A multigene genetic programming based fuzzy regression approach for modelling customer satisfaction based on online reviews

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Abstract

In previous studies, customer survey data were commonly adopted to perform the modelling of customer satisfaction (CS). However, it could be time-consuming to conduct surveys and obtain their data. On the other hand, respondents' responses are quite often confined by pre-set questions. Nowadays, a huge number of customer online reviews on products can be found on various websites. The reviews can be extracted easily in a very short time. Customers can freely express their concerns and views of products in their online reviews. Those reviews provide a valuable source of information for manufacturers to improve their existing products and develop their new products. Previous studies have attempted to develop CS models based on survey data by using various computational intelligence techniques. However, no attempt at developing explicit CS models based on online reviews was reported in literature. In this paper, a methodology for the modelling of CS based on customer online reviews and a multigene genetic programming based fuzzy regression (MGGP-FR) approach is proposed. In the proposed methodology, relevant textual reviews of products are extracted from e-commerce websites. Then, opinion mining is conducted on the reviews and sentiments scores of customer concerns are derived. A MGGP-FR approach is then introduced to develop CS models based on the derived sentiment scores. A case study on developing CS models for electronic hairdryers is conducted to illustrate the proposed methodology and validate the effectiveness of MGGP-FR in the modelling of CS. The validation results show MGGP-FR outperforms the other three modelling approaches, fuzzy regression, genetic programming, and genetic programming based fuzzy regression, in the CS modelling in terms of prediction accuracy.

Keywords: Customer satisfaction; Opinion mining; fuzzy regression; genetic programming; multigene genetic programming.

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1. Introduction

The proliferation of e-commerce websites has generated lots of incentives for both manufacturers and consumers since the advent of web 2.0 technologies. On the consumers' side, it is beneficial for them to freely express their opinions by leaving the reviews of their purchased products on e-commerce platforms. The reviews always reflect real concerns, satisfaction, and dissatisfaction of customers about products. It is also beneficial for prospective consumers to read these kinds of reviews to make an informed decision (Alfrjani et al. 2019; Ankit & Saleena 2018). With the advent of e-commerce websites allowing consumers to express their opinions, more advanced methods such as machine learning (ML) and natural language processing (NLP) approaches have been proposed to process online reviews into the forms that allow product manufacturers to gain useful insights. Text processing methods have become necessary because online reviews are usually voluminous (Pookulangara & Koesler 2011). In various industries, companies quite often adopt surveys based on questionnaires and/or interviews to understand customer needs and their expectations. Conducting the surveys could be time-consuming and may not be able to obtain insightful information from the surveys as the response of respondents are confined by pre-defined questions and even some respondents may be reluctant to answer the questions (Groves 2006). Numerous studies were attempted in the past to model customer satisfaction (CS) based on survey results (He et al. 201; Kwong et al. 2013; Saylor 2015). As a result of the limitations associated with using surveys, researchers are shifting towards the extraction of information from online reviews. Online reviews could provide more insightful information and are normally generated from the willingness of customers. The reviews can be obtained at a low or no cost in a short time.

Amid various computational intelligence techniques for modelling CS, genetic programming (GP) and genetic programming based fuzzy regression (GP-FR) approaches were found to be promising ones for CS (Chan et al. 2012). Nevertheless, models generated based on the conventional GP may have poor generalizability (Castelli et al. 2011; Naik and Dabh 2013). Generated GP models are incapable of generalising new datasets stems from the constant growth in the size of individual solutions without any increase in fitness (Castelli et al. 2011). Thus far, none of computational intelligence approaches for modelling CS satisfaction have been attempted to model CS based on online reviews. This study proposes a new methodology for modelling CS based on online reviews. Modelling of CS also involves the development of highly complex and nonlinear models that are inherently fuzzy. The fuzziness associated with the CS models is attributed to the subjective opinions of customers. This study addresses the issues of fuzziness and nonlinearity in CS modelling by proposing a multigene genetic programming based fuzzy regression (MGGP-FR) approach to modelling. With the MGGP, a better generalization on testing datasets can be achieved. In the MGGP-FR, the fuzzy regression (FR) is deployed to address the fuzziness associated with CS modelling. This study aims to generate CS models based on online reviews and MGGP-FR which have better prediction performance compared to existing approaches.

The MGGP was proposed Searson et al. (2007) to genetically generate a population of solutions with an underlying structure that fits a phenomenon without any prior form of a model. The genetic programming (GP) aspect of the MGGP iteratively transforms populations of solutions through genetic operations such as crossover, mutation, and reproduction (Poli & Koza 2014). In this study, MGGP is introduced to generate various terms of the polynomials of CS models including linear, interaction and high order terms. The coefficients of the terms, namely fuzzy coefficients, are then determined by using Tanka's fuzzy regression which are able to address the fuzziness associated with CS modelling. To illustrate the proposed methodology, a case study on electronic hair dryers was conducted. Validation tests were performed to validate the performance of the proposed modelling approach by comparing it with the three well-known approaches for modelling CS which are fuzzy regression (FR), genetic programming (GP) and genetic programming based fuzzy regression (GP-FR). This paper is organized as follows. In Section 2, a literature review of related studies is presented. In Section 3, the proposed methodology for modelling customer satisfaction based on online reviews is described. Section 4 presents the implementation of the proposed methodology by using a case study. In Section 5, the validation tests and their results are described. The discussion of the results and conclusion of this study is presented in Section 6.

2. Related literature

Opinion mining, also known as sentiment analysis, is used to study people's opinions, mindset and feeling towards entities, events, topics and their characteristics (Liu and Zhang 2012). In recent studies, some machine learning and computational intelligence methods have been applied to extract people's sentiments on social media platforms such as blogs, forum discussions, social networks etc. For instance, Ankit and Saleena (2018) proposed an ensemble classification system for Twitter sentiment analysis. In their study, various classification methods such as the random forest classifier, naive Bayes classifier, logistic regression, and support vector machine (SVM) were combined to create an individual classifier with a better performance compared to the existing standalone classifiers. Wang et al. (2018) presented a method for fine-grained opinion mining using an end-to-end deep learning model without any pre-processing of user-generated texts. Alfrjani et al. (2019) developed a hybrid semantic knowledge-based method for mining opinions. The hybrid approach improved the preciseness of review sentiments by implementing a new domain feature-sentiment association algorithm. Similarly, Fernández-Gavilanes et al. (2016) created a lexicon based on a semi-automatic polarity expansion algorithm for predicting the sentiment of online textual messages. Shuang et al. (2018) formed an architecture based neural network for sentiment analysis to accept textual messages as matrix input and then extracted the sentiment information via three sub-contractors. Also, Chen et al. (2016) incorporated a background knowledge into an aspect clustering method to identify relevant product features from online reviews.

Quite a few previous studies have attempted to improve product design based on customer online reviews. Jin et al. (2016) suggested a framework that identified product attributes and their sentiment polarities from online reviews. With the sentiments of the product features, a Kalman filter and a Bayesian method were used to determine the trends and perform competitive product analysis. Wang et al. (2018) proposed a multi-label and a binary classification with a deep learning method to perform sentence-level sequence labelling of reviews for product design. To analyse features among heterogenous products, Zhang et al. (2016) suggested an opinion mining extraction method to collectively discover opinion mining elements while using a fuzzy measurement of opinion strength to analyse product features. Similarly, Ireland & Liu (2018) presented a design structure to examine online product reviews. Their study involved online product reviews, design theory and method, as well as knowledge discovery. Wang et al. (2014) proposed an opinion-aware analytical framework to find out product weakness by using opinion mining. Furthermore, Chen et al. (2017) developed a framework to measure word-of-mouth from a market perspective for product design and sales prediction. Mirtalaie et al. (2017) developed a framework that incorporated online reviews into the ideation stage of new product development in order to assist designers in identifying novel product features. Zhang et al. (2019) extracted product features and the associated sentiments based on semantic similarity. In their study, a target feature selection model was developed to identify features that needed to be improved. Wang et al. (2019) proposed an heuristic method to aggregate the outcomes of text mining and deep learning in order to understand the affective needs of consumers. In a similar fashion, Yang et al. (2019) established a user experience knowledge system based on online reviews to discover significant factors such as user preference, usage context, and product features for product design.

Quite a number of previous studies have attempted the modelling of CS for relating product attributes or features to customer satisfaction. Most of the studies made use of survey data to develop CS models. However, in surveys, respondents quite often give unprecise responses on how satisfied they are with various aspects of a product. The responses are not definite, and as such, do not provide a specific response about a customer's affection and satisfaction towards product attributes. Moreover, CS models could be highly nonlinear ones as the underlying relationship between customer preferences on product attributes and their overall satisfaction is complex. In an effort to address the fuzziness associated with developing CS models, fuzzy rule-based approach (Park and Han 2004), fuzzy regression method (Chen et al. 2004), generalised fuzzy least-squares regression approach (Kwong et al. 2010), and forward selection based fuzzy regression (Chan and Ling, 2016) were proposed. These studies relied on prior forms of models and performed the modelling based on survey data. Chan et al. (2011) addressed the nonlinearity of CS modelling by adopting a genetic programming approach.

Previous studies also attempted to resolve the issue of fuzziness and nonlinearities simultaneously in CS modelling. An example of such a study is the use of artificial neural network (ANN) to search for the combination of product attributes that satisfy consumers the most (Chen & Chiang, 2010). More so, some previous studies adopted rough set and particle swarm optimization (PSO) based adaptive neuro-fuzzy inference system (ANFIS) to generate a CS model for affective design (Jiang et al. 2013). In the study, the rough set theory was employed to generate fuzzy rules. A PSO was used to determine the parameter setting of ANFIS in order to generate models with better prediction accuracy. A modified dynamic evolving neural-fuzzy (DENFIS) approach was also proposed to model customer satisfaction based on time-series data (Kwong et al., 2013). A genetic programming (GP) approach was proposed to develop polynomial structures of CS models (Chan et al. 2011). The coefficients of individual terms of the structures were determined using a Tanaka's fuzzy regression method. However, the modelling of CS in previous studies is solely based on survey data. Moreover, the CS models developed based on conventional GP based methods could not adapt to new datasets due to overfitting (Chen et al. 2019; Chen et al. 2017; Rivero et al. 2019). On the other hand, the solutions generated based on chaos-based optimisation could be unstable due to the likelihood of the unstable structures generated for CS models. It is because the use of chaos approach relies on a random search for solutions which could potentially lead to the searching activity being concentrated in poor regions of solutions when a poor solution set is generated previously (Laili et al. 2015). With the availability of online reviews, product designers are presented with numerous opportunities to understand the needs and preferences of their customers. Unfortunately, there are still challenges on how a huge amount of online reviews can be utilised effectively for product design.

3. A proposed methodology for modelling customer satisfaction based on online reviews

In this section, a methodology for modelling customer satisfaction is described which mainly involves opinion mining from online reviews, fuzzy set theory and MGGP-FR. Fig.1 outlines the proposed methodology which mainly contains the following steps:

1. Collect product reviews using web crawler and pre-process the reviews for cleaning the unstructured texts.
2. Conduct opinion mining on the text reviews
3. Derive the sentiment scores of customer concerns (product attributes)
4. Define the fuzzy numbers and fuzzify the sentiments scores for individual customer concerns
5. Generate polynomial structures of CS model using a multigene genetic programming method
6. Determine the fuzzy coefficients of individual terms of the polynomial structures using a fuzzy regression method and then generate fuzzy polynomial models

The first step is to crawl for online reviews of a product from e-commerce websites. The reviews need to be processed as most of the reviews are made up of unstructured texts. Opinion mining is then conducted on the texts to extract customer concerns. The sentiment scores associated with individual customer concerns are derived and stored in an excel sheet. As customer opinions tend to be fuzzy, the sentiments of customer concerns are defined by a triangular fuzzy number in this study in order to address the fuzziness. The fuzzy numbers of customer concerns are aggregated and is then defuzzified by using a centroid defuzzification method. The next step is to generate the polynomial structure of a CS model by using MGGP which would contain linear, nonlinear and/or interaction terms. Tanka's fuzzy regression is then employed to determine the fuzzy coefficients of individual terms. Hence, a fuzzy polynomial model (i.e. CS model) for relating customer satisfaction and customer concerns is generated.

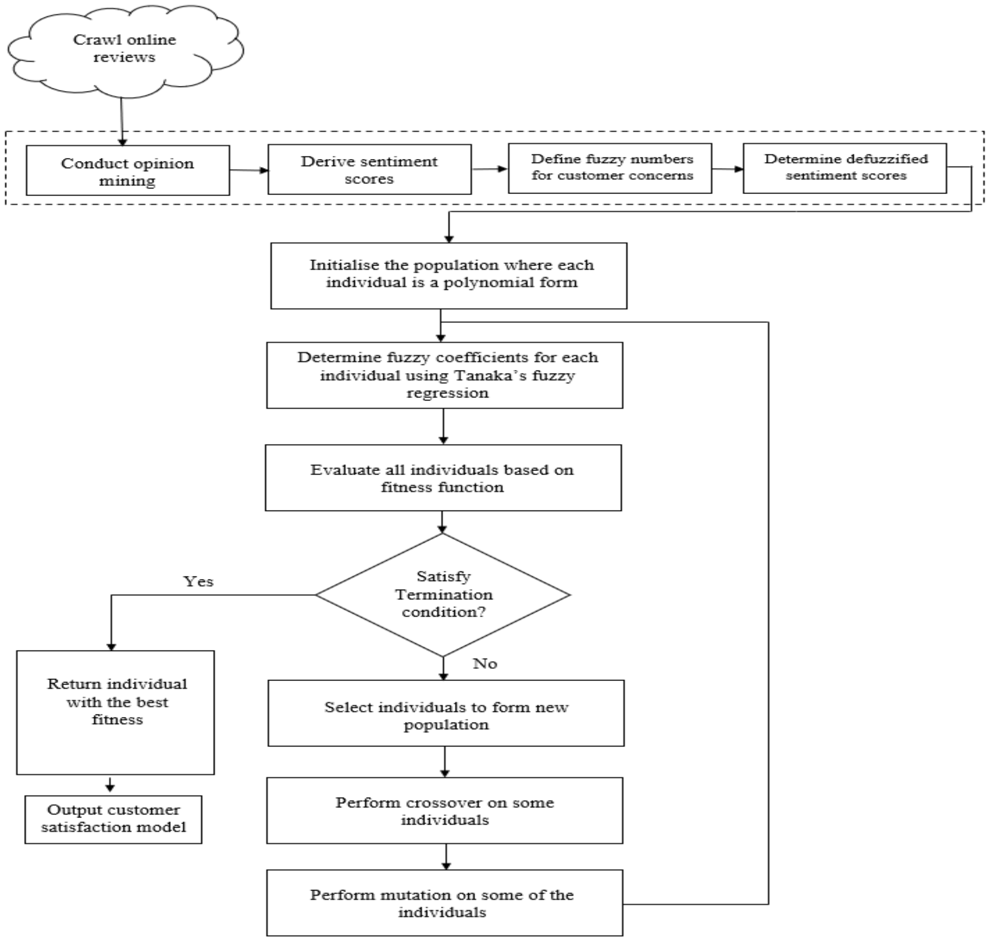

Fig. 1 An outline of the proposed methodology

3.1 Opinion mining

Opinion mining involves a series of steps to classify unstructured texts from online reviews into three categories of sentiments; namely neutral sentiments, negative sentiments and positives sentiments. The first step of conducting opinion mining is to collect product reviews by using a web crawler. This is followed by pre-processing of the reviews to clean the unstructured texts. The whole document of each review is broken down into components in order to identify its structural elements by a process known as part-of-speech (POS) tagging. The components (words) of the documents are tagged as either nouns, adverbs, or adjectives. Redundant words are removed, and features of products available in the documents are extracted. The phrases available in the documents are also grouped under different categories by using a K-means clustering method. For instance, in a hairdryer review, the phrases “fast dryer” and “low heat” are grouped under a category called “drying”. The semantic orientation and sentiment scores of opinion words of individual customer concerns (product attributes) are determined based on words and phrases databases such as SentiWordnet. Different text analysis tools exist in the market to facilitate opinion mining. With many choices to select from, this study employed Semantria text analysis tool that performs sentiment analysis through an application programming interface (API) or Semantria excel plugin. Semantria performs sentiment analysis by analysing large amounts of texts using natural language processing techniques and machine learning methods to derive sentiment scores of a topic, theme, sentence, and/or phrase. Semantria is able to extract various components including entities, concept topics, query topics, concept matrix, themes and summaries. The sentiment scores of components ranges between -10 and 10, while the sentiment score of a document ranges between -1 and 1. The sentiment scores of components are used in this study for the modelling of CS. As this study focuses on analysing text-based online reviews extracted from e-commerce websites, the analysis of the "voice of customer" category in Semantria is used. In this study, different brands and models of products under the same category are considered. As most e-commerce websites have sections for customers to leave their reviews of products, a web crawler needs to be customised to extract the reviews. The information extracted includes customer or reviewer ID, reviews, and the ratings of products. On the other hand, the development of CS models requires the information of customer concerns of products which are extracted and stored in an excel spreadsheet for further processing by using Semantria excel plug in.

3.2 Fuzzification of sentiment scores

As a huge amount of online reviews are extracted from e-commerce websites, a large number of sentiment scores are derived by Semantria and they would have a wide range. The wide range of sentiment scores depicts the level of customer satisfaction associated with each customer concern mentioned in the review documents. Thus, sentiment scores generated from semantria can be considered as a set of possible values instead of a single value. In this study, the set of possible values is represented by using a fuzzy number. Fuzzy numbers were introduced by Zadeh (McAllister 1996) to deal with imprecise numerical quantities. In real life, expressions used to describe opinions tend to be imprecise and not well defined when giving opinions on product attributes. It is difficult to model CS if there is a lack of a well-defined value to describe the overall sentiment of a customer concern. There exist different types of fuzzy numbers that are used to describe vagueness and uncertainty such as triangular fuzzy numbers, trapezoidal fuzzy number, and gaussian fuzzy numbers. In this study, sentiments scores of customer concerns for all extracted review documents are converted into the triangular fuzzy numbers (Chakraverty et al. 2019). A triangular fuzzy number can be described as (x, y, z) where x is the left value; y is the central value; and x is the right value.

Fig. 2 shows a triangular fuzzy number. Every triangular fuzzy number is expressed as a fuzzy set defining an interval on a real number $\Re$. Each member of the fuzzy set has a degree of membership that shows the degree of belonginess to the set. μ_{Aj} is the degree of membership. a_j is the central value and c_j is the spread value. The spread value is the difference between the left or right value and the central value. Thus, the fuzzy number shown in Fig.2 can be expressed as

$$\text{Triangular Fuzzy number} = (\ a_j - c_j\ ,\ a_j,\ \ a_j + c_j). \qquad (1)$$

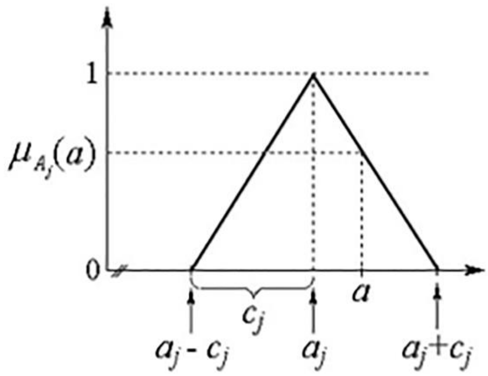

Fig. 2. Asymmetric triangular fuzzy number

The fuzzified sentiment scores (i.e. fuzzy numbers) then are defuzzified to obtain a crisp sentiment score value by using a centroid defuzzification method (McAllister, 1996). Based on the defuzzification method, fuzzy number can be defuzzified according to equation (2):

$$x^* = \frac{\int x\, \mu_{\tilde{C}}\,(x)dx}{\int \mu_{\tilde{C}}\ \ (x)dx} \qquad (2)$$

where x^*denotes the well-defined single value of the sentiment score for a customer concern. $\mu_{\tilde{C}}$ represents a fuzzy membership function that describes the degree of belonginess to the fuzzy number in equation (1).

3.3 Generation of fuzzy polynomial models using MGGP based fuzzy regression approach

Nonlinear regression has commonly been used to develop CS models in previous studies. The developed models could contain interaction explanatory variables and higher-order explanatory variables. However, most of the studies rarely addressed the fuzziness associated with the modelling. In this study, a methodology is proposed develop fuzzy polynomial CS model. First, the structure of a fuzzy polynomial CS model is generated by using MGGP. Then, Tanaka's fuzzy regression method is introduced to determine the coefficients of individual terms of the structure.

A fuzzy polynomial CS model developed based on MGGP-FR can be expressed as follows:

$$\tilde{y} = \widetilde{\mathrm{A}}_0 + \widetilde{\mathrm{A}}_1 x'_1 + \widetilde{\mathrm{A}}_2 x'_2 \ldots . + \widetilde{\mathrm{A}}_{\mathrm{N}} x'_N \tag{3}$$

Where $\tilde{y}$ is the fuzzy value of customer satisfaction; x'_n, where n = 1, … N, could be a single customer concern, interaction term involving several customer concerns or a higher-order term of a customer concern; and $\tilde{A}_N$ are the fuzzy coefficients of the terms of the model.

$\tilde{A}_N$ is expressed as (a^c, a^s) , where a^c and a^s are the central value and the spread of the fuzzy coefficients, respectively. Thus, the fuzzy polynomial model show as (3) can be rewritten as follows:

$$\tilde{y} = (\ a_0^c, a_0^s) + (a_1^c\ , a_1^s) x'_1 + \ (a_2^c\ , a_2^s) x'_2 + \cdots + (a_N^c\ , a_N^s) x'_N \tag{4}$$

3.3.1 Multigene genetic programming

In this study, a multigene genetic programming (MGGP) approach is proposed to generate the polynomial structures of CS model. MGGP is a variant of GP. GP is an evolutionary computation method that generates a population of individuals based on the principle of the survival of the fittest. It can generate better offspring from the fittest parents after they are evaluated based on fitness functions (Tran et al. 2019). Conventional GP begins by generating random equations from the combination of input variables, numbers and functions. The equations are represented as trees or graphs. For the trees to be represented, the set of terminals known as the leaf nodes or independent variables and a set of functions known as internal nodes are required to be specified. On the other hand, the setting of the fitness measure for determining the fitness of population and the setting of the control parameters as well as the termination criterion are required to be determined. The fitness of the generated solutions is evaluated, and the best individuals are selected. The selected individuals undergo certain genetic operators such as reproduction, mutation and crossover to enhance the diversity and quality of the solution generated (Sivapragasam et al. 2010).

Contrary to GP, each individual in MGGP is represented by a combination of multiple trees (Danandeh et al. 2017). MGGP is expressed as the weighted linear combination of outputs from a large number of GP trees. Moreover, each gene in an individual is represented by a tree. The arrangement of trees in each gene allows compact models to be developed, unlike in GP where there is a higher chance of developing complex and over parameterised models (Yang et al. 2019; Zhang et al. 2016). Higher transparency, ease of interpretation and a possible better prediction accuracy of a developed model are achieved by allowing more outputs per GP individual. They can also be achieved by combining more function outputs per individual. The structure of MGGP models is quite common to be a polynomial one. By using an ordinary least square method, the coefficients of individual terms of the structure can be determined (Gandomi and Alavi 2012) MGGP ensures that a parsimonious polynomial structure with significant terms and tree depths are generated. The solutions or individuals that come the closest to achieving the underlying behaviour in the dataset are selected for "breeding". The fitness function used to determine the best individuals is the root mean square error (RMSE), as shown in equation (5). The symbolic regression of MGGP is purported to be computationally more efficient than the conventional GP (Searson et al. 2007).

$$RMSE = \sqrt{\frac{1}{N_{train}} \sum_{k=1}^{N_{train}} \left(\tilde{y}(k) - y(k)\right)^2} \tag{5}$$

where $\tilde{y}(k)$ is the predicted customer rating in the k^{th} data; $y(k)$ is an actual customer rating; and N_{train} being the number of samples.

The genes in MGGP are developed by a multigene symbolic regression. Symbolic regression can be used to remove redundant models based on a model complexity analysis. In the MGGP crossover operation, a set of genes of parents can be swapped depending on how beneficial a particular section of a gene is in comparison with swapping a whole gene. This is known as the low-level crossover operation. To prevent the generation of an infeasible mathematical tree, crossover is performed at the same depth for both parents. In the crossover operators, random nodes from two-parent trees representing a pair of solutions are selected. The chosen nodes could be a subtree (sub-expressions), which are exchanged between two main trees. Thus, the new pair of offspring (new trees) inherit characteristics from each parent. In mutation, a node is randomly selected from a tree, and it is replaced by a random sub-tree to generate a new solution and to introduce diversity into the genetic population. An example of a multigene model is illustrated in Fig. 3. The output of the model shown in Fig. 3 is determined based on the three explanatory variables (b_0, b_1, b_3). The MGGP model is a linear one which comprises functional terms such as square root and sin (x). The parameters setting of the MGGP is characterised by the maximum number of genes, known as T_{max}, and the maximum tree depth D_{max} of each gene in a chromosome. The pseudocode of MGGP is shown in Fig. 4.

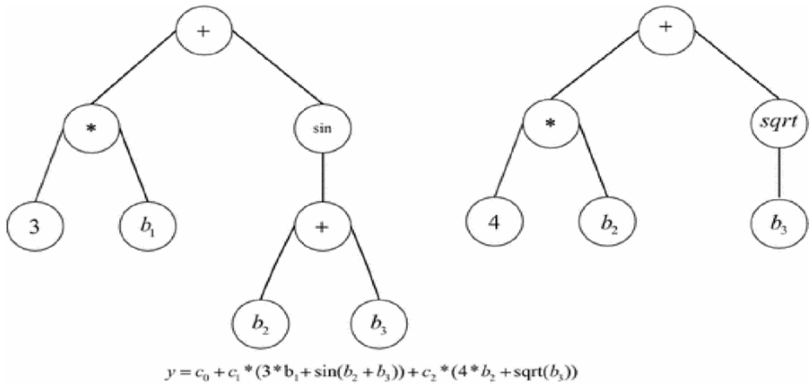

Fig. 3. An example of genes in multigene genetic programming

Input: Training dataset, Parameters
Output: The best polynomial structures
Begin
Initialize a population of GP individuals. Each individual is array of trees.
while *Maximum generation* is not reached **do**
01: Compute the fitness of each individual;
02: Order the population, compute evaluation value;
03: Select parent individuals using the tournament selection for breeding;
04: Use the crossover operator and check the feasibility;
05: Employ mutation operator and check feasibility;
06: Update the population for the next generation;
END

Fig 4. Pseudocode of MGGP

3.3.2 Determination of the fuzzy coefficients using fuzzy regression analysis

Most systems influenced by human judgements are accompanied with fuzziness. The fuzziness have been addressed in many studies using Tanaka's fuzzy regression analysis in which the parameters are represented by fuzzy sets. Zadeh's extension principle defines a fuzzy linear function. In Tanka's fuzzy regression, inputs, outputs, and coefficients can be represented by fuzzy numbers. To evaluate the output, two criteria are considered: the least absolute deviation and the minimum spread. The deviations are regarded as the fuzziness of the parameters of a system and are reflected as linear functions with fuzzy parameters. Thus, it presents a good model to develop the relationship between dependent and independent variables (Peters 1994; Tanaka et al.1982). The linear programming problem of Tanaka's fuzzy regression can be formulated as follows:

$$Min\, J \sum_{j=0}^{N_{NR}} \left(a_j^{s'} \sum_{i=1}^{M} \left| x_j'(i) \right| \right) \tag{6}$$

The objective function J of equation (6) describes the fuzziness of the system. There are $1 + N_{NR}$ terms in the fuzzy model. M is the number of data points and $\left| x_j'(i) \right|$ is the jth absolute value transformed variable of the ith dataset in the model. The constraints of the linear programming problem are defined as follows:

$$\sum_{j=0}^{N_{NR}} \left(a_j^{c'} x_j'(i) + (1-h) \right) \sum_{j=0}^{N_{NR}} a_j^{c'} \left| x_j'(i) \right| \geq y_i \tag{7}$$

$$\sum_{j=0}^{N_{NR}} \left(a_j^{c'} x_j'(i) - (1-h) \right) \sum_{j=0}^{N_{NR}} a_j^{c'} \left| x_j'(i) \right| \leq y_i \tag{8}$$

$$a_j^{s'} \geq 0, a_j^{c'} \in R, j = 0,1,2,\ldots,N_{NR}$$

$$x_0'(i)=1 \text{ for all } i \quad \text{and } 0 \leq h \leq 1$$

The h-factor, which take on values between 0 and 1, measures the degree of fitness of the fuzzy polynomial model and y_i is the value of the ith dependent variable. The constraint in equation (7) and (8) ensures the dependent variable has at least h degree of belongingness to $\tilde{y}_i$ with $\mu_{\tilde{y}_i} \geq h, i = 1,2,\ldots,M$. The last constraint ensures that $a_j^{s'}$ and $a_j^{c'}$ are non-negative. The fuzzy parameters $\widetilde{A}_j'$ $where\ (j = 0,1,2\ldots,N_{NR})$ can be determined by solving the linear programming problem subject to $\mu_{\tilde{y}_i} \geq h$.

4. Implementation

A case study on electric hairdryers was implemented to illustrate the proposed methodology for modelling customer satisfaction based on online reviews and MGGP-FR. In the case study, online reviews of twenty-two electronic hairdryers (www.amazon.com) were crawled from Amazon e-commerce website during the period between January 2017 to January 2018. A total of 13,920 reviews were extracted. The data and information extracted from the reviews include the reviewers' ID, the reviewed text and the customer rating of the hairdryers. The hairdryers were selected based on the popularity of the brand, as indicated by the number of reviews. For convenience, the twenty-two hairdryers are denoted as “A”, “B”,”C”, … , to “V”. Fourteen customer concerns were extracted from the online reviews using Semantria. They are “safety”, “quality”, “efficiency”, “price”, “temperature-setting”, “appearance”, “usability”, “reliability”, “comfortable to hold”, “robustness”, “speed”, “weight”, “size” and “easy controls” and are denoted as $x_1, x_2, x_3, \ldots,$ and x_{14} respectively. The sentiment scores associated with each of the customer concerns were derived by using Semantria. The sentiment scores were fuzzified and converted into asymmetrical triangular fuzzy numbers, as described in section 3.2. Table 1 shows some examples of the reviews and their extracted data and information. Table 2 shows the fuzzified sentiment scores of individual customer concerns of the 22 hairdryers. After the defuzzification process, the defuzzified sentiment scores of individual customer concerns of the 22 hairdryers were obtained as shown in Table 3. With regards to the MGGP parameters, the control parameters setting were determined with reference to the suggested settings of some previous studies (Mousavi et al. 2010; Searson, Leahy and Willis 2011). The parameter "maximum tree depth" defines the maximum size of the individual solutions generated. The parameter has substantial influence on the size of search space and the number of solutions explored within the search space. To avoid over-growth of individual solutions and also to allow for easy interpretability, the “maximum tree depth” was set to 4 and the “number of individual genes” was set to 3. In this study, basic arithmetic operators $(+, -, *)$ and the mathematical function square were employed as the functional set in MGGP to generate the best MGGP model. The probability of mutation was set low at 0.14 as a low probability of mutation reduces the degradation of “fit” solutions set (Gandomi and Alavi, 2012).

The fourteen independent variables $x_1, x_2, x_3, \ldots, x_{14}$ were used as model input functions. The data sets were split into two. The first set is the datasets of eighteen products that were used as training datasets, and the remaining four were used as the testing datasets. The fitness of the polynomial structures generated was evaluated based on RMSE. The best model structure generated by MGGP was obtained at the 160th generation after 200 generations, as shown in Fig. 5. The parameter setting of MGGP for generating the polynomial structures for the CS model is shown in Table 4. Finally, the h value for the fuzzy regression analysis was set to 0.5 as the size of datasets was small. The fuzzy coefficients of individual terms of the generated polynomial structures were determined by using Tanaka’s fuzzy regression analysis. The proposed MGGP-FR was implemented by using MATLAB programming language. Equation (9) shows a fuzzy polynomial CS model of electric hairdryers that was developed based on the proposed methodology.

Table 1. Examples of customer online reviews and their extracted data and information

Reviewer ID	Review	Extracted concept topic	Sentiment score	Rating
1	“Not worth price paid as does not have power of other 1875W hairdryers. Unfortunately, due to being out of state for unexpected family emergency, I missed time window to return and there is no way to contact the seller that I can see.”	Price	-0.55	1
2	“Good design, love the colour.”	Appearance	0.55	4
3	“After a couple of months, it does not work on high - only blows at the lower speed. The heat options still work.”	Speed setting	-0.57	2

Table 2. Fuzzified sentiment scores of customer concerns

	Safety	Quality	Efficiency	Price	Temp_Setting
A	$[-1.05, 0.00, 0.46]$	$[-0.49, 0.89, 2.2\ ]$	$[0.30, 0.36, 0.60]$	$[-0.40, 0.32, 3.47]$	$[-2.10, 0.60, 2.90]$
B	$[\ -1.07, 0.00, 0.60]$	$-0.82,0.21,0.52\ ]$	$[0.45, 0.46, 0.50]$	$[-1.5, 0.00, 1.03]$	$[-0.40, 0.04, 0.60]$
C	$[\ -0.10, 0.48, 1.71]$	$[-0.01,0.67,2.22]$	$[0.450, 0.55, 0.67]$	$[0.00, 0.39, 1.20]$	$[-0.57, 0.48, 2.22]$
	…	...	...	…	…
U	$[\ 0.00, 0.02, 0.034]$	$[-0.52, 0.00, 0.49]$	$1.00, 1.19, 1.3]$	$[-0.2, 0.4, 2.4]$	$[0.51, 0.63, 1.44]$
V	$[\ 0.00, 0.07, 0.08]$	$[-1.31, 0.37, 2.09]$	$[0.3, 1.77, 3.24]$	$[-0.98, 0.35, 1.45]$	$[-0.53, 0.61, 3.2]$

	Appearance	Usability	Reliability	Comfortable to hold	Robustness
A	$[-0.55, 0.49, 0.87]$	$[-1.5, 0.00, 1.02]$	$[0.00, 0.17, 1.02\ \ ]$	$[0.44, 0.45, 045]$	$[-1.5, 0.00, 1.44]$
B	$[-0.49, 0.85, 0.98]$	$[-1.45, 0.00, 0.05]$	$[-0.60, 0.41, 2.10]$	$[-1.39, 0.31, 0.00]$	$[-1.47, 0.00, 0.6]$
C	$[0.49, 0.814, 2.91]$	$[-0.66, 035, 2.10]$	$[-0.66, 0.50, 2.00]$	$[-0.05, 0.089, 0.5]$	$[-0.60, 0.07, 2.09]$
	…	…	…	…	…
U	$[0,0.5,2.45]$	$[-0.40, 0.49, 0.8]$	$[-0.38, 0.5, 1]$	$[-.105, -0.17, 1.2]$	$[-1.10, 0.30, 1.16]$
V	$[0,0.49,1.24]$	$[-0.23, 0.52, 1.72]$	$[-0.23,0.54, 1.7]$	$[-1.19, 0.00, 1.50\ ]$	$[\ 0, 0.43, 0.60]$

	Speed	Weight	Size	Easy to use

A	$[-0.57, 0.36, 3.45]$	$[-1.05, 0.00, 1.28]$	$[-0.56, 0.17, 0.83]$	$[-0.13, 0.588, 1]$
B	$[-0.60, 0.68, 1.16]$	$[-0.88, 0.00, 059]$	$[-0.88, 0.00, 0.59]$	$[-1, 0.00, 0.29]$
C	$[0.00, 0.76, 2.27]$	$[0.00, 0.21, 0.49]$	$[0.00, 0.21, 0.49]$	$[0, 0.582, 1.30]$
	…	…	…	…
U	$[0.00, 0.01, 0.03]$	$[0.02, 0.23, 0.36]$	$[0.013, 0.23, 0.36]$	$[0, 0.45, 1.20]$
V	$[0.00, 0.36, 0.60]$	$[0.00, 0.52, 0.74]$	$[[0.00, 0.52, 0.74]$	$[-0.30, 0, 1.35]$

Table 3. Defuzzified sentiment scores of customers concerns

Product	Safety	Quality	Efficiency	Price	Temp_Set	Appearance	usability
	(X1)	(X2)	(X3)	(X4)	(X5)	(X6)	(X7)
A	-0.2454	1.0785	0.5096	2.3034	0.7226	0.2114	-0.1231
B	-0.1748	-0.0873	0.4642	-0.1149	0.2142	0.3943	-0.4828
C	1.1229	1.5027	0.5836	0.8008	1.2352	2.1815	1.1398
D	1.1229	1.5027	1.5432	0.8008	1.2352	2.1815	1.1398
E	-0.3126	0.4522	0.1961	1.1625	0.9729	0.5211	0.7557
F	0.2004	2.1521	0.7323	1.8431	1.7052	0.9955	0.6467
G	0.0107	0.1065	0.4500	1.4096	0.9067	1.3747	0.8189
H	0.3920	1.6742	0.6500	1.5725	1.7805	0.9900	1.0923
I	-0.0001	1.5218	1.6303	3.0849	2.4834	1.6634	1.1807
J	0.1600	1.7057	1.1131	0.4892	0.7404	0.7465	0.0060
K	0.3177	1.3651	0.8363	0.8684	2.0127	0.1146	0.8753
L	0.2969	1.6390	0.5723	1.0247	1.0148	0.6485	0.5374
M	0.0249	0.3307	1.6779	0.2568	1.4888	0.5662	0.2470
N	0.3423	0.4702	0.3024	0.5397	0.3014	0.6551	0.6570
O	-0.0638	1.0093	0.7541	1.6599	0.4269	0.7916	0.3648
P	-0.2446	1.3122	1.1582	1.9209	1.2661	1.2509	0.3207
Q	0.0186	0.0553	1.2633	1.6067	1.1572	1.7116	0.2914
R	0.0465	0.6939	2.0150	0.3843	1.9898	0.7916	1.0235
S	0.2413	1.2399	0.3848	2.1453	2.3349	0.8294	0.5648
T	0.7956	0.5058	0.2710	0.7593	0.6596	0.8095	0.4776
U	-0.2929	0.4404	1.9066	1.5955	1.7712	1.1409	0.9330
V	-0.0977	1.1581	0.9867	2.9503	2.0995	1.1787	1.0034

Table 3 cont. . Defuzzified sentiment scores of customers concerns

Product	Reliability (X8)	Comfortable (X9)	Robustness (X10)	Speed (X11)	Weight (X12)	Size (X13)	easy control (X14)
A	0.4512	0.2002	2.2359	0.3703	0.2299	0.4754	0.7164
B	-0.6314	-0.4892	0.3495	-0.0871	-0.2647	-0.2931	0.3305
C	0.3299	1.2669	1.5133	0.3043	0.8825	0.7543	1.0820
D	0.3299	1.2665	1.5133	0.3043	1.1999	0.7598	1.0820
E	-0.9927	0.9900	1.5642	0.1857	-0.0937	0.5240	0.2685
F	0.0436	0.3203	1.1761	-0.0497	0.2409	0.0140	0.5474
G	0.0195	0.4144	0.7226	0.5272	0.5976	0.5253	0.8189
H	0.2037	1.0063	1.5414	0.9267	0.3500	0.6366	1.0538
I	0.4600	1.2586	3.3960	1.0278	0.5294	0.5402	1.1911
J	0.2336	0.2071	2.2217	0.2278	0.1865	0.4571	-0.2194
K	0.2067	1.1411	1.5500	1.3933	0.1782	0.7186	0.8158
L	-0.5785	0.2891	1.5129	0.1604	0.2450	-0.2032	0.6342
M	0.6811	-0.1619	1.6731	0.0555	0.1435	-0.0503	0.1523
N	-0.7437	-0.1500	2.0568	0.3509	0.7674	-0.5121	0.6045
O	1.2800	0.5860	1.7488	0.6181	0.7298	0.9212	0.7224
P	-0.5784	0.6031	1.1989	0.0518	0.4747	0.0848	0.5987
Q	0.3967	0.1445	0.1229	0.0220	0.1999	0.7769	0.2914
R	0.6394	-0.0333	0.3214	0.3272	0.3949	0.8529	1.0096
S	1.0985	1.3592	1.5608	0.1125	0.1853	0.0402	0.3770
T	-0.3044	0.8626	1.2527	0.5274	0.0377	1.6246	0.4727
U	0.4928	1.2311	0.7442	0.5762	0.5230	0.9745	0.9578
V	0.0669	1.0085	3.2248	0.2850	0.3016	0.4000	0.9402

Table 4. Parameters setting of MGGP

Parameters	Settings
Population size	250
Number of generations	200
Maximum tree depth	4
Maximum number of genes in individuals	3
Probability of crossover	0.84
Probability of mutation	0.14
Number of inputs	14
Functional set	TIMES, MINUS, PLUS, SQUARE
Selection method	Tournament

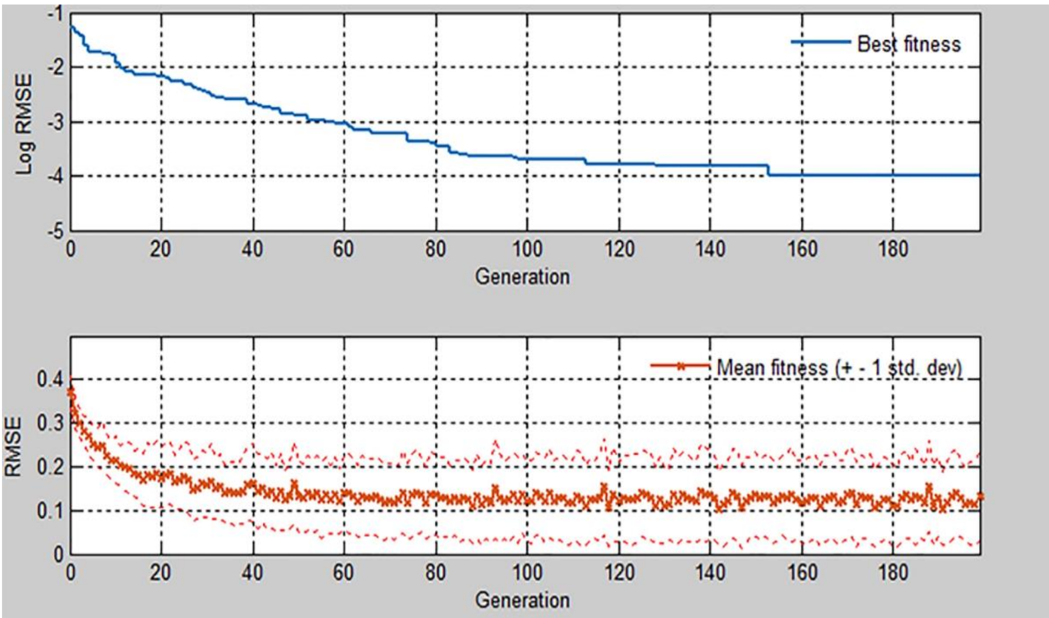

Fig. 5. Fitness values after 200 generations

$$\tilde{y} = (3.9174, 0.3570) + (0.5987, 8.7842 * 10^{-23}){x_{14}}^4$$
$$+(-0.5474, 6.6743 * 10^{-23})x_5x_9 + (0.5507, 9.092 * 10^{-23})x_4x_9$$
$$+(0.2937, 7.125 * 10^{-23})x_2 + (-0.3553, 0.0656)x_8$$
$$+(-0.3288, 6.210 * 10^{-23})x_5 + (-0.2136, 8.095 * 10^{-23})x_{10} * x_{12} \quad (9)$$

5. Validation

To validate the performance of the proposed approach to modelling customer satisfaction, the training and prediction errors obtained based on the proposed approach are compared to those based on fuzzy regression (FR), genetic programming (GP) and genetic programming based fuzzy regression (GP-FR). Four sets of model validation were defined, and each set involves four validation tests. For each validation test, eighteen datasets were randomly selected to train the FR, GP, GP-FR and MGGP-FR models. The parameter settings used in GP and the GP of GP-FR are same with the setting used in MGGP. The remaining four data sets were used to evaluate their prediction accuracy. None of the data sets was repeated for training and testing when conducting the validation tests. In the validation, mean relative error (MRE) and the variances of errors (VoE) were used to evaluate the prediction performance of the developed models which are calculated by using equations (10) and (11) respectively.

$$MRE = \frac{1}{N_{train}} \sum_{k=1}^{n_{train}} \frac{|\tilde{y}(k) - \ y(k))|}{y(k)} \tag{10}$$

$$VoE = \frac{1}{N_{train} - 1} \sum_{k=1}^{N_{train}} \left(\frac{|\tilde{y}(k)-) \ y(k)|}{y(k)} - MRE \right)^2 \tag{11}$$

Table 5 shows the models generated based on the four approaches for a particular validation test. The CS model generated based on FR is a linear one. It contains all the fourteen customer concerns (variables) while the others contain some of the fourteen customer concerns. The models generated based on GP, GP-FR and MGGP-FR involved higher-order and interaction terms. With the exception of GP models, all the other models contain fuzzy coefficients that can help address the fuzziness associated with the CS modelling. To compare the performance of the four approaches in CS modelling, a k-fold validation method with k = 4 was employed and the experimental plan is shown in Table 6. The validation results are shown in Table 7 which contain the prediction errors of individual generated models in each validation test, as well as the mean relative prediction errors and variance of prediction errors of individual generated models in each validation set. From the validation results, it can be seen that the mean relative prediction errors based on MGGP-FR are the least for all the test sets. For the variance of prediction errors, MGGP-FR outperforms the other three approaches in the test sets 1, 2 and 4 while in the test set 3, the variance of prediction error of MGGP-FR is less than those of GP and GP-FR but slightly higher than that of FR. Fig. 6 and 7 respectively summarise the mean relative prediction errors and the variance of prediction errors of the four approaches under the four test sets.

To study the significance of the differences of the prediction performance, a two-sample test was conducted. The null hypothesis is that there is no significance of prediction performance between MGGP-FR and one of the other three approaches. The significance in the difference between two methods was evaluated by using a t-test. The t-value of t-test can be calculated by using equation (11).

$$t - value = \frac{\mu_1 - \mu_2}{\frac{\sqrt{var_1 + var_2}}{N}} \tag{12}$$

where N is the number of trials; μ_1 and μ_2 are the mean errors of two approaches; Var_1 and Var_2 are the variances of two approaches.

Table 8. shows the t-values between MGGP-FR and the other three approaches. Significance level α wass set at 0.05 and the critical value was determined to be 2.776. From the table, the t values for both the prediction errors and the variance of errors are all greater than 2.7776 which indicate there is a significance difference between the MMGP-FR and the other three methods.

Table 5. Generated models in one validation test

Algorithms	Generated models
Fuzzy regression (FR)	$\tilde{y} = (2.69418, 5.148 * 10^{-16}) + (-1.5342, 7.657 * 10^{-16})x_1$ $+(0.600107, 1.63706 * 10^{-16})x_2 + (-0.92925 , 0.35248)x_3$ $+(-0.9638543,1.5779 * 10^{-16})x_4 + (0.577187,2.548 * 10^{-16})x_5$ $+(1.23319,0.877348)x_6 + (-0.88612,4.14537 * 10^{-16})x_7$ $+(-0.242427, 4.16184 * 10^{-16})x_8 + (-0.310344, 1.735 * 10^{-16})x_9$ $+(0.4496734, 8.2799 * 10^{-17})x_{10} + (-0.56292, 2.32851 * 10^{-16})x_{11}$ $+(0.100540, 8.369 * 10^{-16})x_{12} + (0.8021364, 4.133642 * 10^{-16})x_{13}$ $+(1.59059, 3.223 * 10^{-16})x_{14}$
Genetic programming (GP)	$y = 3.857866 - 0.867910(x_{12} - (x_2 + x_{14})x_{12}) + 0.457820(x_7 - x_5)x_8$
Genetic programming based fuzzy regression (GP-FR)	$\tilde{y} = (3.611575 , 5.186783) + (0.178491 , 0)x_1 +$ $(0.363831 , 0.000000)\, x_6 + (-0.378673 , 0)x_8$
Multigene genetic programming based fuzzy regression (MGGP-FR)	$\tilde{y} = (4.4939,1.887 * 10^{-14}) + (-0.4846,0.522)x_1$ $+(-0.4490, 1.002 * 10^{-14})x_2 + (1.149, 7.046 * 10^{-15})x_5$ $+(0.2772, 2.4075 * 10^{-13})x_6 - (-0.7998,1.7949)x_5x_{14}$ $+(-0.6287,1.552)x_{11} + (-0.5994, 1.4458)x_{12}$

Table 6. Experimental plan used for validation of the four approaches

Test set	Validation test no.	Defuzzified sentiment scores of the products which are used as training data	Rating of CS of the product to be predicted based on the generated model
I	1	A, B, C, …, R	S
	2	A, B, C, …, R	T
	3	A, B, C, …, R	U
	4	A, B, C, …, R	V
II	5	E, F. G, …, V	A
	6	E, F. G, …, V	B
	7	E, F. G, …, V	C
	8	E, F. G, …, V	D
III	9	A, B, C, …, V	K
	10	A, B, C, …, V	L
	11	A, B, C, …, V	M
	12	A, B, C, …, V	N
III	13	A, B, C, …, V	P
	12	A, B, C, …, V	Q
	15	A, B, C, …, V	R
	16	A, B, C, …, V	S

Table 7. Validation results

Test set	Validation test no.		FR	GP	GP-FR	MGGP-FR
I	1	Product A	0.0523	0.0853	0.1166	0.0402
	2	Product B	0.0005	0.0379	0.0958	0.062
	3	Product C	0.2566	0.1761	0.0578	0.0329
	4	Product D	0.1661	0.4087	0.1663	0.0175
		Mean relative prediction error	0.1189	0.177	0.1091	0.0381
		Variance of prediction errors	0.0132	0.0271	0.002	$3.4185*10^{-4}$
II	5	Product K	0.3934	0.1762	0.2369	0.0072
	6	Product L	0.0064	0.033	0.0061	0.1351
	7	Product M	0.1513	0.1673	0.1183	0.1105
	8	Product N	0.0841	0.0651	0.107	0.0594
		Mean relative prediction error	0.1588	0.1104	0.1171	0.0781
		Variance prediction of errors	0.028	0.0052	0.0089	0.0032
III	9	Product P	0.0162	0.0051	0.0332	0.1183
	10	Product Q	0.0843	0.3725	0.3389	0.1086
	11	Product R	0.0305	0.1588	0.121	0.0022
	12	Product S	0.0916	0.0144	0.0533	0.0842
		Mean relative prediction errors	0.0557	0.1377	0.1366	0.0783
		Variance of prediction errors	0.0014	0.0295	0.0196	0.0028
IV	13	Product E	0.0641	0.0058	0.1054	0.018
	14	Product F	0.1526	0.0344	0.3809	0.0374
	15	Product G	0.0787	0.0003	0.0224	0.0525
	16	Product H	0.0067	0.0267	0.129	0.0058
		Mean relative prediction errors	0.0755	0.0168	0.1594	0.0285
		Variance of prediction errors	0.0036	$2.6759*10^{-4}$	0.0239	$4.2699*10^{-4}$

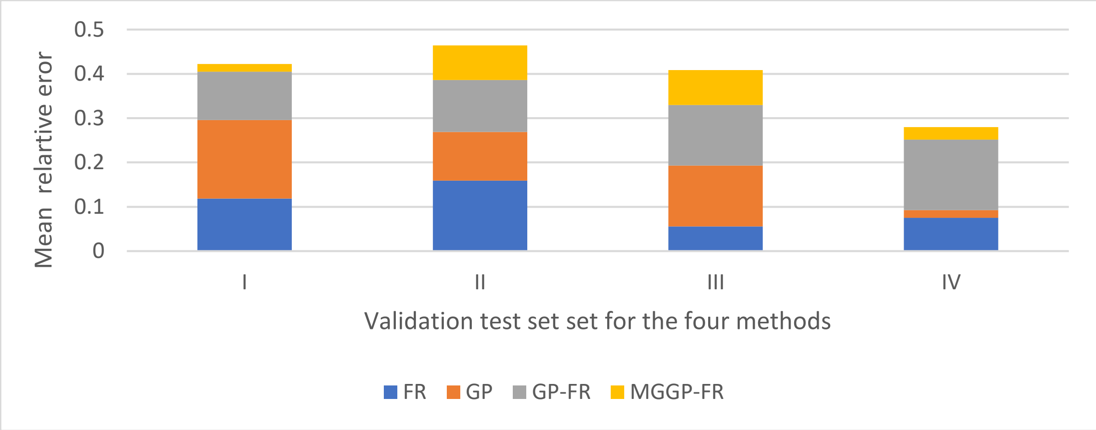

Fig. 6. Mean relative errors of the four test sets

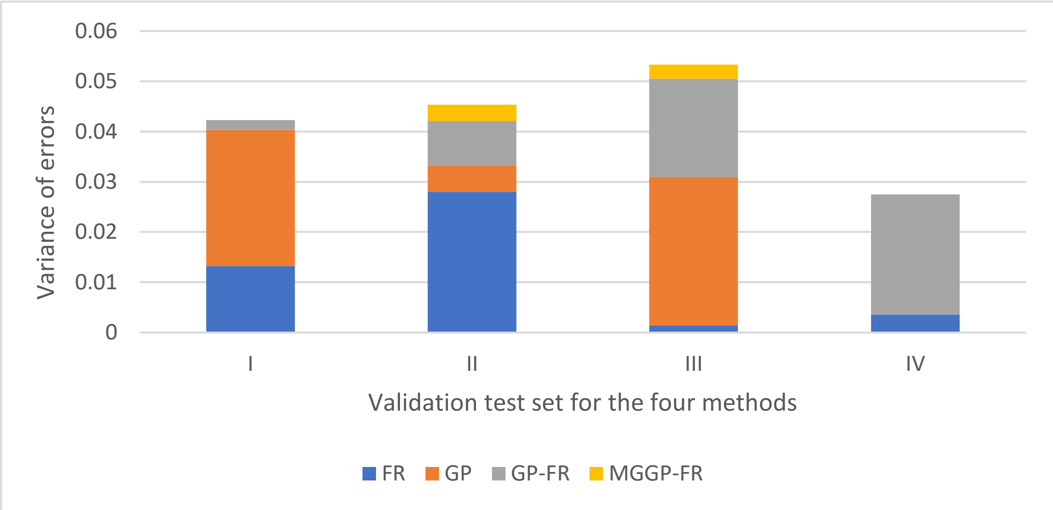

Fig. 7. Variance of errors of the four test sets.

Table 8. t-values of prediction errors

	t-value for prediction errors	t-value for variance of prediction errors
t-Test between FR and MGGP-FR	3.604	4.588
t-Test between GP and MGGP-FR	3.0507	8.289
t-Test between GP-FR and MGGP-FR	3.8712	5.153

6. Conclusion

In previous studies, CS models were developed mainly based on customer survey data. However, survey data does not contain much sentimental expression from customers. In recent years, a tremendous amount of customer online reviews on products has been generated on various websites. The reviews serve as a valuable source of information and data for the modelling of CS. In this paper, a methodology for modelling CS based on online reviews and MGGP based FR is described. In the proposed methodology, online reviews are crawled from various e-commerce websites. The customer concerns are extracted, and their sentiment scores are derived by using opinion mining. To address the fuzziness of customer opinions, the sentiment scores are transformed into asymmetrical fuzzy numbers. The fuzzy numbers are then defuzzified and crisp sentiment score values can be obtained. With the defuzzified sentiment scores, MGGP is employed to develop polynomial structures of a CS model. Tanaka's fuzzy regression is then employed to determine the fuzzy coefficients of individual terms of the polynomial structure. A case study of electric hairdryers was conducted to illustrate the proposed methodology and validate the effectiveness of MGGP-FR in CS modelling. In total, sixteen validation tests were conducted to compare the performance of MGGP-FR in modelling CS with that of FR, GP, and GP-FR. The results of the validation tests indicated that MGGP-FR outperformed the other three approaches in terms of prediction accuracy. On the other hand, the variance of prediction errors of MGGP-FR was found the smallest in three out of the four test sets. With the developed CS models, product manufacturers can perform a sensitivity analysis of customer concerns in order to determine an attribute setting of a new product by which customer needs of the product can be largely satisfied.

It is common for consumers nowadays to search for products online before they make any purchase. By extracting the interest of prospective consumers on certain product attributes, manufacturers could predict which aspects of products would be of interest to consumers when a new product is being planned. Some search indexes such as Google search index provide a means to measure the interestedness of a product over a period of time. Future studies could consider how the search indexes could be incorporated into CS modelling.

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