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Model variational consumer preferences based on online reviews using sentiment analysis and PSO-based DENFIS approaches

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Abstract. Previous studies developed consumer preference models mainly through customer surveys, ignoring the variability of consumer preferences over time. In addition, it is difficult to obtain time series data based on the customer surveys. In recent years, some previous studies tried to analyse consumer preferences based on online reviews. However, they have not solved the problems of modelling variational consumer preference based on time series data with the consideration of the ambiguity of emotions expressed by customers in online reviews. To solve the above problems, this article proposes the particle swarm optimization (PSO) based dynamic evolving neural-fuzzy inference system (DENFIS) method to model variational consumer preferences based on online customer reviews. Using the time series data mined by the sentiment analysis method and the product attribute settings of the review products, the PSO-based DENFIS method is offered to dynamically model consumer preferences, in which PSO is used to adjust DENFIS parameters adaptively.

Keywords: Consumer preference, opinion mining, DENFIS, particle swarm optimization, new product development

1. Introduction

With the increasing improvement of business, consumers' need-oriented product design becomes increasingly critical. For supporting the design, lots of methods and processes have been developed. Questionnaire is the method most companies apply to understand their users. However, consumer preferences change over time. If the survey is still used to obtain consumer preferences, not only the investment cost will be huge, but the lag of the time by using the questionnaire will still affect the prediction of consumer preferences. Therefore, to better study consumer preferences, their time series data should be collected. However, collecting these data is very difficult, especially for the interview surveys. The company and researchers must conduct many surveys in different periods, which consume lots of survey time and resources. Consequently, previous research and industrial practice have similar problems, that is, time-series data of consumer preference for product design are unavailable for consumer preferences modelling.

Nowadays, the company can easily find customer reviews about products on e-commerce sites. Customers share their buying experience and product

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experience through comments, which can significantly affect potential customers to purchase products. Therefore, companies can extract consumers' opinions on products through these online products comments and obtain the valuable sources of information for product development. In addition, time-series data can be efficiently collected from online reviews with very little expenditure.

Recently, there has been much research on data and information mining that support product design. Some studies focus on obtaining customer needs and consumer preferences through online customer reviews. Other studies employ rule mining to study the relationships between product attributes and consumer preferences. However, there are some limitations in previous studies. First, the modelling process is very complicated as the relationships in the model may be highly nonlinear and fuzzy. Second, the developed relationship based on the rule-mining is usually not enough to determine the new product attribute settings. Third, there is no research on modelling the relationship between consumer preferences and product attributes based on the time-series data from online reviews.

To solve these problems, this article proposes a particle swarm optimization (PSO)-based dynamic evolving neural-fuzzy inference system (DENFIS) method to model variational consumer preferences based on the online customer reviews. The proposed method first collects online reviews of selected products at different periods and uses opinion mining to calculate the sentiment scores of customer preferences. Secondly, PSO-based DENFIS method is used to model the relationship between the sentiment scores of consumer preferences and the settings of product attributes. The model developed by this method can help determine the optimal product attributes of a new product. DENFIS is an ecological model [1] which can effectively and adaptively learn complex time series and is superior to adaptive neuro-fuzzy inference system (ANFIS), multilayer perceptions and evolved self-organizing maps, in time series prediction. However, the complexity of the parameters of DENFIS may cause a local minimum and affect the modelling accuracy. To overcome the deficiency and further enhance the modelling accuracy of DENFIS, in this article, PSO is applied in DENFIS to determine the optimal parameters.

The structure of this article is as follows: Section 2 introduces the related works. The proposed method of modelling variational consumer preferences through online customer reviews is presented in Section 3. The proposed methodology is implemented in the case study of the sweeping robots, which is described in Section 4. Section 5 acquaints the verification tests of the dynamic modelling. At the end of the article, the conclusions are presented.

2. Related works

Sentiment analysis is a research field that extracts people's views and emotions from the written language, also known as opinion mining. It can analyse customers' sentiments and reveal customers' preferences for various product functions [2]. Therefore, many sentiment analysis research work has been carried out. Recently, affective computing and sentiment analysis was emerged which leverage human-computer interaction, information retrieval, and multimodal signal processing for mining sentiments from the online social data [3]. Cambria et al. [4] applied the top-down and bottom-up learning via an ensemble of symbolic and subsymbolic AI tools to detect the polarity in text. Stappen et al. [5] used the SenticNet to extract the natural language concepts from the video transcriptions. Mowlaei et al. [6] employed the statistical methods and genetic algorithm to enhance the performance of sentiment analysis lexicon generation. To alleviate the limitations of the traditional context-based word embedding technique, Song et al. [7] introduced a sentiment lexicon embedding method to increase the sentiment classification performance. Li et al. [8] proposed a new perspective for neural tensor networks on conversational sentiment analysis. Kumar et al. [9] introduced a convolutional stacked bidirectional long short-term memory with a multiplicative attention mechanism for aspect category and sentiment polarity detection. To handle the issue of neutrality in sentiment analysis, Valdivia et al. [10] proposed consensus vote models for detecting and filtering neutrality to improve sentiment classification in sentiment analysis. A multi-level fine-scaled sentiment sensing with ambivalence handling was presented to reveal the multi-level fine-scaled sentiments as well as the different types of emotions [11]. In recent years, deep learning techniques have gained attention in sentiment analysis. Rezaeinia et al. [12] proposed an improved word vector (IWV) for the sentiment analysis to enhance the precision of the pretrained word embedding. They tested the method through the diverse deep learning models and the benchmark sentiment datasets. A deep learning literature for aspect-based sentiment analysis was carried out by Do et al [13].

Many methods have been discovered by employing opinion mining to obtain consumer preferences from the online reviews. Chen et al. [14] introduced an ontology-learning customer needs representation system to generate more accurate consumer preference statements. Zhou et al. [15] proposed an opinion mining method using a hybrid combination of sentiment dictionary and rough set technology to mine customer information about their preferences of products from online reviews to enhance the feature model. Zhang et al. [16] offered a sentiment analysis extraction algorithm that uses fuzzy logic to identify features, opinion expressions, and feature opinions jointly. Zhou et al. [17] applied a two-layer model that combines sentiment analysis and use-case-oriented analogy reasoning to obtain the potential customer needs. A case-based method was proposed by Chiu and Lin [18], which uses an integrated method of text mining and perceptual engineering to extract consumer preferences from the online customer reviews. Kang and Zhou [19] proposed a method based on the Rube unsupervised rules to obtain both subjective and objective features from online consumer comments.

By using various modelling methods, a consumer preference model is established to link product attributes with consumer preferences, which can predict consumer preferences for new products and formulate optimization models to maximize the overall consumer preferences. However, the relationship between product attributes and consumer preferences is very complicated and non-linear. So far, no theoretical model that can simulate the complex relationship has been developed [14]. Therefore, the empirical methods are always used to simulate consumer preferences in the academic field. You et al. [20] and Nagamachi [21] applied statistical linear regression and partial least squares analysis to simulate consumer preferences. Chen et al. [22] proposed the artificial neural networks to simulate the relationship between design attributes and consumer preferences. Yang et al. [23] introduced a method using the belief rules to determine design attributes by simulating consumer preferences. Nevertheless, the methods mentioned above cannot solve the modelling fuzziness from the consumers' subjective judgments. According to the mentioned problem, quite a few fuzzy methods have been adopted, including fuzzy linear regression [24], fuzzy regression based on non-linear programming [25], fuzzy rule-based systems [26], and fuzzy inference methods [27]. In addition, some fuzzy regression based polynomial modelling methods have also been proposed, such as fuzzy regression based on forwarding selection [28], fuzzy regression based on the chaos optimization [29], stepwise-based fuzzy regression [30], and fuzzy based on genetic programming [31]. However, previous studies disregarded the variability of consumer preferences and only used the survey data for a fixed period of time to model consumer preferences. The prediction of the dynamic consumer preferences is undoubtedly significant for product development. Therefore, time-series data based on online customer reviews should be employed in modelling consumer preferences.

Prior to this, there have been a few studies using survey data to predict the future consumer preferences, such as a grey theoretical model developed by Wu et al. [32], a method based on artificial immune and neural system developed by Chong and Chen [33], and an artificial immune system based support vector machine method introduced by Huang et al. [34]. However, limited research has been found on the future consumer preferences forecasting by using online comments. A fuzzy time series method based on online customer reviews was developed by Jiang et al. [35]. To associate consumer preferences and product attributes, Jiang et al. [36] introduced the association rules which are generated from a multi-objective PSO method, while Chung and Tseng [37] proposed the If-Then rules developed from a rule induction framework. However, the generated rules are not enough to determine the optimal settings of product attributes for the new product design. To solve this issue, Jiang et al. [38] proposed the DENFIS for dynamic modelling of customer preferences for product design, but the effectiveness of the proposed method is limited by the parameter settings.

3. Proposed methodology

After reviewing the relevant research, many original research on the relationships between consumer preferences and product attributes based on the online reviews were found. However, most studies fail to consider the changes in consumers preferences over time. Based on the time series online reviews, this article supports a consumer-initiated model based on the online reviews. The specific process of the proposed method is illustrated in Fig. 1.

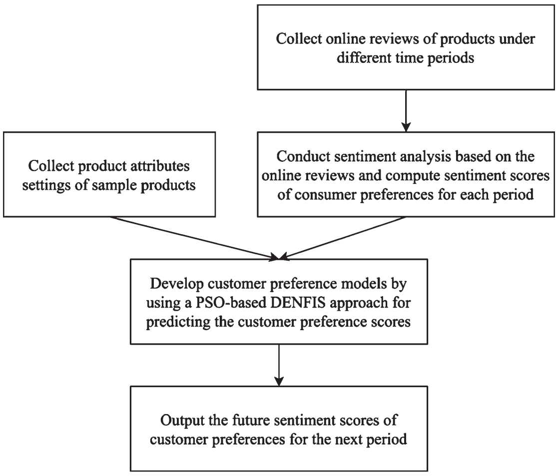

Fig. 1. Proposed methodology.

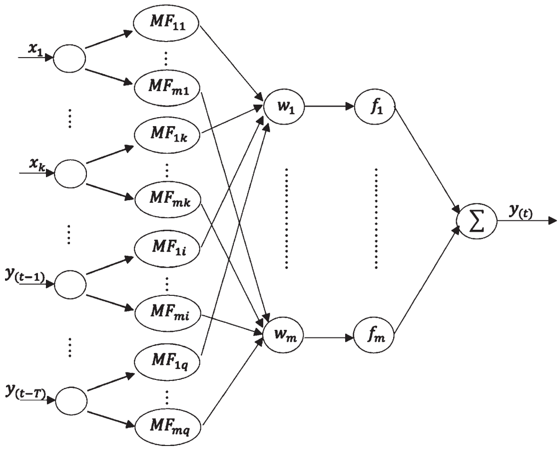

Fig. 2. Architecture of DENFIS.

3.1. Sentiment analysis from online customer reviews

First of all, the sample products are determined. The web crawlers are used to obtain consumer reviews of the sampled products on the e-commerce platform. Then the online comments are divided into the different periods and put into the separated Excel files. Then the sentiment analysis is used to obtain the dimensions of consumer preferences and calculate the corresponding sentiment scores.

The six steps of the sentiment analysis are described as follows. First, the preprocessing on the unstructured text is conducted, including eliminating stop-words and non-alphanumeric symbols, and changing letters into lowercase. Second, the words are labelled according to their different parts of speech. In our research, the general nouns refer to the consumers' preferences, while the adverbs and adjectives are the corresponding emotional expressions. Third, the emotional words of consumer preferences are extracted from the online reviews. Fourth, feature pruning is used to remove the errors and the redundant attributes. Fifth, the K-means clustering method is employed to group the phrase into the different categories according to the phrases' meaning. For example, the terms "good cleaner", "high performance", and "useful" are all categorized as "clean well. Finally, SentiWordNet gives the emotional scores that reflect consumer preferences for the different settings of product attributes. SentiWordNet is an opinion dictionary derived from the WordNet database, in which each synset is represented by several positive, neutral, and negative sentiment information. In this study, Semantria, a well-known text analysis software tool, is used for the sentiment analysis based on the online comments. It provides text analysis through Excel plug-in, extracts emotions based on positive, neutral, and negative dimensions, and calculates the corresponding emotional scores.

3.2. PSO-based DENFIS method

To predict the future consumer preference scores, a PSO-based DENFIS method is proposed for modelling dynamic consumer preferences. Taking the obtained consumer preferences scores and the product attributes as inputs, the evolutionary clustering method (ECM) is employed in DENFIS to divide the inputs into clusters. And the antecedents of new fuzzy rules are formed by using the cluster centres. Based on the weighted recursive least squares estimation method, a first-order linear model is developed for each fuzzy rule. Moreover, PSO algorithm is used to determine the optimal parameters of DENFIS to improve the accuracy of modelling. Based on PSO-based DENFIS method, a dynamic consumer preference model is generated. An architecture of a DENFIS is shown in the Fig. 2, where $x_1 \sim x_k$ represent k product attributes; $y_{(t-1)} \sim y_{(t-T)}$ describe the values of consumer preferences scores in the past periods $t-1 \sim t-T$ respectively, while $y_{(t)}$ is the corresponding predicted value of the consumer preference score in the future period t.

3.2.1. Evolving clustering method (ECM)

As a clustering method, ECM dynamically estimates the number of clusters and their corresponding centres on the input data. In the process of clustering, the input data set is firstly divided into different clusters based on their centre and radius. For each input data $Z_i, i = 2, 3, \cdots, n$, is presented, where n denotes the number of data sets. For the first cluster, C_1, its centre, Cc_1, and radius, Ru_1, are firstly initialized as the first data set and zero, respectively. To determine the number of clusters and limit the new cluster radius, a threshold value, D_{thr}, is presented. The Euclidean distance is applied to determine the distances, D_{ij}, by (1) from Z_i to the existing clusters, $C_j, j = 1, 2, \cdots, m$.

$$D_{ij} = ||Z_i - Cc_j||, j = 1, 2, ..., m \quad (1)$$

where Cc_j represents the cluster centre of C_j and m indicates the number of clusters. To compute the minimum distance, equation (2) is used.

$$D_{i\,min} = \min D_{ij} = ||Z_i - Cc_{min}|| \quad (2)$$

C_{min} is the cluster with $D_{i\,min}$, while its centre and radius are determined as Cc_{min} and Ru_{min}, respectively. If $D_{i\,min} \leq Ru_{min}$, Z_i belongs to the cluster C_{min}. If $D_{i\,min} > Ru_{min}$, the existing cluster is updated, or a new cluster is created. Equation (3) and (4) are used to determine the value V_{ij} and the minimum value of V_{ij}, V_{ia}, respectively.

$$V_{ij} = D_{ij} + Ru_j, j = 1, 2, ..., m \quad (3)$$

$$V_{ia} = \min V_{ij} = D_{ia} + Ru_a \quad (4)$$

C_a is the cluster with V_{ia}, while its cluster centre and radius are determined as Cc_a and Ru_a, respectively. The distance between Z_i and C_a is denoted as D_{ia}. The cluster C_a is updated if $V_{ia} \leq 2 \times D_{thr}$. Its radius Ru_a is replaced as Ru'_a and set as the half of the minimum value, $V_{ia}/2$. Its center Cc_a is updated by the new center, Cc'_a, which is located at a point on the line connecting Z_i and Cc_a, and the distance from Cc'_a to Z_i is equal to Ru'_a. If $V_{ia} > 2 \times D_{thr}$, Z_i belongs to a new created cluster. The centre and radius of the new cluster are set as Z_i and zero, respectively. After processing all data sets, the ECM algorithm is completed.

3.2.2. Learning process in DENFIS model

The inputs of DENFIS have two parts, one part is the product attributes of the sampled products, $x_1 \sim x_k$, and another part is the consumer preference score $y_{(t-1)} \sim y_{(t-T)}$. The ith input of the model is represented as $x_i, i = 1, 2, \cdots, q$, where the inputs number is q, $q = k + T$. When i is in different ranges, x_i represents the diverse input. It is equal to $x_1 \sim x_k$ and $y_{(t-1)} \sim y_{(t-T)}$, when $i = 1, 2, \cdots, k$, and $i = k + 1, \cdots, q$, respectively. Using the clusters of the input, a set of fuzzy rules can be generated as follows:

$$
\begin{aligned}
&If\ x_1\ is\ MF_{11}, x_2\ is\ MF_{12}, ..., and\ x_q\ is\ MF_{1q},\\
&\quad then\ y\ is\ f_1(x_1, x_2, ..., x_q)\\
&If\ x_1\ is\ MF_{21}, x_2\ is\ MF_{22}, ..., and\ x_q\ is\ MF_{2q},\\
&\quad then\ y\ is\ f_2(x_1, x_2, ..., x_q)\\
&\qquad\vdots\\
&If\ x_1\ is\ MF_{m1}, x_2\ is\ MF_{m2}, ..., and\ x_q\ is\ MF_{mq},\\
&\quad then\ y\ is\ f_m(x_1, x_2, ..., x_q)
\end{aligned}
$$

"x_i is MF_{ji}", $j = 1, 2, \cdots, m$, $i = 1, 2, \cdots, q$, are $m \times q$ fuzzy propositions as q antecedents from m fuzzy rules respectively. As the *jth* membership function of x_i, MF_{ji} has m membership function, which is equal to the number of clusters based on ECM; $f_j(x_1, x_2, \cdots, x_q)$, $j = 1, 2, \cdots, m$ are the first-order Sugeno fuzzy models in the consequent parts of the fuzzy rules; and y is the output of the fuzzy rule. In this study, triangular-shaped membership functions defined below are used.

$$\mu_j(x_i) = \begin{cases} 0, & x_i < a_j \\ \frac{x_i - a_j}{b_j - a_j}, & a_j \leq x_i \leq b_j \\ \frac{c_j - x_i}{c_j - b_j}, & b_j \leq x_i \leq c_j \\ 0, & x_i > c_j \end{cases} \quad (5)$$

For the *jth* cluster, the centre, left and right value are represented as b_j,a_j and c_j, respectively; where $a_j = b_j - d \times D_{thr}$ and $c_j = b_j + d \times D_{thr}$, $1.2 \leq d \leq 2$.

For the consequent parts of the fuzzy rules, the first-order Sugeno fuzzy models are employed and the linear function of the consequences is developed by the linear least-squares estimation method (LSE). Each of the linear models can be expressed as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_q x_q \quad (6)$$

The data sets with n data pairs, $\{[x_1^l, x_2^l, \cdots, x_q^l], y_l\}$, $l = 1, 2, \cdots, n$, are used to obtain the regression coefficients, $\beta = [\beta_0, \beta_1, \beta_2, \cdots, v_q]^T$. $x_1^l, x_2^l, \cdots, x_q^l$ and y_l are the inputs and actual output of the lth data pair, respectively. The initial inverse matrix P and coefficients β are calculated based on the least square estimation method using the following Equations (7) and (8), respectively.

$$P = \left(A^T WA\right)^{-1} \tag{7}$$

$$\beta = PA^T WY \tag{8}$$

where

$$A = \begin{pmatrix} 1 & x_1^1 & x_2^1 & \dots & x_q^1 \\ 1 & x_1^2 & x_2^2 & \dots & x_q^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_1^n & x_2^n & \dots & x_q^n \end{pmatrix}$$

$$W = \begin{pmatrix} W_1 & 0 & \dots & 0 \\ 0 & W_2 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & W_n \end{pmatrix}$$

$$Y = \left[y_1, y_2, \dots, y_n\right]^T$$

where $()^{-1}$ expresses the inverse matrix and $[]^T$ represents the transpose of the matrix. W_l can be computed as follows:

$$W_l = 1 - Dis_l, l = 1, 2, ..., n \tag{9}$$

$$Dis_l = \frac{\left(\sum_{i=1}^{q} \left|x_i - b_{ji}\right|^2\right)^{\frac{1}{2}}}{q^{\frac{1}{2}}} \tag{10}$$

The distance between the lth data set and the current cluster centre is represented as Dis_l. As a normalized Euclidean distance, it can be determined by (10), where b_{ji} is the *ith* value in the *jth* cluster centre.

When entering a new data set, the initialized P and β are updated. At the $(l+1)th$ iteration, the inverse matrix $P_{(l+1)}$ and coefficients $\beta_{(l+1)}$ are updated respectively as follows.

$$\beta_{l+1} = \beta_l + W_{l+1} P_{l+1} \alpha_{l+1} \left(y_{l+1} - \alpha_{l+1}^T \beta_l\right) \tag{11}$$

$$P_{l+1} = \frac{1}{\lambda}\left(P_l - \frac{W_{l+1} P_l \alpha_{l+1} \alpha_{l+1}^T P_l}{\lambda + \alpha_{l+1}^T P_l \alpha_{l+1}}\right) \tag{12}$$

The $(l+1)th$ row vector of matrix A is represented as α_{l+1}^T, $\alpha_{l+1}^T = [1 \; x_1^{l+1} \; x_2^{l+1} \; \cdots \; x_q^{l+1}]$, while the $(l+1)th$ component of Y is described as y_{l+1}. λ is a forgetting factor with $0 < \lambda \leq 1$.

Based on the above learning process, the lth predicted output of DENFIS is calculated which is the weighted average of each rule's output.

$$y_l'(t) = \frac{\sum_{j=1}^{m} w_j f_j(x_1^l, x_2^l, \dots, x_q^l)}{\sum_{j=1}^{m} w_j} \tag{13}$$

$$w_j = \sum_{i=1}^{q} \mu_j(x_i^l) \tag{14}$$

where $\mu_j\left(x_i^l\right)$ is calculated by (5).

3.2.3. Determination of parameters for DENFIS using PSO

PSO is a popular optimization method, simulating the social behaviour of a bird flock. The task of the PSO is to obtain the global optimal solution which can help us to determine the parameters for DENFIS. In PSO, every potential optimization solution can be regarded as the "particle" in a D-dimensional search space. Particles have only two attributes which are speed and position. Speed describes the speed of movement to the potential best position, and position means the location in the movement. PSO is performed based on a group of randomly initialized particles. All particles in the particle swarm update their speed and position based on the current best position, p_{best}, and the current global best position, g_{best}, shared by the entire particle swarm using the following formulas.

$$\begin{aligned} v_{id}^{k+1} &= \omega v_{id}^k + c_1 r_1(p_{id}^k - x_{id}^k) \\ &\quad + c_2 r_2(g_{jd}^k - x_{jd}^k) \end{aligned} \tag{15}$$

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \tag{16}$$

v_{id}^{k+1} and x_{id}^{k+1} are the vectors of speed and position of the ith particle at the kth iteration, respectively. In the D-dimension, a swarm is initialized as m particles with a certain speed. The position of the ith particle is $x_i = (x_{i1}, x_{i2}, \cdots, x_i)$, where $1 \leq i \leq m$ and $1 \leq d \leq D$. As the dimension of the search space, D is the number of parameters to be determined. The speed for the *ith* particle is $v_i = (v_{i1}, v_{i2}, \cdots, v_{id})$. The historical best local position, p_{best}, of the *ith* particle is $p_i = (p_{i1}, p_{i2}, \cdots, p_{id})$, while the best global position, g_{best}, for the entire swarm is $g_i = (g_{j1}, g_{j2}, \cdots, g_{jd})$, $j \in 1, 2, \cdots, m$. w is the inertia weight. As a non-negative value, w can help to balance the global search by deciding the quantity inherited from the current speed of the particle. The learning factors are represented as c_1 and c_2, which are usually set as 2. r_1 and r_2 are random numbers, chosen from the range [0, 1].

To determine the best position, the mean relative error (MRE) and the variance of error (VoE) are adopted as shown in (17) and (18), respectively. In this article, the sum of MRE and VoE is used as the fitness value of the particle. The position of the particle corresponding to the minimum sum value is the best position.

$$MRE = \frac{1}{n}\sum_{l=1}^{n}\frac{\left|y_l'(t) - y_l(t)\right|}{y_l(t)} \tag{17}$$

$$VoE = \frac{1}{n-1}\sum_{i=1}^{n}\left(\frac{\left|y_l'(t) - y_l(t)\right|}{y_l(t)} - MRE\right)^2 \tag{18}$$

3.3. Computational procedures

Based on online customer reviews, the processes of dynamic modelling consumer preference for product development are described as follows:

Step 1: Online customer reviews of the sampled products are collected from e-commerce shopping websites within four pre-defined time periods and are stored in different Excel files after data preprocessing. Semantria, as the sentiment analysis method introduced in Section 3.1, is then applied for each Excel files to obtain the sentiment scores of consumer preferences. Taking the obtained consumer preferences scores and the product attributes as inputs, the data sets for modelling variational consumer preferences for product development are generated.

Step 2: The PSO algorithm is used to optimize the parameters, D_{thr} and λ, in the DENFIS method. Firstly, the particle swarm is initialized, including the number of iterations, swarm size, search space dimension, search range, and learning factors. The speed and position of each particle are initialized randomly. And the iteration starts.

Step 3: In the first iteration, the initial position of every particle is used as the initial individual best position p_{best}, and the position vector of each particle is used as the parameters of DENFIS in sequence, including D_{thr} and λ. The initialization for the first cluster C_1 is conducted as described in Section 3.2.1. The initial inverse matrix P and regression coefficients β are obtained using (7) and (8), respectively. The clusters of the input are updated using ECM according to the process described in Section 3.2.1. Based on the clusters, the membership function $\mu_j(x_i)$ is generated using (5) and the weight of each fuzzy rule is calculated using (14). The linear model is developed based on (6). Based on the weight of each fuzzy rule and the linear model, the predicted output $y'_{l(t)}$ is then computed based on (13). After that, the MRE and the VoE for the *ith* particle are calculated. The sum of them is obtained as the fitness value, fn_i^1, of the ith particle in the first iteration. fn_i^1 is set as the initial individual best fitness value p_{best}. The particle which has the smallest fn_i^1 value is recorded as the best particle. Its position vector is set as the initial global best position g_{best}.

Step 4: The iteration is continued by $k+1 \rightarrow k$. In each iteration, the speed vector v_{id}^{k+1} and the position vector x_{id}^{k+1} for each particle are updated based on (15) and (16), respectively. Then, the fitness value of the *ith* particle at the *kth* iteration, fn_i^k, is computed based on the updated particles. For each particle, the values of fn_i^k and p_{best} are compared. If the value of fn_i^k is smaller, the p_{best} is updated as the value of fn_i^k as individual best fitness value, and the particle's new position and individual optimal position are set as $p_{best} = x_{id}^{k+1}$.

Step 5: The iteration stops once the predefined number of iterations is reached. By selecting the smallest value in p_{best}, the global best fitness value g_{best} is updated. The values of g_{best} are the identified optimal settings for D_{thr} and λ in DENFIS model.

Step 6: Based on the above parameters, the models for variational consumer preferences are generated, and the future emotional scores of consumer preferences can be predicted.

4. Implementation

Nowadays, when online shopping is prevalent, numerous online customer comments can be easily collected. By using the sentiment analysis, the emotional scores of consumer preferences can be obtained. However, for consumer preferences forecasting and product development, these sentiment analysis results are not enough. In this section, PSO-based DENFIS approach is introduced to model the variational customer preferences in a case study of sweeping robots.

To develop a new sweeping robot, 10 competitive sweeping robots have been identified as references, denoted by $A \sim J$. Online customer reviews of competitive sweeping robots were collected on Amazon.com using 4 fixed time period strategies. The Semantria Excel plug-in was used to perform sentiment analysis on the collected online comments

Table 1
The setting of product attributes of ten products

Product	Product attributes			
	Volume	Max suction power (Pa)	Dust box capacity (L)	Wet mopping
A	438.178	1400	0.5	1
B	490.100	1800	0.6	0
C	417.720	850	0.3	1
D	515.573	2000	0.75	0
E	417.720	1000	0.3	0
F	442.368	1400	0.3	0
G	642.105	1800	0.5	0
H	645.979	1800	0.4	0
I	643.500	2000	0.7	0
J	466.215	1500	0.6	0

Table 2
The sentiment scores of ten products under 4 periods

Product	Clean well			
	Period 1	Period 2	Period 3	Period 4
A	0.36	0.43	0.47	0.40
B	0.37	0.29	0.35	0.20
C	0.28	0.32	0.44	0.24
D	0.32	0.33	0.38	0.24
E	0.33	0.33	0.33	0.30
F	0.43	0.40	0.41	0.39
G	0.33	0.31	0.27	0.30
H	0.33	0.32	0.37	0.31
I	0.30	0.31	0.30	0.30
J	0.32	0.32	0.37	0.28

stored in an Excel file. Firstly, words or phrases, which are excavated from online comments are grouped based on the synonyms, and the relevance to the consumer preferences. For example, the excavated phrases “good cleaner”, “high performance”, and “useful” were grouped as a category of “clean well”, which is one of the consumer preferences of the sweeping robots. In this case, there are four common consumer preferences summarized, which are quality, smart operation, clean well and working sound. Using Semantria’s user category analysis, keywords and phrases which are relevant to the consumer preferences are set as the “user category”. Sentiment analysis was then repeated based on each time period to obtain emotional scores of consumer preferences.

In this article, consumer preference “clean well” is used as an example to illustrate the proposed method. There are four product attributes related to the consumer preference “clean well”, which are volume, max suction power, dust box capacity, and wet mopping, and are denoted as x_1, x_2, x_3 and x_4, respectively. The units of x_1, x_2 and x_3 are cubic inch, pascal (Pa) and litre (L), respectively. For x_4, 1 denotes that the sweeping robot has the function of wet mopping while 0 means it cannot provide this function. The product attributes settings of the 10 sampled products were collected and are shown in Table 1.

In this case study, four product attributes, $x_1 \sim x_4$, and consumer preference scores of the three past periods, periods 1-3, which are expressed respectively as $y_{(t-3)}$, $y_{(t-2)}$, and $y_{(t-1)}$, are used for developing PSO-based DENFIS models to predict the consumer preference score of the “clean well” in Period 4, $y_{(t)}$. The sentiment scores of 10 products under 4 periods are shown in Table 2.

For the PSO-based DENFIS approach, eight parameters including λ and $D_{thr\,1} \sim D_{thr\,7}$ need to be determined based on the PSO. λ is a forgetting factor with $0 < \lambda \leq 1$, while $D_{thr\,i}$, $i = 1, 2, \cdots, 7$, represent the threshold values of seven DENFIS inputs, respectively. In the proposed approach, the parameter d was set as 1.2, which is a common setting used in previous studies. To initialize the particle swarm, we set the number of the particles as 100, initial value of the fitness as nan, the optimal fitness value threshold as 0.00000000001, and number of the iterations as 1000.

Using the products $C \sim J$ as the training sets for an example, based on their product attributes, the matrix A, and Y in (8) can be obtained as shown below.

$$A = \begin{pmatrix} 1 & 0.13 & 0.48 & 0.50 & 1.00 & 0.36 & 0.43 & 0.47 \\ 1 & 0.23 & 0.80 & 0.55 & 0.50 & 0.37 & 0.36 & 0.41 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0.50 & 0.80 & 0.53 & 0.50 & 0.36 & 0.36 & 0.37 \end{pmatrix}$$

$$Y = [0.40, 0.20, 0.24, 0.24, 0.30, 0.39, 0.30, 0.31]^T$$

To improve the training performance of DENFIS, the values of x_1, x_2 and x_3 in columns 2, 3 and 4 of the matrix A are normalized. Columns 6-8 of the matrix are the values of x_5, x_6 and x_7, which are also the values of the consumer preference scores of Periods 1–3, respectively. In the vector Y, the values of $y_1 \sim y_8$ represent the consumer preference scores of the products $C \sim J$ in Period 4. Suppose the data set of product G belongs to the kth cluster and its centre is [0.24, 0.16, 0.53, 0.50, 0.33, 0.36, 0.40]. W_1 of [W] shown in (7) and (8) can be calculated by using (9).

Fuzzy rules of products $C \sim J$ are obtained as follows.

Fuzzy rule 1:

$$\begin{aligned} &\textit{If } x_1 \textit{ is } MF_{11},\ x_2 \textit{ is } MF_{12},\ x_3 \textit{ is } MF_{13},\\ &\quad x_4 \textit{ is } MF_{14},\ y_{(t-3)} \textit{ is } MF_{15},\\ &y_{(t-2)} \textit{ is } MF_{16}, \textit{and } y_{(t-1)} \textit{ is } MF_{17} \textit{ then}\\ &\quad y(t) = 0.1595 + 0.1258x_1 + 0.1717x_2\\ &\qquad +0.1015x_3 + 0.2156x_4 + 0.0215y_{(t-3)}\\ &\qquad +0.3241y_{(t-2)} - 0.0315y_{(t-1)} \end{aligned}$$

Fuzzy rule 2:

$$\begin{aligned} &\textit{If } x_1 \textit{ is } MF_{21},\ x_2 \textit{ is } MF_{22},\ x_3 \textit{ is } MF_{23},\\ &\quad x_4 \textit{ is } MF_{24},\ y_{(t-3)} \textit{ is } MF_{25},\\ &y_{(t-2)} \textit{ is } MF_{26}, \textit{and } y_{(t-1)} \textit{ is } MF_{27} \textit{ then}\\ &\quad y(t) = 0.0202 + 0.0160x_1 + 0.0218x_2\\ &\qquad +0.0129x_3 + 0.0274x_4 + 0.0027y_{(t-3)}\\ &\qquad +0.0411y_{(t-2)} - 0.0040y_{(t-1)} \end{aligned}$$

Fuzzy rule 3:

$$\begin{aligned} &\textit{If } x_1 \textit{ is } MF_{31},\ x_2 \textit{ is } MF_{32},\ x_3 \textit{ is } MF_{33},\\ &\quad x_4 \textit{ is } MF_{34},\ y_{(t-3)} \textit{ is } MF_{35},\\ &y_{(t-2)} \textit{ is } MF_{36}, \textit{and } y_{(t-1)} \textit{ is } MF_{37} \textit{ then}\\ &\quad y(t) = 0.0766 + 0.0604x_1 + 0.0825x_2\\ &\qquad +0.0487x_3 + 0.1035x_4 + 0.0103y_{(t-3)}\\ &\qquad +0.1556y_{(t-2)} - 0.0151y_{(t-1)} \end{aligned}$$

Fuzzy rule 4:

$$\begin{aligned} &\textit{If } x_1 \textit{ is } MF_{41},\ x_2 \textit{ is } MF_{42},\ x_3 \textit{ is } MF_{43},\\ &\quad x_4 \textit{ is } MF_{44},\ y_{(t-3)} \textit{ is } MF_{45},\\ &y_{(t-2)} \textit{ is } MF_{46}, \textit{and } y_{(t-1)} \textit{ is } MF_{47} \textit{ then}\\ &\quad y(t) = 0.0797 + 0.0629x_1 + 0.0859x_2\\ &\qquad +0.0507x_3 + 0.1078x_4 + 0.0108y_{(t-3)}\\ &\qquad +0.1620y_{(t-2)} - 0.0157y_{(t-1)} \end{aligned}$$

Fuzzy rule 5:

$$\begin{aligned} &\textit{If } x_1 \textit{ is } MF_{51},\ x_2 \textit{ is } MF_{52},\ x_3 \textit{ is } MF_{53},\\ &\quad x_4 \textit{ is } MF_{54},\ y_{(t-3)} \textit{ is } MF_{55},\\ &y_{(t-2)} \textit{ is } MF_{56}, \textit{and } y_{(t-1)} \textit{ is } MF_{57} \textit{ then}\\ &\quad y(t) = 0.1595 + 0.1258x_1 + 0.1717x_2\\ &\qquad +0.1015x_3 + 0.2156x_4 + 0.0215y_{(t-3)}\\ &\qquad +0.3241y_{(t-2)} - 0.0315y_{(t-1)} \end{aligned}$$

Fuzzy rule 6:

$$\begin{aligned} &\textit{If } x_1 \textit{ is } MF_{61},\ x_2 \textit{ is } MF_{62},\ x_3 \textit{ is } MF_{63},\\ &\quad x_4 \textit{ is } MF_{64},\ y_{(t-3)} \textit{ is } MF_{65},\\ &y_{(t-2)} \textit{ is } MF_{66}, \textit{and } y_{(t-1)} \textit{ is } MF_{67} \textit{ then}\\ &\quad y(t) = 0.0574 + 0.0453x_1 + 0.0618x_2\\ &\qquad +0.0365x_3 + 0.0776x_4 + 0.0077y_{(t-3)}\\ &\qquad +0.1167y_{(t-2)} - 0.0113y_{(t-1)} \end{aligned}$$

Fuzzy rule 7:

$$\begin{aligned} &\textit{If } x_1 \textit{ is } MF_{71},\ x_2 \textit{ is } MF_{72},\ x_3 \textit{ is } MF_{73},\\ &\quad x_4 \textit{ is } MF_{74},\ y_{(t-3)} \textit{ is } MF_{75},\\ &y_{(t-2)} \textit{ is } MF_{76}, \textit{and } y_{(t-1)} \textit{ is } MF_{77} \textit{ then}\\ &\quad y(t) = 0.0686 + 0.0541x_1 + 0.0738x_2\\ &\qquad +0.0436x_3 + 0.0927x_4 + 0.0092y_{(t-3)}\\ &\qquad +0.1393y_{(t-2)} - 0.0135y_{(t-1)} \end{aligned}$$

Fuzzy rule 8:

$$\begin{aligned} &\textit{If } x_1 \textit{ is } MF_{81},\ x_2 \textit{ is } MF_{82},\ x_3 \textit{ is } MF_{83},\\ &\quad x_4 \textit{ is } MF_{84},\ y_{(t-3)} \textit{ is } MF_{85},\\ &y_{(t-2)} \textit{ is } MF_{86}, \textit{and } y_{(t-1)} \textit{ is } MF_{87} \textit{ then}\\ &\quad y(t) = 0.0749 + 0.0591x_1 + 0.0807x_2\\ &\qquad +0.0477x_3 + 0.1013x_4 + 0.0101y_{(t-3)}\\ &\qquad +0.1523y_{(t-2)} - 0.0148y_{(t-1)} \end{aligned}$$

5. Validation

To evaluate the effectiveness of the PSO-based DENFIS method in modelling variational consumer preferences, five validation tests were conducted, which selected the data sets of products A and B, C and D, E and F, G and H, as well as I and J as the verification test data, respectively. The training data sets in each verification test use the remaining data sets. And there are no duplicate data sets in the verification test. In this article, the MRE and the VoE were adopted as the prediction errors to evaluate the effectiveness of the proposed method. The values of MRE and VoE obtained by the PSO-based DENFIS approach were compared with those obtained by DENFIS, ANFIS, subtractive cluster-based ANFIS (SC-ANFIS), fuzzy c-means-based ANFIS (FCM-ANFIS), and K-means-based

Table 3
The validation results based on the five approaches

Validation test		Validation data sets	SC-ANFIS	FCM-ANFIS	K-means-ANFIS	DENFIS	PSO-based DENFIS (proposed approach)
1	MRE	A, B	0.3855	0.3843	0.3854	0.3648	0.2800
	VoE		0.0434	0.0443	0.0442	0.0150	0.0032
2	MRE	C, D	0.4456	0.4429	0.4430	0.4070	0.4070
	VoE		0.0152	0.0151	0.0151	0.0142	0.0142
3	MRE	E, F	0.3717	0.3685	0.3693	0.2957	0.0870
	VoE		0.0024	0.0024	0.0025	0.0032	0.0001
4	MRE	G, H	0.1131	0.1110	0.1110	0.0371	0.0188
	VoE		0.0004	0.0004	0.0004	0.0004	0.0001
5	MRE	I, J	0.0407	0.0364	0.0373	0.0313	0.0313
	VoE		0.0017	0.0017	0.0018	0.0005	0.0005

ANFIS. In SC-ANFIS, FCM-ANFIS and K-means-based ANFIS, the SC, FCM and K-means methods are combined into ANFIS to decide the membership function of ANFIS respectively. In SC, under the assumption that the potential cluster centre can be any data point, the centre of the cluster is determined according to the density measurement. The FCM method proposes to divide the data set into fuzzy clusters through the minimization of the cost function. Therefore, a given data point can belong to multiple clusters with a certain degree of membership. K-means groups the data set into K clusters by minimizing the value of the objective function. It alternates between assigning each data point to the cluster with the nearest average and updating the cluster centre until the value of the objective function does not improve further.

In each verification, the same data sets were used in the modelling of variational consumer preferences based on PSO-based DENFIS, DENFIS, ANFIS, SC-ANFIS, FCM-ANFIS, and K-means-based ANFIS. Nevertheless, because many inputs are involved in the training, the ANFIS training process was failed with "out of memory" errors, and the ANFIS model cannot be developed. In the proposed approach, based on the PSO, D_{thr} and λ values settings were determined, which lead to the smallest sum of MRE and VoE. In DENFIS, for the validation tests 1–5, the values of D_{thr1} were set as 0.5, 0.03, 0.41, 0.04, 0.5; D_{thr2} were set as 0.1, 0.03, 0.88, 0.04, 0.3; D_{thr3} were set as 0.6, 0.6, 0, 0.2, 0.2; D_{thr4} were set as 0.4, 0.9, 0.56, 0.2, 0.7; D_{thr5} were set as 0.7, 0.02, 0.73, 0.09, 0.8; D_{thr6} were set as 0.6, 0.16, 0.94, 0.6, 0.7 and D_{thr7} were set as 0.4, 0.4, 0, 0.8, 0.4. The values of λ were set as 0.4, 0.88, 0.42, 0.35 and 1 in the validation tests $1 \sim 5$, respectively. The number of clusters is usually less than or equal to $\sqrt{n}$, where n is the number of data sets [39]. Therefore, the number of clusters was set as 3 for all the validation tests for FCM-ANFIS and K-means-based ANFIS. The five approaches for modelling "clean well" were implemented using MATLAB software.

Based on the generated models, the predicted emotional scores of consumer preference of the fourth period for products A to J can be obtained. The MRE and VoE of the five validation tests based on the five methods are shown in Table 3. It can be seen from the tables that the MRE and VoE based on the proposed approach are all smaller than those based on the other four approaches. With the predicted consumer preference scores of the competitive products, the great reference value can be provided for the company in the product development. On the other hand, by using the developed PSO-based DENFIS models, the appropriate product attribute settings of the sweeping robot can also be determined based on the optimization algorithms.

6. Conclusion

Nowadays, the development of new products to meet consumer preferences has become an important issue that enterprises need to solve. Therefore, modelling the relationship between the product design attributes and consumer preferences is crucial. In previous studies and industries, customer survey data are applied to analyse consumer preferences and develop consumer preference models. Nevertheless, it is difficult for customer surveys to obtain the time series survey data that reflect the dynamic changes of consumer preferences under different time periods. Unlike the traditional survey data, online reviews are written by consumers on the e-commerce platform after completing the purchase of the product. It contains the consumer's evaluation of the product, which can be easily obtained and used in some research to develop the consumer preference models. However, previous research failed to resolve the ambiguity existing in the customer emotional expressions in the online reviews. To resolve the limitations mentioned above, a DENFIS method for dynamic modelling of consumer preferences based on the online customer reviews has been proposed in previous study. Nevertheless, the parameters setting in DENFIS method is complex and it is difficult to determine, which affects the accuracy of the modelling. This article proposes a PSO-based DENFIS method, in which PSO can determine the optimal parameters setting for the DENFIS method. At the same time, the accuracy of the model is improved based on the proposed method. To illustrate the proposed method, a case study of sweeping robot products used for modelling variational consumer preferences was carried out based on the online comments. In order to evaluate the effectiveness of the PSO-based DENFIS method, the prediction results obtained based on the PSO-based DENFIS method were compared with those obtained by DENFIS, ANFIS, SC-ANFIS, FCM-ANFIS, and K-means-based ANFIS. The forecasted results are compared. The comparison results show that the PSO-based DENFIS method is superior to the other five methods in terms of the MRE and the VoE. However, some limitations still exist in the paper. In the sentiment analysis, the problems of neutrality and ambivalence are not considered,which may affect the sentiment scores of the customer preferences. The filtering of neutrality and the handling of ambivalence will be conducted in the future work to enhance the accuracy of the results of the sentiment analysis. In the proposed PSO-based DENFIS approach, to determine the parameters in the PSO such as the size of particle swarm and the number of iterations, different trials with different parameters settings were conducted, which has long time-consuming. The determination of the parameters of the PSO adaptively can be considered to obtain the optimal settings. In order to further evaluate the effectiveness of the proposed method in dynamic modelling of customer preferences, future research work will involve studying various issues, such as determining the minimum and the optimal number of time periods, adopting Gaussian membership functions, and incorporating the backpropagation algorithm into the learning algorithm of the DENFIS approach.

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