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Development of Customer Satisfaction Models for Affective Design Using Rough Set and ANFIS Approaches

Huimin Jiang^{a, *}, C.K. Kwong^a, M.C. Law^b, W.H. Ip^a

^aDepartment of Industrial and Systems Engineering, The HongKong Polytechnic University, Kowloon, Hong Kong, China
^bG.E.W. Corporation Ltd., Hong Kong, China

Abstract

Rough set (RS)- and particle swarm optimization (PSO)- based adaptive neuro-fuzzy inference system (ANFIS) approaches are proposed to generate customer satisfaction models in affective design that address fuzzy and nonlinear relationships between affective responses and design attributes. The RS theory is adopted to reduce the number of fuzzy rules generated using ANFIS and simplify the structure of ANFIS. PSO is employed to determine the parameter settings of an ANFIS from which customer satisfaction models with better modeling accuracy can be generated. A case study of mobile phone affective design is used to illustrate the proposed approaches.

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Keywords: Affective design; Customer satisfaction; Rough set theory; Particle swarm optimization; ANFIS.

1. Introduction

Affective design has been shown to excite psychological feelings of customers and can help improve the emotional aspects of customer satisfaction. Design attributes, such as shape and color, evoke the affective responses of customers to products. Products with good affective design can help attract customers and influence their choices and preferences, such as loyalty and joy of use [1] [2]. The process of affective design includes identifying, measuring, analyzing, and understanding the relationship between the affective needs of the customer domain and the perceptual design attributes in the design domain [3].

* Corresponding author. Tel.: +852-95379360; fax: +852-23625267.
E-mail address: huimin.jiang@connect.polyu.hk.

In today's competitive marketplace, a key issue is how the optimal settings of new product design attributes can be determined such that high, or even optimal, customer satisfaction of new products can be obtained. Customer satisfaction models that relate affective responses of customers to design attributes need to be developed first to achieve these settings. Kansei engineering [4] was developed as a consumer-oriented method for affective product design to translate customer psychological feelings and image into design elements of a new product. Artificial intelligence-based fuzzy techniques have been used to address the fuzziness and nonlinearity of affective modeling. Hsiao and Tsai [5] proposed a method that enables an automatic product form or product image evaluation via neural network-based fuzzy reasoning and genetic algorithms (GA). The method was then applied to establish relationships between design attributes of a new product and customer affective image. Park and Han [6] proposed a fuzzy rule-based approach to examine customer satisfaction levels towards office chair designs. They reported that the fuzzy rule-based approach outperformed the multiple linear regression approaches in terms of the number of design attributes to be considered in modeling. A fuzzy expert system with gradient descent optimization was proposed to develop models that relate affective responses to customer satisfaction for fashion product development [7]. Chan et al. [8] introduced genetic programming into fuzzy regression for affective product design. The limitation of this approach is that the size of search space increases exponentially with the number of nodes and the tree depth. An adaptive neuro-fuzzy inference system (ANFIS) was examined by Kwong and Wong [9] to generate nonlinear and explicit customer satisfaction models. The conventional learning algorithms for ANFIS are gradient descent, in which the calculation of gradients in each step is difficult and the use of chain rules may cause a local minimum. These issues have been proven to affect modeling accuracy. On the other hand, ANFIS is not suitable for problems with several inputs. If the number of inputs is large, the number of generated fuzzy rules increases exponentially. These increases would cause long running-time and even execution errors. To overcome these limitations, rough set (RS)- and particle swarm optimization (PSO)- based ANFIS approaches to modeling customer satisfaction are proposed, by which survey data fuzziness and modeling nonlinearity can be addressed, and explicit models for relating customers' affective responses and design attributes can be generated. In this paper, Section 2 first describes the proposed methodology. In Section 3, a case study of mobile phone design is described to illustrate the proposed approaches. The validation of the proposed approaches is shown in Section 4. Finally, conclusions are given in Section 5.

2. Modeling Customer Satisfaction Using RS- and PSO- based ANFIS

In the proposed approaches, the RS theory is introduced to determine indispensable design attributes for generating customer satisfaction models. The PSO- based ANFIS approach is introduced to develop nonlinear customer satisfaction models, 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 and the actual customer satisfaction values can be minimized.

2.1. ANFIS structure

ANFIS is a multilayer feed-forward network in which the neural network is regarded as the learning algorithm. Fuzzy reasoning is used to map inputs into output [10]. Figure 1 shows the architecture of a typical ANFIS with two inputs and one output, where each input is assumed to have two linguistic descriptions.

If both inputs, x_1 and x_2 , have two linguistic descriptions (e.g., low and high), a membership function is used to represent each description. Hence, $\mu_i(x_1)$ denotes the membership function for the i -th linguistic description of x_1 , and $\lambda_j(x_2)$ denotes the membership function of the j -th linguistic description of x_2 , where $i=1,2$ and $j=1,2$. In this study, the triangular-shaped membership functions defined below are used.

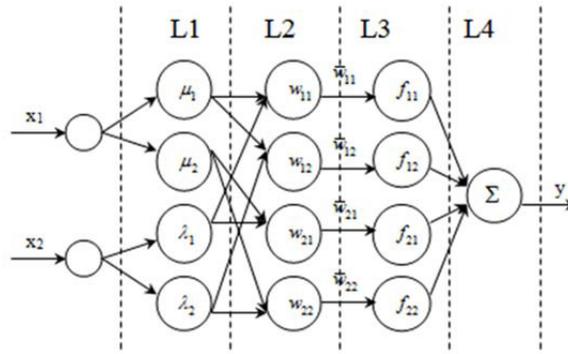


Fig. 1. An ANFIS with four layers and two inputs

$$\mu_i(x_1) = \begin{cases} \frac{x_1 - a_i}{b_i - a_i} & a_i \leq x_1 \leq b_i \\ \frac{c_i - x_1}{c_i - b_i} & b_i \leq x_1 \leq c_i \\ 0 & \text{Otherwise} \end{cases} \quad \text{and} \quad \lambda_j(x_2) = \begin{cases} \frac{x_2 - s_j}{t_j - s_j} & s_j \leq x_2 \leq t_j \\ \frac{u_j - x_2}{u_j - t_j} & t_j \leq x_2 \leq u_j \\ 0 & \text{Otherwise} \end{cases} \quad (1)$$

where (a_i, b_i, c_i) and (s_j, t_j, u_j) are triangular fuzzy numbers and are referred as antecedent parameters.

At L2, one rule is used to denote the outcome for each combination of x_1 and x_2 . Hence, the total number of rules is $2 \times 2 = 4$. The fuzzy rules can be generally expressed as follows:

$$R_{ij} : \text{IF } x_1 \text{ is } \mu_i \text{ AND } x_2 \text{ is } \lambda_j, \text{ THEN } f_{ij} = p_{ij}x_1 + q_{ij}x_2 + r_{ij} \quad (2)$$

where p_{ij} , q_{ij} , and r_{ij} are the parameters of the internal models f_{ij} of the fuzzy rules R_{ij} . These parameters are consequent parameters. The outputs of this layer are described as follows:

$$w_{ij} = \mu_i(x_1) \cdot \lambda_j(x_2) \quad (\forall i = 1 \dots 2, j = 1 \dots 2) \quad (3)$$

where w_{ij} represents the firing strength of each fuzzy rule. The firing strength indicates the degree to which R_{ij} is satisfied. The connection weight between L2 and L3 is \bar{w}_{ij} , as defined by (4), which is the normalized firing strength. This relationship means that the larger the value of \bar{w}_{ij} , the more significant R_{ij} becomes.

$$\bar{w}_{ij} = \frac{w_{ij}}{W} \text{ where } W = \sum_i \sum_j w_{ij} \quad (\forall i = 1 \dots 2, j = 1 \dots 2) \quad (4)$$

At L3, the internal model of R_{ij} is a first-order Sugeno fuzzy model [11], as defined by (5).

$$f_{ij} = p_{ij}x_1 + q_{ij}x_2 + r_{ij} \quad (\forall i = 1 \dots 2, j = 1 \dots 2) \quad (5)$$

At L4, a single node is used to compute the overall output as the summation of all incoming signals. The mathematical formulation of the node is defined by (6).

$$y = \sum_{i=1}^2 \sum_{j=1}^2 O_{ij} = \sum_{i=1}^2 \sum_{j=1}^2 \bar{w}_{ij} \cdot f_{ij} = \sum_{i=1}^2 \sum_{j=1}^2 \bar{w}_{ij} \cdot (p_{ij}x_1 + q_{ij}x_2 + r_{ij}) \quad (6)$$

From (6), a single output (y) of an ANFIS is the linear combination of all normalized firing strengths and the corresponding internal models of all the fuzzy rules. The learning algorithm of an ANFIS is to determine the parameters (a_i, b_i, c_i) , (s_j, t_j, u_j) , and (p_{ij}, q_{ij}, r_{ij}) , such that the error between the ANFIS output and the training data can be minimized.

2.2. Determination of inputs for ANFIS using RS method

Attribute reduction is a process of finding an optimal subset of all attributes following certain criteria so that the attribute subset is sufficient to represent the classification relation of data. A proper choice of attribute subsets can reduce the input number of ANFIS, simplify the structure, and shorten computational time. The RS theory was proposed by Pawlak [12]. The basic philosophy behind the RS theory is based on equivalence relations or indiscernibility in the classification of objects.

A design table with 4-tuple can be expressed as $S = (U, Q, V, \rho)$, where U is the universe that is a finite and non-empty set of objects. Q is a finite set of attributes. $V = \cup_{q \in Q} V_q$, where V_q is a domain of the attribute q . $\rho: U \times Q \rightarrow V$ is the information function, such that $\rho(s, q) \in V_q$ for every $q \in Q, s \in U$, and $\exists(q, v). q \in Q$ and $v \in V_q$ are descriptions of S .

Assuming a subset of the set of attributes, $R \in Q$, two objects, $x, y \in U$, are indiscernible with respect to R if and only if $\rho(x, r) = \rho(y, r)$ for $\exists r \in R$. The indiscernibility relation, which is the equivalence relation defined on set U , is written as $ind(R)$. $ind(R)$ partitions the universe U into disjoint subsets, and $U/ind(R)$ is used to denote these partitions of U . The lower and upper approximation of a set $Y \subseteq U$ can be defined as follows:

$$\underline{R}Y = \cup \{X: X \in U/ind(R), X \subseteq Y\} \quad (7)$$

$$\overline{R}Y = \cup \{X: X \in U/ind(R), X \cap Y \neq \emptyset\} \quad (8)$$

where $\underline{R}Y$ consists of all objects in U that certainly belong to Y , and $\overline{R}Y$ consists of all objects in U that possibly belong to Y under the equivalent relation R . Elements belonging only to the upper approximation compose the boundary region BN , or the doubtful area. BN represents the area that cannot be classified into Y or to its complement. Mathematically, a boundary region can be expressed as:

$$BN(Y) = \overline{R}Y - \underline{R}Y \quad (9)$$

The positive region $Pos_R(Y)$ and the negative region $Neg_R(Y)$ of Y on R are defined as follows:

$$Pos_R(Y) = \underline{R}Y \quad (10)$$

$$Neg_R(Y) = U - Pos_R(Y) \quad (11)$$

In attribute reduction, redundant attributes are removed, and the important attributes are retained as the indispensable information used to evaluate the relationship between affective responses and design attributes. Based on the above definitions, attribute reduction is defined as follows:

If R is a set of equivalent relation, $r \in R$, and $Pos_R(Y) \neq Pos_{R-\{r\}}(Y)$, namely, $ind(R) \neq ind(R - \{r\})$, R is the independent attribute and r is the indispensable attribute in R , otherwise r is dispensable.

If R is independent, $R \subseteq P$ and $ind(R) = ind(P)$, R is a reduction of P , $R \in RED(P)$. $RED(P)$ represents the set of all the attribute reductions of P . The intersection of $RED(P)$ is the core of P , which is expressed as $Core(P)$.

2.3. Determination of ANFIS parameter settings using PSO and LSE

The learning algorithm of an ANFIS aims to determine the antecedent and consequent parameters, such that the error between the ANFIS outputs and the actual data can be minimized. In the forward pass, the antecedent parameters are fixed, and the input signals go forward to calculate each node output. The consequent parameters are then determined using the least square estimation (LSE) method. In the backward pass, the error rates propagate backward, and the antecedent parameters are updated. The conventional algorithm for updating the antecedent parameters is the gradient descent method. In the gradient descent method, the determination of the best learning rate is very difficult, and the convergence of parameters is slow. In this study, a PSO algorithm is

introduced to determine and update the antecedent parameters. PSO does not rely on the learning rate and has been demonstrated to have fast convergence.

A swarm is composed of m particles flying in the N dimension in a certain speed. Every particle changes its position based on considering its own historical best position and other particles' historical best position. The position and the speed for the i -th particle is $x_i = (x_{i1}, x_{i2}, \dots, x_{id})$ and $v_i = (v_{i1}, v_{i2}, \dots, v_{id})$, respectively, where $1 \leq i \leq m$, $1 \leq d \leq N$ and N is the dimension of the search space as well as the number of antecedent parameters. The historical best position of the i -th particle, which has the minimum fitness value, is $p_i = (p_{i1}, p_{i2}, \dots, p_{id})$. The best position for the whole swarm is $p_g = (p_{g1}, p_{g2}, \dots, p_{gd})$. The final result of p_g denotes the optimal values of the antecedent parameters. The process of updating the speed and the position of the particle based on the idea of inertia weight [13] is expressed as follows:

$$v_i^{k+1} = \omega v_i^k + c_1 r_1 (p_i^k - x_i^k) + c_2 r_2 (p_g^k - x_i^k) \quad (12)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (13)$$

where v_i^k and x_i^k are the speed vector and the position vector, respectively, of the i -th particle at the k -th iteration. k is the number of iterations. ω is the inertia weight, the value of which decides the quantity inherited from the current speed of the particle. c_1 and c_2 are learning factors and are usually set as 2. The values of r_1 and r_2 are randomly chosen from the range $[0,1]$.

2.4. Processes of modeling customer satisfaction using RS- and PSO- based ANFIS approaches

The processes of modeling customer satisfaction for affective design based on the proposed approaches are shown as follows:

Step 1: A customer survey is designed and conducted to obtain affective responses of customers on products.

Step 2: Once survey data is obtained, RS theory is introduced to identify redundant attributes and generate a list of attribute reductions. Then, the number of each design attribute appearing in the list is calculated, which reflects the importance of each design attribute. Important design attributes are then selected as the inputs of PSO- based ANFIS.

Step 3: Using the extracted design attributes as the inputs, the ANFIS is trained by the hybrid learning algorithm of PSO and LSE. The initialization for a particle swarm is first conducted, including the iteration number, swarm size, search space dimension, search range, and learning factors. The speed and position of every particle are initialized randomly. In the first iteration, the initial position of every particle is used as the initial individual best position p_i , and the position vector of each particle is used as the antecedent parameters of ANFIS in sequence. The initial iteration is followed by calculating the values of membership functions μ_i and λ_j , the firing strength w_{ij} , and the normalized firing strength \bar{w}_{ij} using (1), (3) and (4). Based on the input data sets and the initial values of the consequent parameters, the values of the fuzzy rule f_{ij} are determined based on (5). Therefore, the outputs of all nodes reach L4. The final output y is then obtained using (6). LSE is used to identify the consequent parameters $\hat{\theta}$ and then the value of the predictive output \hat{y} is computed. Next, the mean absolute error (MAE) between the model output \hat{y} and the actual survey data for the i -th particle is calculated. MAE is also the fitness value MAE_i^1 of the i -th particle in the first iteration. MAE_i^1 is recorded as the initial individual best fitness value p_i . The particle that has the smallest value in MAE_i^1 is selected as the best particle. The particle's position vector is defined as the initial global best position p_g , and its fitness value is defined as the initial global best fitness value. The iteration is continued. The speed vector v_i and the position vector x_i for each particle are updated based on (12) and (13), respectively. Then, the MAE_i^k of the i -th particle in the k -th iteration is calculated based on the updated particle positions. The current MAE_i^k is compared with p_i for each particle. If the value of MAE_i^k is smaller than p_i , the individual best fitness value is set as the value of MAE_i^k , and the particle's individual optimal position, along with its new position are updated. The iteration stops when the pre-defined number of iterations is satisfied. The global best fitness value is updated by

selecting the smallest value in p_i . The number of the best particle is then recorded. The global best position p_g is decided as the position of the selected best particle. The values of p_g are the identified antecedent parameters, and the values of $\hat{\theta}$ are the identified consequent parameters.

Step 4: Based on the antecedent and consequent parameters, the customer satisfaction models can be obtained using (1), (3), (4), (5), and (6). The fuzzy rules are generated based on (2).

3. Case Study

A case study of mobile phone design is used in this study to illustrate the proposed approaches to model the relationships between affective responses and design attributes. A total of 32 mobile phones of various brands were selected. Morphological analysis was used to study the representative attributes of mobile phones as numerical data sets. Nine representative design attributes: top shape, bottom shape, side shape, function button shape, number buttons style, screen size, thickness, layout, and weight, are denoted as $x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8$, and x_9 , respectively. Each design attribute has various alternatives. The affective dimension, simple-complex (S-C), was used to evaluate the affective design of the mobile phones. A survey was conducted using a questionnaire, in which a five-point scale was used to assess the mobile phone appearance based on the affective dimension.

Based on the survey data, RS based on Rosetta software, which is a table logical data analysis toolkit, was used to extract indispensable design attributes. The set of attribute reductions for S-C was obtained from the software. The numbers for design attributes $A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8, A_9$ are 14, 11, 18, 13, 9, 19, 14, 10, and 17, respectively. Based on the numbers, the ranking of importance of the design attributes is $A_6 > A_3 > A_9 > A_7 = A_4 > A_1 > A_2 > A_8 > A_5$. The first two design attributes in the ranking, A_3 and A_6 , are selected as the inputs.

Both inputs have three linguistic descriptions: small, medium, and large. Therefore, six sets of the antecedent parameters $\{a_i, b_i, c_i\}$ are available, and the number of antecedent parameters to be identified is $6 \times 3 = 18$. The number of fuzzy rules is $3 \times 3 = 9$, and the number of consequent parameters to be trained is $9 \times 3 = 27$. The size of the particle swarm is set as 30, and the dimension of the search space for PSO is 18. The iteration number is determined as 200 through the repeated operations to make sure that the least number of the iteration and proper search range can be obtained. The values of the inertia weight w are chosen randomly in the range $[0.1, 0.9]$. The proposed approaches were implemented using the Matlab software package to generate models that relate S-C and the two design attributes. As the PSO-based ANFIS is a stochastic method, 30 runs on the proposed approaches were conducted, and the mean of the 30 runs was calculated. To evaluate the effectiveness of the proposed approaches, the modeling results based on the proposed approaches are compared with those based on fuzzy least-squares regression (FLSR), fuzzy regression (FR), and genetic programming-based fuzzy regression (GP-FR). *MAE* and mean absolute deviation (*MAD*) are adopted to compare the modeling results, as defined by (14) and (15), respectively.

$$MAE = \frac{1}{t} \sum_{k=1}^t \frac{|\hat{y}_k - y_k|}{y_k} \cdot 100 \quad (14)$$

$$MAD = \frac{1}{t-1} \sum_{k=1}^t \left(\frac{|\hat{y}_k - y_k|}{y_k} \cdot 100 - MAE \right)^2 \quad (15)$$

where t is the number of data sets. \hat{y}_k is the k -th predictive output based on the identified model, and y_k is the k -th actual output based on the survey data.

The same survey data was used to develop an ANFIS model. However, the training process of ANFIS was failure and ‘out of memory’ error occurred because its structure was too complex. The same survey data was

also used to develop the models based on the proposed approaches, FLSR, FR and GP-FR approaches for S-C. The developed models, training errors, and *MAD* are shown in Table 1. The table shows that the values of *MAE* and *MAD* based on the proposed approaches are the smallest compared with those based on the other three approaches. This observation indicates that the models based on the proposed approaches are better to fit the survey data sets.

Table 1. Training results and models of the four modeling methods.

Method	Trained models	Training error (%)	Variance (%)
FR	$y = (2.2926, 0.0398) + (0.0794, 0.8812)x_1 + (-0.0532, 1.5028)x_2 + (0.0268, 0.4970)x_3 + (0.0080, 0.4426)x_4 + (-0.0299, 11.4561)x_5 + (-0.3197, 0.1294)x_6 + (0.1200, 0.1075)x_7 + (0.0898, 0.0815)x_8 + (0.1048, 0.0391)x_9$	10.5370	99.3563
FLSR	$y = (2.1624, 2.4883) + (0.1424, 0.4980)x_1 + (-0.1442, 0.4677)x_2 + (0.0350, 0)x_3 + (0.0423, 0.3680)x_4 + (-0.0047, 0)x_5 + (-0.1014, 1.2000)x_6 + (0.0323, 0.8275)x_7 + (0.0487, 0)x_8 + (0.0832, 0)x_9$	11.9358	86.7696
GP-FR	$y = (3.0111, 0) x_1 x_8 + (-0.0655, 1.9000)$	0.0864	0.0063
RS-PSO-ANFIS	$y = \frac{0.1170(x_3)^2 x_6 - 0.1421x_3(x_6)^2 - 0.1561(x_3)^2 + 1.6626(x_6)^2 + 1.0187x_3x_6 - 0.8097x_3 + 0.4499x_6 + 0.0269}{0.3900x_3x_6 - 0.3870x_3 - 0.4065x_6 + 0.4035}$	4.1071×10^{-4}	3.3555×10^{-6}

4. Validation of the Proposed approaches

A total of 30 validation tests were conducted to further evaluate the effectiveness of the proposed methodology. In each validation test, five data sets are randomly selected from the 32 data sets as the testing data sets, and the remaining 27 data sets are used to develop the customer satisfaction models. The validation tests primarily aim to compare the validation errors of the generated customer satisfaction models based on the RS- and PSO- based ANFIS approaches with those based on FLSR, FR, and GP-FR.

In this study, the threshold level of FLSR was set as 0.9. The threshold level of FR was set as 0.9. The population size and the number of iteration were set as 40 and 200, respectively. The generation gap, crossover probability, and mutation probability were set as 0.8, 0.7, and 0.3, respectively. The maximum depth of tree was set as 5. The parameter settings of the generated models based on the proposed approaches are shown in Section 3. Considering that GP-FR and the PSO- based ANFIS are stochastic algorithms, 30 runs were carried out for each validation test, and the mean validation errors were calculated. The validation errors and *MAD* were obtained using (14) and (15). The 30 validation results for S-C models based on the four methods are shown in Figure 2. The lines with '+', '*', 'O', and the solid line '-' denote the validation results of the FLSR, FR, GP-FR, and the proposed approaches, respectively. The prediction errors of the customer satisfaction models based on the proposed approaches are the smallest. The mean validation errors and the mean *MAD* for the affective response S-C based on the four methods are shown in Table 2. Based on the table, it can be seen that the proposed approaches outperform the other three approaches in terms of mean validation errors and mean *MAD*.

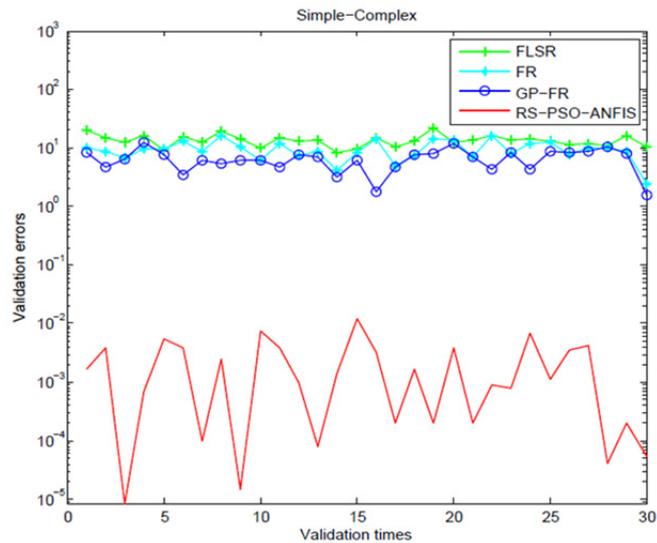


Fig. 2. Validation results of the models for S-C

Table2. Mean validation errors and mean absolute deviation based on the four methods

Validation error	FR	FLSR	GP-FR	RS-PSO-ANFIS
<i>MAE</i> (%)	9.5727	13.5352	6.7991	0.0024
<i>MAD</i> (%)	83.2105	74.5989	35.8331	$4.7686 \cdot 10^{-5}$

5. Conclusion

In this paper, RS- and PSO- based ANFIS approaches to model customer satisfaction are proposed and described. In the proposed approaches, the RS method is introduced to determine the indispensable information and redundant attributes. PSO is employed to determine the parameter settings of the ANFIS from which better customer satisfaction models can be generated in terms of modeling accuracy. On the other hand, the proposed approaches can solve the computational problems of ANFIS as mentioned in Section 1 when the number of inputs to the ANFIS is large. The generated customer satisfaction models are explicit and capable of addressing the nonlinearity and fuzziness that existed in modeling.

A case study of the affective product design of mobile phones was used to illustrate and validate the proposed approach. The affective dimension, S-C, was considered. A total of 30 validation tests were conducted to evaluate the effectiveness of the proposed approaches. From the training and validation results, the smallest training errors and validation errors are obtained based on the proposed approaches compared with those based on the FLSR, FR, and GP-FR. Future work will involve a study of determining optimal settings of design attributes based on the generated customer satisfaction models. On the other hand, outliers may exist in the survey data sets. Thus, detection and elimination of outliers can be conducted for improving the quality of the survey data.

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