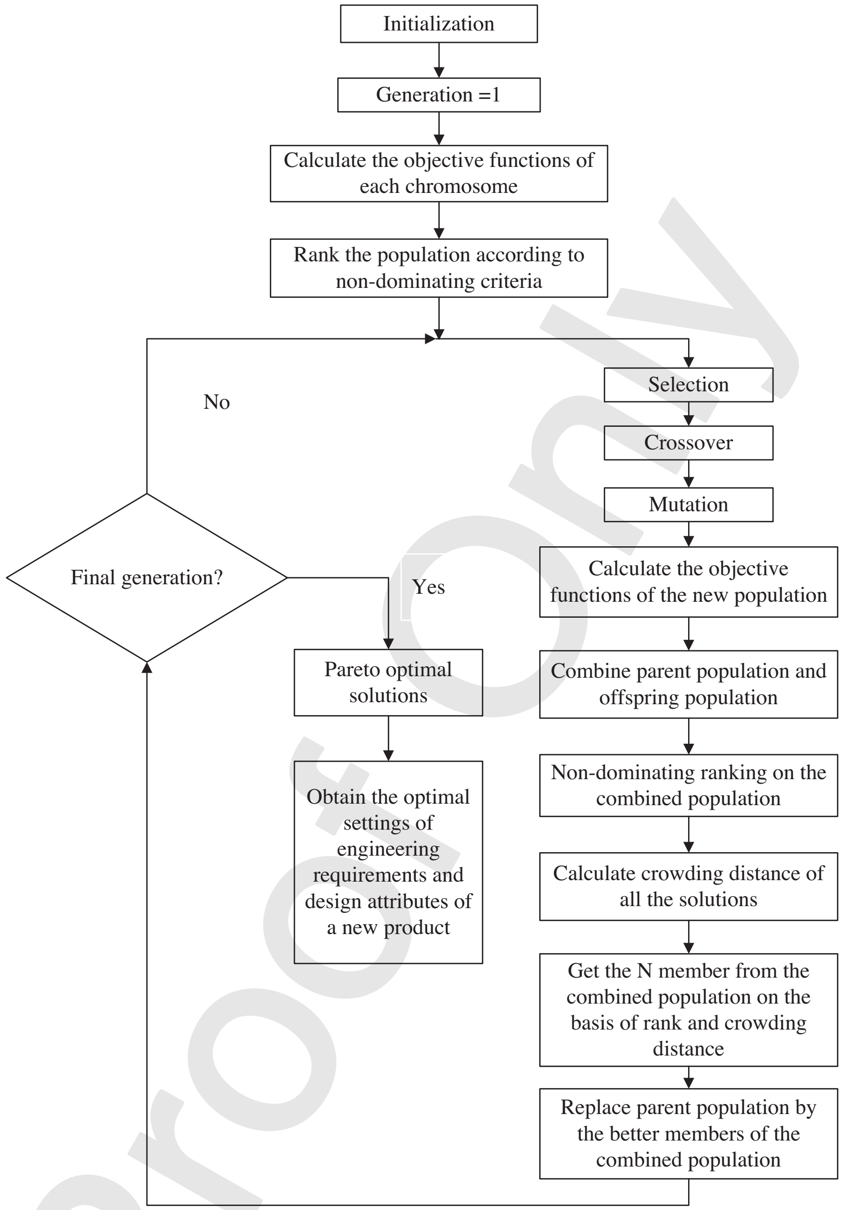
Yang, C. C., and M. D. Shieh. 2010. "A Support Vector Regression Based Prediction Model of Affective Responses for Product Form Design." *Computers & Industrial Engineering* 59 (4): 682–689.

Zhai, L. Y., L. P. Khoo, and Z. W. Zhong. 2009. "A Rough Set Based Decision Support Approach to Improving Consumer Affective Satisfaction in Product Design." *International Journal of Industrial Ergonomics* 39 (2): 295–302.

Zhang, X. P., J. Bode, and S. J. Ren. 1996. "Neural Networks in Quality Function Deployment." *Computer & Industrial Engineering* 31 (3–4): 669–673.

Zhou, M. 1998. "Fuzzy Logic and Optimization Models for Implementing QFD." *Computers & Industrial Engineering* 35 (1–2): 237–240.

Appendix 1



Appendix 2. Adaptive chaos search

COA is a stochastic search algorithm in which chaos is introduced into the optimisation strategy to accelerate the optimum seeking operation and find the global optimal solution (Cong, Li, and Feng 2010). COA employs chaotic dynamics to solve optimisation problems. In the optimisation process, the carrier wave method is used in linearly mapping the chosen chaos variables to the space of optimisation variables, and then the optimal solutions are searched based on the ergodicity of the chaos variables. The logistic model used in chaos optimisation is shown in (A1), and the logistic mapping can generate chaos variables by iteration.

$$c_{n+1} = f(c_n) = \mu c_n (1 - c_n) \tag{A1}$$

where $\mu = 4$ and $c_n \in [0, 1]$ is the nth iteration value of the chaos variable c.

COA is incorporated into the process of NSGA-II for two purposes: initialization and refining the search range to conduct narrow searching. The initialization of population P_1 is conducted by COA. Chaos variables c_{ij}, $1 \le i \le N$, $\le j \le V$, are generated using (A1), where N is the population size and V is the number of design variables. The individuals x_{ij} in P_1 are initialized by mapping the generated chaos variables into the ranges of the design variables using (A2).

$$x_{ij} = x_{j\min} + (x_{j\max} - x_{j\min}) \cdot c_{ij} \tag{A2}$$

where $x_{j\min}$ and $x_{j\max}$. are the minimum and maximum values of the jth design variable, respectively.

To avoid converging prematurely in the process of NSGA-II, COA is introduced to facilitate the algorithm to further search in the new ranges which are adjusted adaptively based on the current population. The range of the design variables j is adjusted to be $[x'_{j\min}, x'_{j\max}]$ as follows:

$$\begin{cases} x'_{j\min} = \hat{x}_{ij} - \gamma(x_{j\max} - x_{j\min}) \\ x'_{j\max} = \hat{x}_{ij} + \gamma(x_{j\max} - x_{j\min}) \end{cases} \tag{A3}$$

where $\hat{x}_{ij}$ is the best individual which has the largest crowding distance in the first front F_1 of the current population, and γ is the constriction factor that is usually set as 0.5.

In order to avoid values of $x'_{j\min}$ and $x'_{j\max}$ exceeding the range $[x_{j\min}, x_{j\max}]$, the following examination is performed.

If $x'_{j\min} < x_{j\min}$, then $x'_{j\min} = x_{j\min}$; if $x'_{j\max} > x_{j\max}$, then $x'_{j\max} = x_{j\max}$

The chaos variables c_{ij} generated based on (A1) are mapped into the new ranges as follows:

$$x'_{ij} = x'_{j\min} + (x'_{j\max} - x'_{j\min}) \cdot c_{ij} \tag{A4}$$

The new individuals are obtained by linearly combining the generated x'_{ij} and the individuals x_{ij} in the current population as follows:

$$x''_{ij} = (1 - \mu)x'_{ij} + \mu x_{ij} \tag{A5}$$

where μ is the adaptive adjustment parameter and can be calculated by Equation (A6).

$$\mu = 1 - \left(\frac{k-1}{k}\right)^M \tag{A6}$$

where k is the iteration number of COA and M is the number of objective functions.

Algorithms of chaos-based NSGA-II

The algorithms of the proposed chaos-based NSGA-II are as follows:

Step 1: The initialization of the parameters is first conducted, including the population size N, the number of generations, the distribution index for crossover η_c, the crossover probability, the distribution index for mutation η_m, the mutation probability, the size of the mating pool, the tournament size and the iteration number of COA. The description of objective functions is given, such as the number of objective functions M, the number of design variables V, and the range of the design variables j, $[x_{j\min}, x_{j\max}]$, $1 \le j \le V$.

Step 2: A parent population P_1 is initialized based on COA using (A1) and (A2). The values of the objective functions of each individual are calculated. The parent population P_1 is then sorted based on non-domination, and the crowding distances are calculated for each individual. The generation is set as $t = 1$.

Step 3: The crowded tournament selection is applied to create a mating population. In the selection process, two individuals from the parent population P_t are selected at random for a tournament. The winners chosen are inserted in the mating pool for reproduction and the selection is repeated until the size of the mating pool reaches the predefined value.

Step 4: The SBX operator and the polynomial mutation are conducted in the mating pool to create the offspring population Q_t.

Step 5: A combined population R_t is generated by combining the parent population P_t and the offspring population Q_t, $R_t = P_t \cup Q_t$.

Step 6: The combined population R_t is sorted based on non-domination, and different fronts F_i, $i = 1, \cdots$, are identified. The new population P_{t+1} with size N is obtained based on the process of combination and selection.

Step 7: In the new population P_{t+1}, the number of individuals that belong to the first front F_1 is calculated. If the number is less than the population size N, it indicates the current population is not the optimal population, and the COA is then executed. The population in COA is initialized by $P_C^1 = P_{t+1}$, and the iteration starts from $k = 1$. The first 10% of individuals in P_C^k are updated by the new individuals. The new ranges are defined using (A3) and the new individuals are generated using (A4), (A5) and (A6). The updated P_C^k is sorted based on non-domination, then Steps 3–6 are performed and the new population P_C^{k+1} is obtained. The iteration continues by $k + 1 \rightarrow k$ till the predefined iteration number of COA is reached. The population P_{t+1} is updated by the final population generated from COA.

Step 8: The generation counter is increased by $t + 1 \rightarrow t$. The algorithm is again executed from Step 3 and it stops after the number of generations reaches the predefined value. Finally, the Pareto front is obtained and the individuals belonging to the Pareto front are the optimal settings of the design attributes and engineering requirements.