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AI-based methodology of integrating affective design, engineering, and marketing for defining design specifications of new products

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Abstract

In the early stage of product design, particularly for consumer products, affective design, engineering, and marketing issues must be taken into considerationand they are commonly performed respectively by product designers, engineers, and marketing personnel. However, they have different concerns and focuses with regard to the new product design. Thus, these three processes are commonly conducted separately, leading to a sub-optimal and even sub-standard design. Such scenario indicates the need to incorporate the concerns of the three processes in the early stage of product design. However, no study has explored the incorporation of the concerns of the three processes into the product design. In this paper, an artificial intelligence (AI)-based methodology for integrating affective design, engineering, and marketing for defining design specifications of new products is proposed by which the concerns of the three processes can be considered simultaneously in the early design stage. The proposed methodology mainly involves development of customer satisfaction and cost models using fuzzy regression, generation of product utility functions using chaos-based fuzzy regression, formulation of a multi-objective optimization model and its solving using a non-dominated sorting genetic algorithm-Ⅱ (NSGA-Ⅱ). A case study was conducted for electric iron design to evaluate the effectiveness of the proposed methodology.

Key words: Affective design, Marketing, NSGA-II, Fuzzy regression, Chaos optimization algorithm

1. Introduction

Affective design, engineering, and marketing concerns are always considered in the early design stage of consumer products. Affective design is commonly performed by product designers, which is about the analysis of customer reactions toward candidate designs and the quantification of such reactions and their integration into physical product design parameters for maximizing customer affective satisfaction on the new product to be developed (Barnes and Lillford, 2009). It can help designers generate designs that better appeal to the markets. Affective design has been shown to excite customers' psychological feelings and can help improve customer satisfaction in terms of emotional aspects. It involves the processes of identifying, measuring, analyzing, and understanding the relationship between the affective needs of the customer domain and the perceptual design attributes in the design domain (Lai et al., 2005a). Design attributes, such as shape and color, 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 (Creusen and Schoormans, 2005; Noble and Kumar, 2008).

Various engineering concerns have to be considered by design engineers during the product development stage such as product functionality, technical specification, structural performance, material selection and design for manufacture. Among the engineering concerns, one of the major concerns that needs to be addressed in the early product design stage is to define technical specifications of new products such that customer satisfaction on the new products can be maximized. To define the specifications, design engineers have to consider various issues, such as engineering performance of competitive products and difficulties in attaining high target values of engineering requirements. Competitive product benchmarks are commonly used to help determine the technical specifications of new products in industries. On the other hand, various marketing concerns relating to new product development, such as market opportunities, new product positioning, competitors' performance, price positioning, and customer needs, have to be considered by marketing personnel in the early product design stage who are mainly concerned with the market share, profit and degree of customer satisfaction to be obtained by launching a new product (Crawford and Benedetto, 2006; Luo et al., 2005). Therefore, product designers, engineers, and marketing personnel have different goals and concerns with regard to new product development and some of their concerns are interrelated. For example, in the determination of the screen size of a new smartphone, the product designer considers the issues of portability, ergonomics and user-interface and subsequently, sets the screen size as 4.5 inches. Marketing personnel found that their new smartphones with screen size 5 inches are essential to compete with the competitive smartphones, whereas the design engineer considers the constraints of product cost and weight and concludes that the screen size should be set as 4 inches. In view of the different concerns of designers, marketing staff and engineers, therefore, a coordinating mechanism / framework or a methodology for the simultaneous consideration of their concerns is required in the early product design stage such that the best setting of design variables can be determined. However, no previous study has proposed such framework or methodology. To fill the research gap, an artificial intelligence (AI)-based methodology for integrating the affective design, engineering, and marketing for defining design specifications of new products is proposed by which the concerns of affective design, engineering, and marketing can be considered simultaneously in the early product design stage. The proposed methodology mainly involves a fuzzy regression (FR) approach for modeling customer satisfaction and developing cost models, a chaos-based FR approach for generating product utility functions, and a non-dominated sorting genetic algorithm-II (NSGA-II) for solving multi-objective optimization problems. The rest of this paper is organized as follows. A review of related research is presented in Section 2. The proposed methodology is described in Section 3. Section 4 describes a case study of defining the design specification of a new electric iron based on the proposed methodology. Finally, the conclusion is given in Section 5.

2. Literature review

Although no publication was found thus far regarding the integration of affective design, engineering, and marketing concerns for product design, quite a number of previous studies have explored affective design as well as the integration of engineering and marketing for product design.

2.1. Affective design

Nagamachi (1995) proposed Kansei engineering, also known as affective engineering, which is a product development methodology that uses quantitative methods to acquire and transform customer affections into design attribute settings using quantitative methods. It can be performed by analyzing customers' Kansei and translating how the design matches the Kansei, collecting customers' Kansei experience and establishing mathematical prediction models that relate the Kansei to the design attributes (Lokman, 2010; Marghani et al., 2013). Surveys are always required in Kansei engineering, which is used to analyze the affective meanings related to a product domain based on semantic differential (SD) method (Chuang and Ma, 2001).

Kansei engineering has been applied in various affective product designs, such as automobiles (Zhang and Wang, 2013), drink bottles (Barnes and Lillford, 2009), and surface tactility of plastic products (Choi and Jun, 2007). The framework of Kansei engineering encompasses four tasks (Barnes and Lillford, 2007; Nagamachi, 1995), namely, definition of the product domain, determination of the 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 to evaluate the relationships between defined affective dimensions and design attributes. Previous studies on Kansei engineering have applied various regression analyses, including multiple linear regression (Han et al., 2000), quantification theory I (You et al., 2006; Chang, 2008), ordinal logistic regression (Barone et al., 2007), partial least squares analysis (Nagamachi, 2008), and multilevel regression (Seva et al., 2007). Various computational intelligence techniques have been attempted to model the relationships such as artificial neural networks (Hsiao and Huang, 2002; Lai et al., 2005b), radial basis function neural networks (Chen et al., 2003), fuzzy rule-based modeling (Park and Han, 2004), fuzzy expert system with gradient descent optimization (Lau et al., 2006), and fuzzy neural networks (Sun et al., 2000; Tsai et al., 2006). Lin et al. (2007) presented a new fuzzy logic approach for consumer-oriented product form design in a case study of mobile phones. Tanaka's fuzzy regression (Sekkeli et al., 2010) and genetic programming based fuzzy regression (Chan et al., 2011) have been proposed to model affective relationships. Recently, the adaptive neural fuzzy inference system (ANFIS) has been applied to generate nonlinear and explicit customer satisfaction models and fuzzy rules based on market survey data for new product design (Kwong et al., 2009).

In the early product design stage, one of the key tasks in undertaking affective design is to determine the optimal settings of the design attributes for the affective aspects of the products to achieve maximum customer satisfaction. Various techniques have been attempted to determine the optimal settings such as conjoint analysis (Shi et al., 2001), multiple response surfaces methodology (Hong et al., 2008), ordinal logistical regression (Aktar Demirtas et al., 2009) and genetic algorithms (Hiso and Tsai, 2005; Kim and Cho, 2000). Although numerous studies were conducted on affective design, simultaneous consideration of affective design and marketing / engineering issues was not addressed.

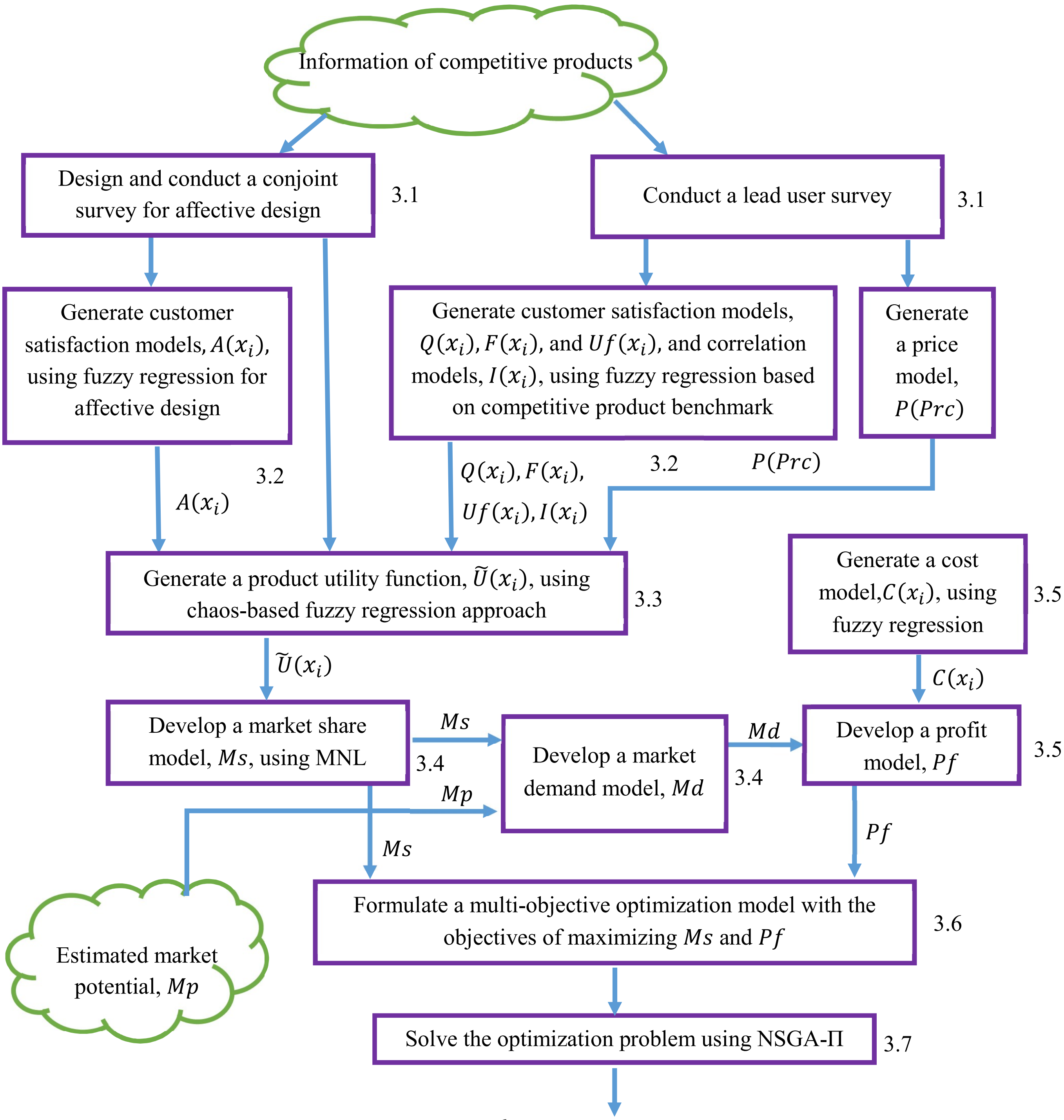
2.2. Integrated marketing and engineering for product design

Some recent research attempting to link up marketing and engineering concerns for new product development have been conducted. The studies mainly involved market surveys, demand modeling techniques, cost modeling, product performance modeling, and optimization model formulation and solution. The objective of the optimization is to maximize profits and/or product performance. Some techniques were employed to coordinate marketing and engineering design problems in order to yield a joint optimal solution such as analytical target cascading (Michalek et al., 2005), multi-objective genetic algorithms (Luo et al., 2005; Besharati et al., 2006) and game-theoretic model (Shiau and Michalek, 2009) Kang et al. (2007) proposed a methodology of marketing and R&D integration for new product development that involves the methods of quality function deployment (QFD), multivariate statistical analysis, conjoint analysis, and the Taguchi method. Kwong et al. (2011a) proposed a methodology of integrating marketing with engineering for defining design specifications of new products using factor analysis, Kano model, and genetic algorithm (GA). Williams et al. (2011) proposed a strategic framework, which involves marketing, strategic design and engineering design to understand how different retail channel structures impact the engineering design of the new product and to determine the optimal design under different channel structure conditions. All the above studies only address the integration issue for a single product design.

Quite a few previous studies were conducted to integrate marketing with engineering concerns for the design of multi-products. Some previous studies developed methodologies of integrating marketing with engineering concerns for product family design (Kumar et al., 2009, Wang et al., 2013) while some others aimed to consider marketing and engineering concerns simultaneously for product line design (Michalek et al., 2006; Michalek et al., 2011; Luo, 2011). Jiao and Zhang (2007) employed conjoint analysis and multi-nomial logit choice models to formulate a product portfolio planning problem, which links the marketing concerns with the determination of product specifications and manufacturing cost for product portfolio planning. It can be noted that various methodologies were developed in previous studies to integrate marketing with engineering concerns for the design of single product and multi-products. However, development of methodologies for simultaneous consideration of affective design, marketing and engineering concerns for product design was not addressed.

3. Proposed methodology

In this paper, an AI-based methodology of integrating affective design, engineering, and marketing for defining design specifications of a new product is proposed. In the proposed methodology, customer satisfaction models and cost model are generated based on FR approach. A conjoint survey is conducted and utility functions are then developed using a chaos-based FR approach. Subsequently, the market share model is developed using the utility functions and the MNL model. The profit model is developed based on the market demand and cost model. Then, a multi-objective optimization model is formulated with the objectives of maximizing the market share and maximizing profit. Finally, NSGA-II is adopted to solve the optimization problem and a set of nondominated solutions of design specifications can be obtained. Figure 1 shows a flowchart of the proposed methodology.



Optimal settings of design specification of new products

Note: 3.1 to 3.7 are the section numbers of this paper.

Fig. 1. AI-based methodology of integrating affective design, engineering, and marketing for defining design specifications.

3.1. Conjoint survey and lead user survey

Rating-, ranking-, and choice-based conjoint surveys are the three types of conjoint survey designs. The rating-based conjoint survey is widely used in previous studies and requires a set of product profiles with respect to pre-defined attributes and attribute levels (Kazemzadeh et al., 2009). In this paper, a rating-based conjoint survey is conducted which contains two parts. The first part is to study the consumer perception of various dimensions of customer satisfaction on products, and the second part is to study the affective satisfaction of consumers on products. To design the first part of the survey, the dimensions of customer satisfaction, such as quality and functionality, have to be identified first. Then, a survey questionnaire is designed based on orthogonal arrays, which contain a number of product profiles. Consumers are then asked to rate the product profiles. The results of the survey are used to generate product utility functions based on chaos-based FR. For the other part, the process of survey design is similar to that of the former one, except that the design attributes of products and affective dimensions have to be identified instead of dimensions of customer satisfaction of products. The results of this survey are used to generate the affective customer satisfaction models using FR.

Besides the conjoint survey, a lead user survey is also conducted to perform competitive product benchmarking and generate price models. In the survey, the product specifications of competitive products are shown and lead users are asked to rate individual ones with respect to various dimensions of customer satisfaction. Lead users are also asked to express their views on several price levels from a scale of 1 to 4, which means low, medium, high, and very high, respectively. Using the collected data sets, the utility function of price can be developed using polynomial modeling.

3.2. Modeling of customer satisfaction using fuzzy regression

In this research, Tanaka's FR (Tanaka, 1987; Liu et al., 2015) is applied to model customer satisfaction. Before conducting a survey for affective design, product samples need to be identified and collected first. Then, affective dimensions and design attributes are defined. The semantic differential (SD) method is adopted in this research to design an SD questionnaire for collecting the affective responses of customers on products. Based on the survey data, FR approach is employed to model the relationships between the affective dimensions and design attributes. To model the relationships between the dimensions of customer satisfaction and engineering requirements, a competitive product benchmark has to be conducted first. Based on the benchmark results, FR is introduced to model the relationships. In the following, a brief description of Tanaka's FR is provided. In Tanaka's FR, fuzzy coefficients with the central point a^c and the spread value a^s are determined by solving the following linear programming (LP) problem:

$$Min\ J = \sum_{j=0}^{n}\left(a_j^s \sum_{i=1}^{M} \left| x_{ij} \right| \right) \tag{1}$$

where J is the objective function that represents the total fuzziness of the system, $1+n$ is the number of terms of the fuzzy polynomial model, M is the number of data sets; x_{ij} is the jth independent variable of the ith data, and $|.|$ refers to absolute value of the independent variable. The constraints can be formulated as follows:

$$\sum_{j=0}^{n} a_j^c x_{ij} + (1-h)\sum_{j=0}^{n} a_j^s \left| x_{ij} \right| \ge y_i + (1-h)e_i \tag{2}$$

$$\sum_{j=0}^{n} a_j^c x_{ij} - (1-h)\sum_{j=0}^{n} a_j^s \left| x_{ij} \right| \le y_i - (1-h)e_i \tag{3}$$

$$a_j^s \ge 0,\ \ a_j^c \in R, j = 0,1,2,\cdots n$$

$$x_{i0} = 1 \text{ for all } i,\ \ i = 1,2,\cdots,M \text{ and } 0 \le h \le 1$$

where h, referring to the degree to which the fuzzy model fits the given data, is between 0 and 1; y_i is the value of the ith dependent variable in the data sets; and e_i is the spread value of the ith dependent variable. Constraints (2) and (3) set the upper and lower boundaries of the estimated data, respectively.

To evaluate the performance of FR, two criterions, the mean absolute percentage error ($MAPE$) and index of confidence (IC), are introduced. $MAPE$ is calculated as follows:

$$MAPE = \frac{1}{M}\sum_{i=1}^{M}\frac{|\tilde{y}_i - y_i|}{y_i} * 100 \tag{4}$$

where $\tilde{y}_i$ is the ith predictive output based on the generated model.

For the fuzzy outputs, an IC was introduced by Wang and Tsaur (2000) and is defined by equation (5).

$$IC = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \tag{5}$$

where SST is the total sum of squares, which considers the measure of the variation between the upper bound and lower bound of the prediction h-certain interval;

$$SST = \sum_{i=1}^{M}\left(y_i - \left(\sum_{j=0}^{n}(a_j^c - (1-h)a_j^s)x_{ij}\right)\right)^2 + \sum_{i=1}^{M}\left(\left(\sum_{j=0}^{n}(a_j^c + (1-h)a_j^s)x_{ij}\right) - y_i\right)^2 \tag{6}$$

SSR is the regression sum of squares, which is the variation of the prediction interval with respect to the center regression line;

$$\begin{aligned} SSR = &\sum_{i=1}^{M}\left(\left(\sum_{j=0}^{n}a_j^c x_{ij}\right) - \left(\sum_{j=0}^{n}(a_j^c - (1-h)a_j^s)x_{ij}\right)\right)^2 \\ &+ \sum_{i=1}^{M}\left(\left(\sum_{j=0}^{n}(a_j^c + (1-h)a_j^s)x_{ij}\right) - \left(\sum_{j=0}^{n}a_j^c x_{ij}\right)\right)^2 \end{aligned} \tag{7}$$

SSE is the error sum of squares, which is formulated by equation (8).

$$SSE = 2 * \sum_{i=1}^{M}\left(y_i - \left(\sum_{j=0}^{n}a_j^c x_{ij}\right)\right)^2 \tag{8}$$

Also,

$$SSE = SST - SSR \tag{9}$$

IC is similar to the determinant confident (R^2) in classical regression. The higher value of IC implies a better estimation of y_i (Azadeh et al., 2011).

3.3. Generation of product utility functions using chaos-based fuzzy regression

In the conjoint survey to study the dimensions of the customer satisfaction of products, respondents are invited to assess all the product profiles using the different ratings. Unavoidably, respondents' ratings on the product profiles involve their subjective judgments, leading to a high degree of fuzziness of the survey data. In this paper, a chaos-based FR approach is introduced to develop utility functions. In the proposed approach, chaos optimization algorithm (COA) is introduced to generate the nonlinear polynomial structures of utility functions that could contain second- and/or higher-order and interaction terms. COA employs chaotic dynamics to solve the optimization problem, which does not rely on learning factors and has been demonstrated to have faster convergence and can search more accurate solutions than the conventional optimization methods. The FR method is employed to determine the fuzzy coefficients for all the terms of the utility function. An example of a product utility function developed based on the chaos-based FR approach is shown as follows:

$$\tilde{U} = \tilde{A}_0 + \tilde{A}_1 x_1 + \tilde{A}_2 x_1 x_2 + \tilde{A}_3 x_3{}^2 + \cdots + \tilde{A}_{n-1}(x_1 x_2 \cdots x_{n-1}) + \tilde{A}_n x_n{}^n \quad (10)$$

or

$$\begin{aligned} \tilde{U} = &\left(a_0^c, a_0^s\right) + \left(a_1^c, a_1^s\right) x_1 + \left(a_2^c, a_2^s\right) x_1 x_2 + \left(a_3^c, a_3^s\right) x_3{}^2 + \cdots \\ &+ \left(a_{n-1}^c, a_{n-1}^s\right)(x_1 x_2 \cdots x_{n-1}) + \left(a_n^c, a_n^s\right) x_n{}^n \end{aligned} \quad (11)$$

where $\tilde{U}$ is the dependent variable, which are the ratings of the respondents on the product profiles; $\tilde{A}_0 = \left(a_0^c, a_0^s\right)$, $\tilde{A}_1 = \left(a_1^c, a_1^s\right)$, $\cdots$, $\tilde{A}_n = \left(a_n^c, a_n^s\right)$ are the fuzzy coefficients in which a^c and a^s are the central value and the spread of fuzzy numbers, respectively; $x_1 \cdots x_n$ and are the independent variables. Details of the chaos-based FR approach to generate the utility function can be found in the authors' publication (Jiang et al., 2013).

3.4. Market share model

The market share model is developed based on the generated product utility function and MNL model. In the recent years, probabilistic choice rules have turned out to be more realistic in representing the customer behavior of purchase decision-making. Some probabilistic choice rules can offer flexibility in calibrating the actual choice behavior, such as the option of mimicking the first choice rule (Kaul and Rao, 1995). A widely-used probability rule is the

MNL choice rule. The estimation of the probability of choosing the *ith* product among the company's existing and competitive products is obtained as follows (Aydin et al., 2014):

$$Pr_i = \frac{e^{\tilde{U}_i}}{\sum_{t=1}^{T} e^{\tilde{U}_t} + \sum_{k=1}^{K} e^{\tilde{U}_k} + e^{\tilde{U}_i}} \tag{12}$$

where Pr_i is the choice probability, indicating how a customer will likely choose the *ith* product; $\tilde{U}_i$ is the utility value of the *ith* product; $\tilde{U}_t$ is the utility of the *tth* competitive product; and $\tilde{U}_k$ is the utility of the *kth* company's existing product. The utility function values and the choice probabilities are considered identical across all customers. Therefore, the market share, Ms, can be treated as the individual choice probability.

$$Ms = \frac{e^{\tilde{U}_i}}{\sum_{t=1}^{T} e^{\tilde{U}_t} + \sum_{k=1}^{K} e^{\tilde{U}_k} + e^{\tilde{U}_i}} \tag{13}$$

Hence, the market demand of a new product, Md, can be estimated as follows:

$$Md = Mp*Ms = Mp\frac{e^{\tilde{U}_i}}{\sum_{t=1}^{T} e^{\tilde{U}_t} + \sum_{k=1}^{K} e^{\tilde{U}_k} + e^{\tilde{U}_i}} \tag{14}$$

where Mp is market potential that is commonly estimated by marketing personnel based on their knowledge and judgments.

3.5. Cost and profit models

In the developed competitive product benchmark, competitive products and their engineering performance are identified. Costing engineers of companies are invited to estimate the product costs of individual competitive products assuming that the products are designed and produced by their own companies. The estimated costs together with the engineering performance data can be used to generate a cost model, C, using FR. Thus, the profit, Pf, of the new product can be estimated as follows:

$$Pf = Md*(Prc - C) = Mp\frac{e^{\tilde{U}_i}}{\sum_{t=1}^{T} e^{\tilde{U}_t} + \sum_{k=1}^{K} e^{\tilde{U}_k} + e^{\tilde{U}_i}}(Prc - C) \tag{15}$$

where Prc is the price of the new product.

3.6. Formulation of an optimization model

The two prime objectives, namely, maximizing the market share and maximizing the profit, are commonly considered in new product development projects for determining the optimal product design (Kwong et al., 2011b; Deng et al., 2014). In this research, the two objectives are also considered. Based on the equations described in the previous sections, a multi-objective optimization model can be formulated as follows.

Objectives:

$$Objective\ 1: Max\ Ms = \frac{e^{\tilde{U}_i}}{\sum_{t=1}^{T} e^{\tilde{U}_t} + \sum_{k=1}^{K} e^{\tilde{U}_k} + e^{\tilde{U}_i}} \tag{16}$$

$$Objective\ 2: Max\ Pf = Mp \frac{e^{\tilde{U}_i}}{\sum_{t=1}^{T} e^{\tilde{U}_t} + \sum_{k=1}^{K} e^{\tilde{U}_k} + e^{\tilde{U}_i}} (Prc - C) \tag{17}$$

Subject to:

$$y_A = f_A(x) \tag{18}$$

$$y_B = f_B(x) \tag{19}$$

$$y_P = f_P(Prc) \tag{20}$$

$$\tilde{U} = f_{\tilde{U}}(y_A, y_B, y_p) \tag{21}$$

$$C = f_c(x) \tag{22}$$

$$x_{j\min} \le x_j \le x_{j\max} \tag{23}$$

$$x_j = g(x_{j_1}), where\ j \ne j_1 \tag{24}$$

where (18) are the customer satisfaction models for affective design. (19) are the models to relate customer satisfaction with engineering requirements based on a competitive product benchmark. Both (18) and (19) are generated based on FR approach. (20) is the utility function of price. (21) is the product utility function developed based on the chaos-based FR approach. (22) is the cost model generated using FR approach. x_j is the *jth* design variable; (23) are the ranges of the settings of the design variables. (24) is the correlation models for relating the *jth* design variable and some other design variables. For example, in the electric iron design, the weight has a correlation with the water tank volume and soleplate material.

3.7. Solving the optimization model using a NSGA-II approach

NSGA-II is an elitist genetic algorithm and is commonly used to solve multi-objective optimization problems. The major features of NSGA-II include low computational complexity, parameter-less diversity preservation, elitism, and real-valued representation (Deb et al., 2002; Haghighi and Asl, 2014). NSGA-II uses a real-coded simulated binary crossover (SBX) operator and a real-coded polynomial mutation operator to support the crossover and mutation operations directly for real-valued decision variables. Deb et al. (2002) found that NSGA-II was able to maintain a better spread of solutions and had better convergence than other multi-objective genetic algorithms, such as Pareto-archived evolution strategy (PAES) and strength-Pareto evolutionary algorithm (SPEA). A flowchart and the algorithms of NSGA-II are shown in Appendix.

4. Case study

A case study of electric iron design was conducted based on the proposed methodology to evaluate its effectiveness.

4.1. Conjoint survey and generation of product utility function

A conjoint survey was conducted to study the consumer perception on the dimensions of customer satisfaction of electric irons. Table 1 shows the survey questionnaire, which contains sixteen product profiles. Four scales labeled "below average," "average," "good," and "very good" (scale from 1 to 4, respectively) are used to describe the five dimensions of the customer satisfaction of electric irons, which are attractiveness A, quality Q, functionality F, user-friendliness Uf, and price P. The conjoint survey was conducted in a university. Respondents were invited to assess all the product profiles by filling out the survey questionnaires using a scale from 1 to 10, where 10 means highly preferred and 1 means not preferred at all. Totally, eighty-four valid questionnaires were received. All the respondents are adults and have more than five-year experience of using electric irons.

Table 1 Survey questionnaire for the electric iron

Product profiles	Attractiveness (A)	Quality (Q)	Functionality (F)	User – friendliness (Uf)	Price (P)	Rating (1–10)*
1	4	4	4	4	4	
2	3	4	3	3	3	
3	2	4	2	2	2	
4	1	4	1	1	1	
5	3	3	4	2	1	
6	4	3	3	1	2	

7	1	3	2	4	3
8	2	3	1	3	4
9	2	2	4	1	3
10	1	2	3	2	4
11	4	2	2	3	1
12	3	2	1	4	2
13	1	1	4	3	2
14	2	1	3	4	1
15	3	1	2	1	4
16	4	1	1	2	3

Based on the collected survey data, the average rating for each product profile was calculated. After that, a chaos-based FR approach was used to generate the product utility function. In the proposed approach, the number of iterations for chaotic searching is set as 500 to ensure that the least number of iterations and the smallest error are obtained. The value setting of h was determined using different values within the range of $[0,1]$. After a number of trials, h was set as 0.2 because it yielded the smallest training error of the FR models. The number of elements in the chaos variable is set as nine to guarantee that the generated model has the chance to include all the five terms. The proposed approach to generate the product utility functions was implemented using Matlab programming software. The following shows a product utility function, which was generated using the survey results.

$$\begin{aligned}\tilde{U} &= (1.7108,\ 0.5048) + (0.1073, 0.0569)A*Uf + (0.5477, 0.0165)F \\ &\quad + (1.1307, 0.2878)Q + (-0.5655, 0)P\end{aligned} \tag{25}$$

The values of $MAPE$ and IC for the utility function are 7.79% and 0.85, respectively. A model with the value of $MAPE$ is smaller than 10%, which normally indicates that the model has good prediction accuracy. Referring to the categorization of the strength of the correlations (Dancey and Riedy, 2011), the absolute values of the correlation coefficients between 0.7 and 0.9 are categorized as strong correlations and 1 means a perfect correlation. Therefore, if the value of IC is larger than 0.7, the corresponding model fits the data sets well.

4.1.1. Modeling the relationships between customer satisfaction and engineering requirements

A lead user survey was conducted to perform a competitive product benchmark for electric irons. Five lead users were involved in the survey who all have more than fifteen-year experience of using electric irons and also have more than three times of selection and purchase of electric irons. In this case study, eight major competitive electric irons were identified and were denoted as A–H, respectively. In the survey, the product specifications of the eight electric irons are shown in Table 2. Lead users of electric irons were invited to assess each electric iron with respect to the three dimensions of customer satisfaction, Q, F, and Uf. The scale of 1 to 4 was used to describe the degrees of customer satisfaction. The average values of the dimensions of customer satisfaction were calculated and are shown in Table 2. The product specifications contain ten engineering requirements, namely, anti-calcium, weight, heat-up time, power, water tank volume, soleplate material, self-cleaning, variable steam setting, auto shut-off, and price, which are denoted as $x_1 \sim x_{10}$, respectively.

Table 2 Competitive benchmark of electric irons

Comp. products	anti-calc	weight (kg)	heat-up time (min)	power (w)	water tank vol. (ml)	soleplate material	self-cleaning	variable steam setting	auto shut-off	Price	Dimensions of customer satisfaction		
	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	Q	F	Uf
A	yes	1.2	3	2200	300	Ceramic	no	yes	yes	478	3.6	3.8	3.8
B	no	0.45	0.5	1000	40	Non-stick	no	yes	no	338	2.6	3.2	3.2
C	no	0.45	1	420	40	Non-stick	no	no	no	230	2.6	1.6	2.5
D	no	1.03	1	800	70	Stainless steel	no	yes	no	155	1.8	2.8	1.5
E	yes	1.24	3	2200	310	Ceramic	yes	yes	yes	435	3.9	4	3.9
F	no	1.3	3.3	2000	300	Stainless Steel	no	yes	no	350	1.8	3.1	1.2
G	yes	1.35	2.5	1800	160	Stainless Steel	yes	yes	yes	428	3.7	3.7	3.1
H	no	0.65	0.7	700	40	Ceramic	no	no	no	210	2.9	2.3	1.8

In the benchmark, x_2, x_3, x_4, x_5, and x_{10} are quantitative variables, which are real numbers. x_1, x_6, x_7, x_8, and x_9 are qualitative variables. In this research, dummy variables were introduced for coding the qualitative variables, which may normally have the value one or zero. One indicates the occurrence, while zero otherwise. If an attribute has k_i levels, it is coded in terms of $k_i - 1$ dummy variables. Taking the soleplate material as an example, it can be coded as follows:

Table 3 Dummy coded for the soleplate material

	x_{61}	x_{62}
Ceramic	1	0

Non-stick	0	1
Stainless steel	0	0

The engineering requirements x_1, x_6, x_7, x_8, and x_9 are all qualitative variables and they are coded using the dummy variables shown in Table 4.

Table 4 Coded engineering requirements with dummy variables

Comp. products	anti-calc	weight (kg)	heat-up time (min.)	power (w)	water tank vol.(ml)	soleplate material		self-cleaning	variable steam setting	auto shut-off	Price
	x_1	x_2	x_3	x_4	x_5	x_{61}	x_{62}	x_7	x_8	x_9	x_{10}
A	1	1.2	3	2200	300	1	0	0	1	1	478
B	0	0.45	0.5	1000	40	0	1	0	1	0	338
C	0	0.45	1	420	40	0	1	0	0	0	230
D	0	1.03	1	800	70	0	0	0	1	0	155
E	1	1.24	3	2200	310	1	0	1	1	1	435
F	0	1.3	3.3	2000	300	0	0	0	1	0	350
G	1	1.35	2.5	1800	160	0	0	1	1	1	428
H	0	0.65	0.7	700	40	1	0	0	0	0	210

Based on the benchmark, the customer satisfaction models of Q, F and Uf were developed using FR approach. The generated models, the values of $MAPE$ and IC are shown in Table 5.

Table 5 Developed customer satisfaction models and their training results

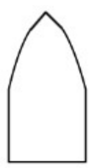
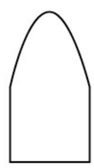
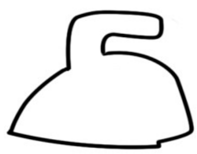
	Models	$MAPE$ (%)	IC
Quality (Q)	$Q=(1.8,0.8)+(0.35,0)x_1+(1.1,0)x_{61}+(0.8,0)x_{62}+(0.75,0.5)x_7+(0.35,0)x_9$	2.96	0.94
Function(F)	$F=(1.2870,0)+(0.0172,0)x_1+(-0.0519,0)x_3+(0.0010,0.0019)x_4+(-0.0033,0)x_5+(0.4314,0)x_{61}+(0.0788,0)x_{62}+(0.2462,0)x_7+(0.9965,0)x_8+(0.0172,0)x_9$	0.39	1

User-friendliness (Uf)	$Uf = (1.0134,0) + (0.8440,0)x_1 + (-0.0201,0)x_2$ $+ (-0.1220,0)x_3 + (-0.0001,0.02)x_5 + (0.8898,0)x_{61}$ $+ (1.6223,0)x_{62} + (0.1093,0)x_7 + (0.6390,0)x_8$ $+ (0.8440,0)x_9$	0.19	1

4.1.2. Modeling customer satisfaction for affective design

For the affective design, five design attributes were defined to model the customer satisfaction "Attractiveness". Table 6 shows the five design attributes: body color tone, soleplate, handle design, spray button design, and water level indicator, which are denoted as x_{11}, x_{12}, x_{13}, x_{14}, and x_{15}, respectively. The design profiles of the eight competitive products are shown in Table 7. Dummy variables were used to code the qualitative variables, and the dummy coded design variables are shown in Table 8. A survey was conducted using a questionnaire in which four scales were used to assess the attractiveness of the eight competitive electric irons. The means of the affective responses of respondents to the "Attractiveness" are shown in the last column of Table 8.

Table 6 Morphological analysis on the eight electric irons

Design attributes	Category			
Body colour tone (x_{11})	(1) Warm tone		(2) Cold tone	
Soleplate (x_{12})	(1) Sharp tip 		(2) Round tip 	
Handle design (x_{13})	(1) Embedded 	(2) "╗" 	(3) "╔" 	(4) "T" 

Spray button design (x_{14})	(1) Flat 	(2) Convex 	(3) Handle 
Water level indicator (x_{15})	(1) Transparent	(2) Sandblasted	

Table 7 Design matrix of the eight competitive products

		Steam iron							
Design attributes	Category	A	B	C	D	E	F	G	H
Body colour tone (x_{11})	(1) Warm	√							
	(2) Cold		√	√	√	√	√	√	√
Soleplate(x_{12})	(1) Sharp tip	√			√	√	√	√	√
	(2) Round tip		√	√					
Handle design(x_{13})	(1) Embedded type	√				√		√	
	(2) “╗ ” type				√				√
	(3) “ ╔” type		√				√		
	(4) “T” type			√					
Spray button design (x_{14})	(1) Flat	√		√		√	√		
	(2) Convex		√		√			√	
	(3) Handle-shape								√
Water level indicator	(1) Transparent	√		√				√	√

(x_{15})	(2) Sandblasted	√		√	√	√

Table 8 Dummy coded design attributes for affective design.

Comp. products	Dummy coded design attributes								Attractiveness (A)
	Body colour tone	Soleplate	Handle design			Spray button design		Water level indicator	
	x_{11}	x_{12}	x_{131}	x_{132}	x_{133}	x_{141}	x_{142}	x_{15}	
A	1	1	1	0	0	1	0	1	3.8
B	0	0	0	0	1	0	1	0	3
C	0	0	0	0	0	1	0	1	2.6
D	0	1	0	1	0	0	1	0	1.9
E	0	1	1	0	0	1	0	0	4
F	0	1	0	0	1	1	0	0	2.8
G	0	1	1	0	0	0	1	1	3.6
H	0	1	0	1	0	0	0	1	3.4

Based on the data sets shown in Table 8, the customer satisfaction model of "Attractiveness" A was developed based on FR as follows:

$$\begin{aligned} A=&(3.0382,0.8)+(-0.4206,0)x_{11}+(-0.8206,0)x_{12}+(2.4412,0)x_{131}+(0.9618,0)x_{132} \\ &+(1.2412,0)x_{133}+(-0.6588,0)x_{141}+(-1.2794,0)x_{142}+(0.2206,0)x_{15} \end{aligned} \tag{26}$$

The values of $MAPE$ and IC for model (26) are $7.72*10^{-14}$ and 1, respectively.

4.1.3. Development of price models

To develop the utility function of price for electric irons, in the lead user survey, lead users were asked to express their views on the prices of household electric irons using the scale from 1 to 4, which denote low, medium, high, very high, respectively. After the survey, the means of ratings were obtained as shown in Table 9.

Table 9 Survey results for the price

Price	Average rating
600	3.7
500	3.2
400	2.8

300	2.2
200	1.4
100	1.1

Based on the above results, the utility function of price was generated based on polynomial modeling. In this research, several common mathematical functions, including exponential function, logarithm function, linear polynomial, power function, and Gaussian function, were employed to generate the utility function. Table 10 shows the values of $MAPE$ and R^2 of the utility functions generated based on the five functions.

Table 10 Comparison results based on the five functions

	Exponential function	Logarithm function	Linear polynomial	Power function	Gaussian function
$MAPE$ (%)	12.44	12.86	7.95	6.97	4.09
R^2	0.90	0.93	0.96	0.97	0.99

The table shows that the values of $MAPE$ and R^2 based on the Gaussian function are the best compared with those based on the other four functions. Therefore, the model generated based on the Gaussian function was selected as the utility function of price.

$$P = 3.828e^{-((Prc-708.5)/532.6)^2} \tag{27}$$

Based on model (27), the P values for the competitive products A–H are calculated as shown in Table 11.

Table 11 P values for the products A-H

Comp. products	Price (x_{10})	Utility
A	478	3.2
B	338	2.4
C	230	1.7
D	155	1.3
E	435	2.9
F	350	2.4
G	428	2.9
H	210	1.6

Based on the results of Sections 4.1.1–4.1.3, the customer satisfaction models of Q, F, Uf, and A and the price model P are substituted into equation (25) and the product utility function can be obtained as follows:

$$\begin{aligned}
\tilde{U} &= (1.7108,\ 0.5048) + (0.1073, 0.0569)A * Uf + (0.5477, 0.0165)F \\
&\quad + (1.1307, 0.2878)Q + (-0.5655, 0)P \\
&= (1.7108,\ 0.5048) + (0.1073, 0.0569) * \{(3.0382, 0.8) + (-0.4206, 0)x_{11} \\
&\quad + (-0.8206, 0)x_{12} + (2.4412, 0)x_{131} + (0.9618, 0)x_{132} + (1.2412, 0)x_{133} \\
&\quad + (-0.6588, 0)x_{141} + (-1.2794, 0)x_{142} + (0.2206, 0)x_{15}\} * \{(1.0134, 0) \\
&\quad + (0.8440, 0)x_1 + (-0.0201, 0)x_2 + (-0.1220, 0)x_3 + (-0.0001, 0.02)x_5 \\
&\quad + (0.8898, 0)x_{61} + (1.6223, 0)x_{62} + (0.1093, 0)x_7 + (0.6390, 0)x_8 \\
&\quad + (0.8440, 0)x_9\} + (0.5477, 0.0165) * \{(1.2870, 0) + (0.0172, 0)x_1 \\
&\quad + (-0.0519, 0)x_3 + (0.0010, 0.0019)x_4 + (-0.0033, 0)x_5 + (0.4314, 0)x_{61} \\
&\quad + (0.0788, 0)x_{62} + (0.2462, 0)x_7 + (0.9965, 0)x_8 + (0.0172, 0)x_9\} \\
&\quad + (1.1307, 0.2878) * \{(1.8, 0.8) + (0.35, 0)x_1 + (1.1, 0)x_{61} + (0.8, 0)x_{62} \\
&\quad + (0.75, 0.5)x_7 + (0.35, 0)x_9\} + (-0.5655, 0) * \{3.828e^{-((Prc-708.5)/532.6)^2}\}
\end{aligned} \tag{28}$$

4.2. Formulation of an optimization model

In this research, two objectives, namely, maximizing the market share and maximizing the profit, are considered in the optimization. In the former one, the objective function can be developed based on the product utility function (28) and the equation (16). In the formulation of the objective function of the latter one, a cost model needs to be developed first. To develop the cost model, an experienced product engineer, who has more than ten-year experience in costing and development of electrical appliance products, was invited to estimate the product costs of individual competitive products based on the assumption that the products were designed and produced by his own company. The estimated product costs by the engineer for products A–H were 312, 182, 124, 104, 338, 234, 273, and 111, respectively. Based on the settings of $x_1 \sim x_9$ shown in Table 4, the cost model C can be generated as follows using FR approach.

$$\begin{aligned}
C &= (31.9734, 0) + (16.0864, 0)x_1 + (-11.5390, 0)x_2 + (-5.0097, 0)x_3 \\
&\quad + (0.0885, 0.1114)x_4 + (0.2157, 0)x_5 + (18.6070, 0)x_{61} + (56.4465, 0)x_{62} \\
&\quad + (20.1316, 0)x_7 + (3.4440, 0)x_8 + (16.0864, 0)x_9
\end{aligned} \tag{29}$$

The values of $MAPE$ and IC for model (29) are 1.92% and 1, respectively. Based on equations (28), (29), and (17), the objective function for maximizing the profit is obtained.

The constraints, (23) and (24), are necessary for the formulation of the multi-objective optimization model. The first constraint is the ranges of the design variables, which are [0.45, 1.35], [0.5, 3.3], [420, 2200], [40, 310], and [155, 600] for x_2, x_3, x_4, x_5, and x_{10}, respectively, and [0, 1] for other design variables. The second constraint is the technical correlation among the design variables. Referring to the competitive product benchmark (Table 2), weight x_2 has technical correlations with the water tank volume x_5 and soleplate material x_6; heat-up time x_3 has technical correlations with power x_4 and soleplate material x_6. The two technical correlations were generated using FR approach as shown in (30) and (31), respectively.

$$\begin{aligned} x_2 = &(0.9121, 0.1403) + (0.0021, 0.0010)x_5 + (-0.3448, 0)x_{61} \\ &+ (-0.5448, 0)x_{62} \end{aligned} \tag{30}$$

$$\begin{aligned} x_3 = &(-0.3346, 0.4104) + (0.0017, 0.0002)x_4 + (-0.1500, 0)x_{61} \\ &+ (-0.0612, 0.8209)x_{62} \end{aligned} \tag{31}$$

The values of IC for models (30) and (31) are 0.91 and 0.82, respectively.

4.3. Determination of design specifications

Based on the formulated multi-objective optimization model, a NSGA-II was introduced to solve the optimization problem and determine the optimal settings of the design variables for the electric iron design. In this paper, both the population size and the number of generations were set as 100. The distribution index for crossover and mutation were 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 two and one half of the population size, respectively. The optimization model and its solving were implemented using Matlab programming software. Fig. 2 shows the Pareto optimal solutions of the multi-objective optimization problem solved by the NSGA-II.

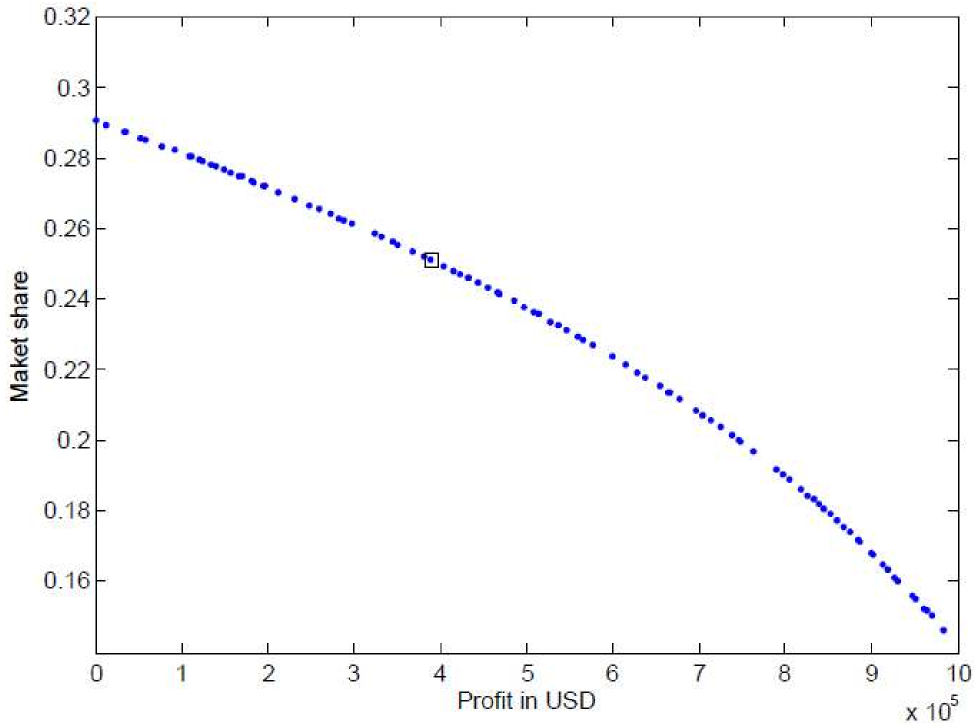
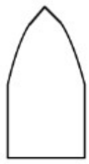
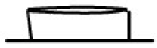


Fig. 2. Pareto solutions

Each optimal solution contains the settings of the design variables. The company can perform a tradeoff between the two objectives and select the best / most preferred one with reference to their business objectives and competitive strategies. If the company would like to develop a new electric iron with the objective of maximizing the profit while achieving a 25% or above market share, the solution, as shown in a black rectangle in Fig. 2, can be considered as the optimal solution. The market share and profit of the optimal solution are 25% and $3.88*10^5$, respectively. The optimal settings of the design variables of the new electric iron are x_1=1, x_2=0.74, x_3=2.07, x_4=1500, x_5=80, x_{61}=1, x_{62}=0, x_7=0, x_8=1, x_9=1, x_{10}=277.27, x_{11}=1, x_{12}=1, x_{131}=1, x_{132}=0, x_{133}=0, x_{141}=0, x_{142}=1, and x_{15}=0. Thus, the design specification of the new electric iron can be obtained in Table 12.

Table 12 Design specification of the new electric iron

Design variables		The optimal settings of design variables
anti-calc	x_1	yes
weight (kg)	x_2	0.74
heat-up time (min.)	x_3	2.07
power (w)	x_4	1500
water tank vol. (ml)	x_5	80

soleplate material	x_6	ceramic
self-cleaning	x_7	no
variable steam setting	x_8	yes
auto shut-off	x_9	yes
price	x_{10}	277.27
body colour tone	x_{11}	warm tone
soleplate	x_{12}	sharp tip 
handle design	x_{13}	embedded type 
spray button design	x_{14}	convex 
water level indicator	x_{15}	sandblasted

5. Conclusion

In the early design stage of consumer products, the concerns of affective design, engineering, and marketing have to be considered simultaneously to generate an optimal product design. However, publications on the simultaneous consideration of those concerns in the early design stage have not been found thus far. To fill the research gap, this paper proposes and describes an AI-based methodology of integrating affective design, engineering, and marketing for defining the design specifications of new products by which concerns of affective design, engineering, and marketing can be considered simultaneously. In the proposed methodology, customer satisfaction models of attractiveness, quality, functionality, and user-friendliness are developed based on FR. The product utility function is generated using a chaos-based FR approach. The market share model is then developed based on the product utility function and MNL model. The profit model is developed based on the market demand and cost model, which the cost model is generated using FR approach. After that, a multi-objective optimization model is formulated for maximizing the market share and profit. The optimization model is solved using a NSGA-II and the optimal settings of the design variables of a new product can be determined. A case study of electric iron design was conducted to evaluate the effectiveness of the proposed methodology.

Future work could further extend the proposed methodology to perform product line design, which involves the design of multi-products to satisfy the needs of various market segments. Furthermore, customer preference and market status are in static forms in the development of the proposed methodology. In reality, they could be quite dynamic. Future work could consider their dynamic effects in the proposed methodology.

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The work described in this paper was fully supported by a grant from the Research Grant Council of the Hong Kong Special Administrative Region, China (Project No: PolyU 517113).

Appendix

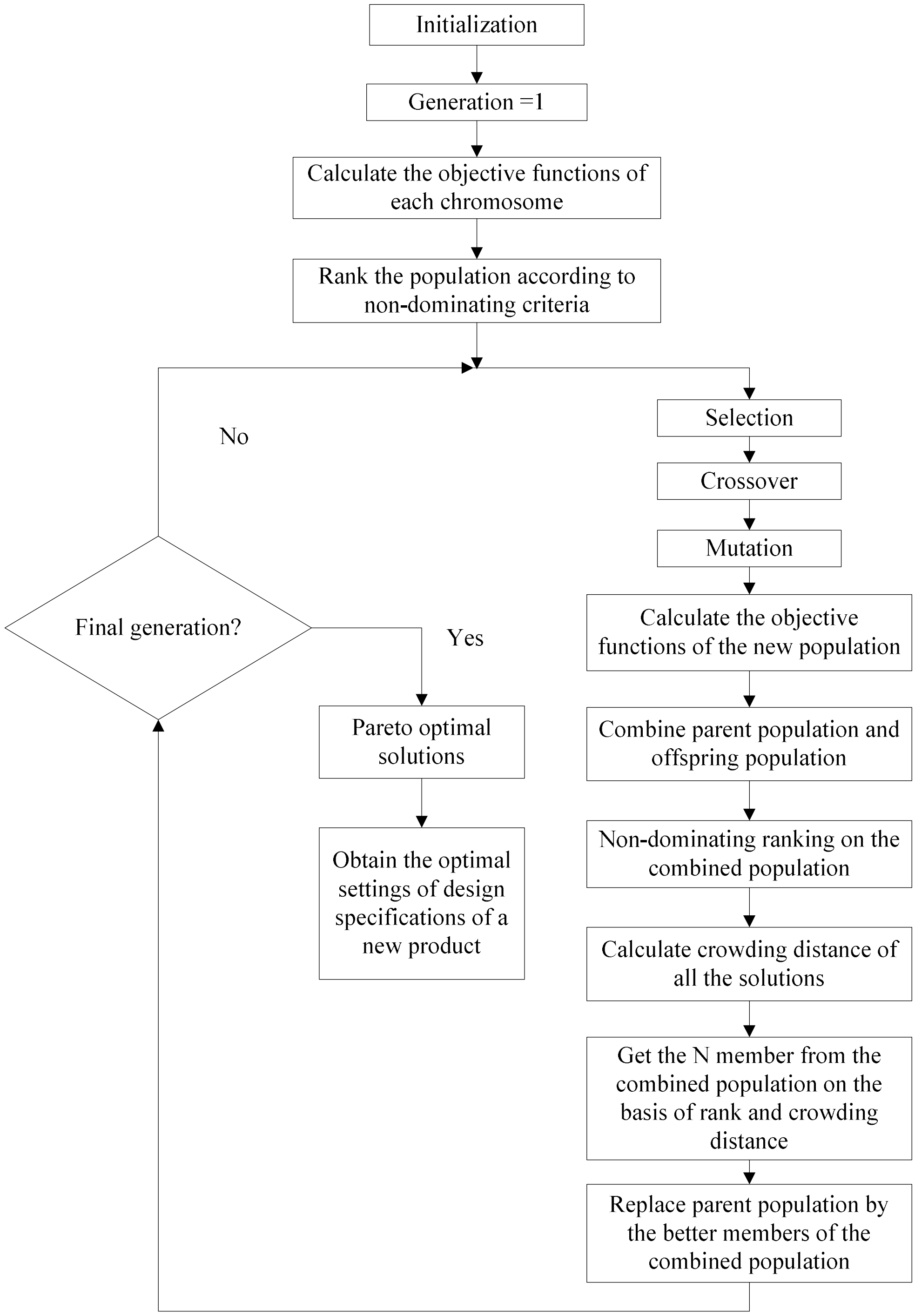

Fig. 3. Flowchart of NSGA-II.

The algorithms of the 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, and the tournament size. The description of the objective functions is given, such as the number of objective functions, 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 randomly. 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. 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 5: The combined population R_t is sorted based on non-domination, and different fronts F_i, $i=1,2,\cdots$, are identified. The new population P_{t+1} with size N is obtained based on the process of combination and selection.

Step 6: The generation counter is increased by $t+1 \rightarrow t$. The algorithm is again executed from Step 3 and 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 specifications.

References

Aktar Demirtas, E., Anagun, A. S., Koksal, G., 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.

Aydin, R., Kwong, C. K., Ji, P., Law, H. M. C., 2014. Market demand estimation for new product development by using fuzzy modeling and discrete choice analysis. Neurocomputing 142(2014), 136–146.

Azadeh, A., Seraj, O., Saberi, M., 2011. An integrated fuzzy regression–analysis of variance algorithm for improvement of electricity consumption estimation in uncertain environments. International Journal of Advanced manufacturing Technology 53(5-8), 645–660.

Barnes, C., Lillford, S. P., 2007. Affective design decision-making—issues and opportunities. CoDesign: International Journal of CoCreation in Design and the Arts 3(Suppl. 1), 135–146.
Barnes, C., Lillford, S. P., 2009. Decision support for the design of affective products. Journal of Engineering Design 20(5), 477–492.
Barone, S., Lombardo, A., Tarantino, P., 2007. A weighted logistic regression for conjoint analysis and Kansei engineering. Quality and Reliability Engineering International 23(6), 689–706.
Besharati, B., Luo, L. Azarm, S., Kanan, P. K., 2006. Multi-objective single product robust optimization: an integrated design and marketing approach. Journal of Mechanical Design 128(4), 884–892.
Chan, K. Y., Kwong, C. K., Dillon, T. S., Fung, K. Y., 2011. An intelligent fuzzy regression approach for affective product design that captures nonlinearity and fuzziness. Journal of Engineering Design 22(8), 523–542.
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, C. H., Khoo, L., Yan, W., 2003. Evaluation of multicultural factors from elicited customer requirements for new product development. Research in Engineering Design 14(3), 119–130.
Choi, K., Jun, C., 2007. A systematic approach to the Kansei factors of tactile sense regarding the surface roughness. Applied Ergonomics 38(1), 53–63.
Chuang, M. C., Ma, Y. C., 2001. Expressing the expected product images in product design of micro-electronic products. International Journal of Industrial Ergonomics 27(4), 233–245.
Crawford, M. and Benedetto A.D., 2006. New products management, McGraw-Hill.
Creusen, M. E. H., Schoormans, J. P. L., 2005. The Different Roles of Product Appearance in Consumer Choice. Journal of Product Innovation Management 22(1), 63–81.
Dancey, C., Reidy, J., 2011. Statistics without maths for psychology, fifth ed. Prentice Hall, Harlow.
Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation 6(2), 182–197.
Deng, S., Aydin, R., Kwong, C. K., Huang, Y., 2014. Integrated product line design and supplier selection: A multi-objective optimization paradigm. Computers & Industrial Engineering 70(2014), 150–158.
Haghighi, A., Asl, A. Z., 2014. Uncertainty analysis of water supply networks using the fuzzy set theory and NSGA-Ⅱ. Engineering Applications of Artificial Intelligence 32(2014), 270-282.
Han, S. H., Yun, M. H., Kim, K. J., Kwahk, J., 2000. Evaluation of product usability: development and validation of usability dimensions and design elements based on empirical models. International Journal of Industrial Ergonomics 26(4), 477–488.

Hong, S. W., Han, S. H., Kim, K. J., 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., Huang, H. C., 2002. A neural network based approach for product form design. Design Studies 23(1), 67–84.

Hsiao, S. W., Tsai, H. C., 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., Kwong, C. K., Ip, W. H., Chen, Z., 2013. Chaos-based fuzzy regression approach to modeling customer satisfaction for product design. IEEE Transactions on Fuzzy Systems 21(5), 926–936.

Jiao, J., Zhang, Y., 2007. Product portfolio planning with customer-engineering interaction. IIE Transactions 37 (9), 801–814.

Kang, N., Kim, J., Park, Y., 2007. Integration of marketing domain and R&D domain in NPD design process. Industrial Management and Data Systems 107(6), 780–801.

Kaul, A., Rao, V. R., 1995. Research for product positioning and design decisions: An integrative review. International Journal of Research in Marketing 12(4), 293–320.

Kazemzadeh, R. B., Behzadian, M., Aghdasi, M., Albadvi, A., 2009. Integration of marketing research techniques into house of quality and product family design. The International Journal of Advanced Manufacturing Technology 41(9–10), 1019–1033.

Kim, H. S., Cho, S. B., 2000. Application of interactive genetic algorithm to fashion design. Engineering Applications of Artificial Intelligence 13(6), 635-644.

Kumar, D., Chen, W., Simpson, T.W., 2009. A market-driven approach to product family design. International Journal of Production Research 47 (1), 71–104.

Kwong, C. K., Chen, Y., Chan, K. Y., 2011a. A methodology of integrating marketing with engineering for defining specifications of new products. Journal of Engineering Design 22 (3), 201–213.

Kwong, C. K., Luo, X. G., Tang, J. F., 2011b. A multiobjective optimization approach for product line design. IEEE Transactions on Engineering Management 58(1), 97–108.

Kwong, C. K., Wong, T. C., Chan, K. Y., 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., Chang, Y. M., Chang, H. C., 2005a. 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., Lin, Y. C., Yeh, C. H., 2005b. Form design of product image using grey relational analysis and neural network models. Computers & Operations Research 32(10), 2689–2711.

Lau, T. W., Hui, P. C. L., Ng, F. S. F., Chan, K. C. C., 2006. A new fuzzy approach to improve fashion product development. Computers in Industry 57(1), 82–92.

Lin, Y. C., Lai, H. H., Yeh, C. H., 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.

Liu, Y., Chen, Y., Zhou, J, Zhong, S, 2015. Fuzzy linear regression models for QFD using optimized h values. Engineering Applications of Artificial Intelligence 39(2015), 45-54.

Lokman, A. M., 2010. Design & Emotion: The Kansei engineering methodology. Malaysian Journal of Computing 1(1), 1–14.

Luo, L. Kannan, P.K., Besharati, B. and Azarm, S. 2005. Design of robust new products under variability: marketing meets design. The Journal of Product Innovation Management 22, 177-192.

Luo, L., 2011. Product line design for consumer durables: an integrated marketing and engineering approach. Journal of Marketing Research 48(1), 128–139.

Luo, L., Kannan, P. K., Besharati, B., Azarm, S., 2005. Design of robust new products under variability: marketing meets design. Journal of Product Innovation Management 22(2), 177–192.

Marghani, V. G. R. E., da Silva, F. C., Knapik, L., Verri, M. A., 2013. Kansei engineering: methodology to the project oriented for the customers, in: Fukuda, S., Emotional Engineering vol. 2. Springer, London, pp. 107–125.

Michalek, J. J., Ceryan, O., Papalambros, P. Y., Koren, Y., 2006. Balancing marketing and manufacturing objectives in product line design. Journal of Mechanical Design 128(6), 1196–1204.

Michalek, J. J., Ebbes, P., Adiguzel, F., Feinberg, F. M., Papalambros, P. Y., 2011. Enhancing marketing with engineering: optimal product line design for heterogeneous markets, International Journal of Research in Marketing 28(1), 1–12.

Michalek, J. J., Feinberg, F. M., Papalambros, P. Y., 2005. Linking marketing and engineering product design decisions via analytical target cascading. Journal of Product Innovation Management 22(1), 42–62.

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., Kumar, M., 2008. Using product design strategically to create deeper consumer connections. Business Horizons 51(5), 441–450.

Park, J., Han, S. H., 2004. A fuzzy rule-based approach to modeling affective user satisfaction towards office chair design. International Journal of Industrial Ergonomics 34 (1), 31–47.

Sekkeli, G., Koksal, G., Batmaz, I., Bayrak, O. T., 2010. Classification models based on Tanaka's fuzzy linear regression approach: The case of customer satisfaction modeling. Journal of Intelligent and Fuzzy systems 21(5), 341–351.

Seva, R. R., Duh, H. B. L., Helander, M. G., 2007. The marketing implications of affective product design. Applied Ergonomics 38(6), 723–731.

Shi, L., Olafsson, S., Chen, Q., 2001. An optimization framework for product design. Management Science 47(12), 1681–1692.

Shiau, C. S. N., Michalek, J. J., 2009. Should designers worry about market systems. Journal of Mechanical Design 131(1), 011011-1-011011-9.

Sun, J., Kalenchuk, D. K., Xue, D., Gu, P., 2000. Design candidate identification using neural network-based fuzzy reasoning. Robotics and Computer-Integrated Manufacturing 16(5), 383–396.

Tanaka, H., 1987. Fuzzy data analysis by possibilitic linear model. Fuzzy Sets and Systems 24(3), 363–375.

Tsai, H. C., Hsiao, S. W., Hung, F. K., 2006. An image evaluation approach for parameter-based product form and color design. Computer-Aided Design 38(2), 157–171.

Wang H. F., Tsaur, R. C., 2000. Insight of a fuzzy regression model. Fuzzy Sets and Systems 112(3), 355–369.

Wang, J., Yannou, B., Alizon, F., Yvars, P. A., 2013. A usage coverage-based approach for assessing product family design. Engineering with Computers 29(4), 449–465.

Williams, N., Kannan, P.K., Azarm, S., 2011. Retail channel structure impact on strategic engineering product design. Management Science 57(5), 897–914.

You, H., Ryu, T., Oh, K., Yun, M. H., Kim, K. J., 2006. Development of customer satisfaction models for automotive interior materials. International Journal of Industrial Ergonomics 36(4), 323–330.

Zhang, F., Wang, J., 2013. Application of Kansei engineering in electric car design. Applied Mechanics and Materials 437(2013), 985–989.