Evaluating Customer Satisfaction: Linguistic Reasoning by Fuzzy Artificial Neural Networks

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Abstract. Customer satisfaction is a measure of how a company meets or surpasses customers' expectations. It is seen as a key element in business strategy; and therefore, enhancing the methods to evaluate the satisfactory level is worth studying. Collecting rich data to know the customers' opinion is often encapsulated in verbal forms, or linguistic terms, which requires proper approaches to process them. This paper proposes and investigates the application of fuzzy artificial neural networks (FANNs) to evaluate the level of customer satisfaction. Genetic algorithm (GA) and back-propagation algorithm (BP) adjust the fuzzy variables of FANN. To investigate the performances of GA- and BP-based FANNs, we compare the results of each algorithm in terms of obtained error on each alpha-cut of fuzzy values.

Keywords: Prediction, customer satisfactory index (CSI), rich data, computing with words, genetic algorithms, fuzzy artificial neural networks.

1 Introduction

Customers' opinion has a key role in business success. Earlier studies have shown that success chance greatly depends on meeting customers' satisfaction. The impact is such that increasing the satisfactory level of customers has been placed into business plan strategies; and consequently, evaluating satisfactory level is become noticed. There are many related studies from different departments of a company to varieties of business sectors; such as marketing [1,2], sales [3,4], finance [5,6], human resource

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[7], product design [8,9], airline [10,11], auto-motive [8], [12], E-commerce [13,14], retailing [15] and so on. Few studies have been even deepen to gender-based analysis [16], where few others have been conducted through lean manufacturing [17,18].

All mentioned studies are to support achieving the targets of business outcome. Though, from processing aspect, two complexities hamper a reliable evaluation. They include: (i) the input data that steams the results, and (ii) the evaluator method (modeling) that processes and build a model base on the input data. The former is related to nature of data, and the latter is to select a proper method compatible with nature of input data – whereby it is also a matter that a method provides the outcome in the required nature. In fact, data can be collected in various methods, e.g., verbal-based or numeric-based, which then a pre-processing method prepares the data to feed the evaluator model. Though, keeping the originality of data is always a matter of reliability of results in the outcome. Undoubtedly, verbal expression of a customer on satisfactory level is the foremost, which is original and rich in content. Many studies have been conducted using verbal data [3], [19,20]. However, the problem is that rich piece of information comes with complexities, and then, it causes the uncertainties that require proper methods to cope with it.

Fuzzy model widely exposes to confront with complexities concealed in linguistic terms. It was emerged in 1996 to deal with complexities in social sciences, and, it suites to compute with words [21]. Fuzzy model keeps the richness of original value; however, it requires certain circumstances for a method to process a set of data of this kind. A fuzzy value is represented by levels of cuts on a membership function (MF). Therefore, α-cuts divide an MF to represent degree of belief in a value. Consequently, a method should be able to deal with α-cuts to process a fuzzy value. Among the reasoning methods that can cooperate with fuzzy values, fuzzy artificial neural networks (FANNs) play the foremost to evaluate the level of customer satisfactory. FANNs were proposed [22] as a generalized form of artificial neural networks (ANNs) through the concept of fuzzy logic (FL), and then, rapidly enhanced for applications [23]. Two directions of enhancing FANNs have been based on genetic algorithms (GAs) [23,24,25] and back-propagation algorithms (BP) [26,27,28]. GAs is employed for its strength to seek for a globally optimum solution [29,30]; in contrast, local optimizers such as BP may trap into local minima [31,32]. Undoubtedly, performances of either GA- or BP-based FANNs are worth studying to evaluate the level of customer satisfaction, as it will transparent the effect of global or local optimization for this application. Trade off between the performances of either method can differentiate them to find whether or not: an absolute prediction is worth taking the complexities of a global optimization – this will then furnish the decision being made.

The rest of this paper is organized in four sections as follows. Section 2 describes the mechanism that this paper uses to evaluate the level of customer satisfaction. Section 3 describes fuzzy evaluator neural networks as the body of idea to construct the customer satisfactory system; subsequently, section 4 explains GA- and BP-based FANNs. Section 5 presents the results and analyses of the proposed methods using fuzzy value data set; where, generated errors on each α-cut of fuzzy variables conduct the comparisons. Section 6 concludes the results and addresses the future works.

2 Satisfactory Evaluation Mechanism

Evaluation mechanism involves with modeling the input and the output, and the structure of evaluator system. It must deal with rich data to furnish decision makers of a company with reliable information in the outcome. This paper deals with verbal words expressed by a customer, as the richest data, and then keeps the original richness for the outcome – therefore, both input and outcome sides of an evaluator are in verbal words. Though, the verbal words are revealed through fuzzy representation to mathematically express the original data. To this end, an MF defines an expressed word – as a linguistic variable – and then α-cuts sharpen the MF of each fuzzy value. This paper uses two levels of α-cuts – support and core – to represent a triangular fuzzy number. Equations below defines the support and core of a triangular fuzzy number $\widetilde{A}$.

$$\widetilde{A} = \{(x, \mu_{\widetilde{A}}(x)) | x \in R, \mu_{\widetilde{A}}: R \mapsto [0,1]\} \tag{1}$$

$$\widetilde{A_1} = \mathrm{Core}(\widetilde{A}) = \{x \in R | \mu_{\widetilde{A}}(x) = 1\} \tag{2}$$

$$\widetilde{A_0} = \mathrm{Support}(\widetilde{A}) = \{x \in R | \mu_{\widetilde{A}}(x) = 0\} \tag{3}$$

$$\widetilde{A_\alpha} = \{x \in R | \mu_{\widetilde{A}}(x) \geq \alpha, \alpha \in (0,1)\} \tag{4}$$

where, $\mu_{\widetilde{A}}$ is a continuous MF, and, R is the set of all real numbers. We use the equations above to provide the evaluator system with fuzzy represented input and outcome data. An overall schema is shown in Fig. 1.

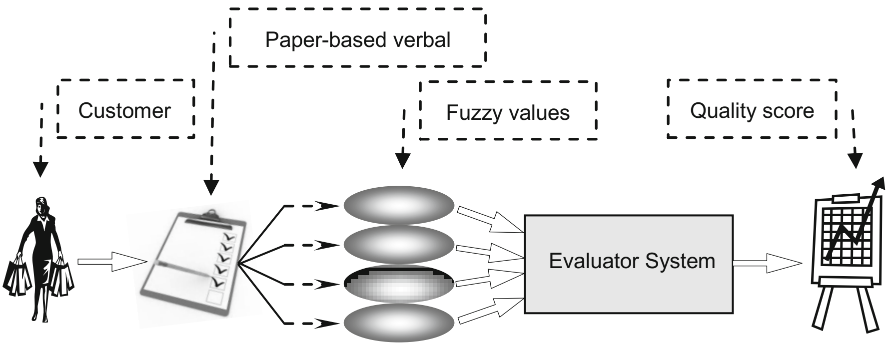

Fig. 1. Mechanism of customers' satisfactory evaluation

The mechanism above associates with Customer Satisfaction Index (CSI). It defines the indicators to measure the satisfactory level of customers. The indicators and its parameters are varies upon each case study, though this paper uses the CSI employed in [19] – which has nine fuzzy instances to predict the gap based on following variables: product, service, network system, and, payment.

Once the linguistic values are provided, evaluating the performance depends on evaluator system. This paper uses FANNs [24,27], as an evaluator, based on GA and BP optimization algorithms. These networks deliver the outcome in fuzzy numbers – as a representation of linguistic variables. It keeps the originality of customer expressions. Eventually, non-expert decision makers in business panel can refer to this outcome.

3 Fuzzy Evaluator Neural Networks

Evaluating the level of customer satisfaction is based on expressed preferences of customers by his/her current expectation. This paper performs the evaluation process by learning the collected data. To perform the learning, we use FANNs as the body of evaluator system to predict the satisfactory level. The FANNs were firstly proposed in 1993 [22]; a mathematically revised version of FANNs, which was enhanced through genetic algorithms, has been investigated in [23,24], [27]. An FANNs version that utilized back-propagation algorithms are studied in [27,33]. This paper uses type three of FANNs; which, all variables of network are based on fuzzy numbers and shown by FANN-3 [24]. The reason of using FANNs-3 is to keep the originality of input data. The variables are input, output, weights, and, biases as shown and defined in Fig. 2.

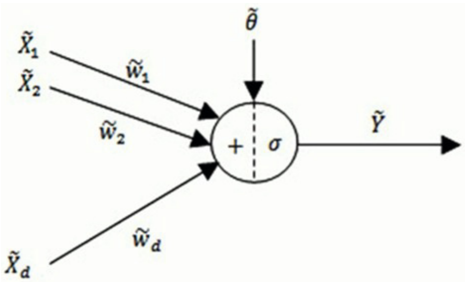

Fig. 2. A fuzzy neuron that constructs a FANN-3

d number of input variables and connection weights are represented by $\tilde{X}_i$ and $\tilde{W}_i$, respectively. All the fuzzy inputs, weights, and biases are fuzzy numbers in $F_0(R)$, where $F_0(R)$ is defined in [34]. The input-output relationship of the fuzzy neuron is determined as follows:

$$\tilde{Y} \triangleq F(\tilde{X}_1, \dots, \tilde{X}_d) = \sigma\left(\sum_{i=1}^{d} \tilde{x}_i . \tilde{w}_i + \tilde{\theta}\right) = \sigma\left(\langle \tilde{X}, \tilde{W} \rangle + \tilde{\theta}\right) \quad (5)$$

where, $\tilde{\theta}$ means a fuzzy bias (or a fuzzy threshold); $\tilde{X}_1, \dots, \tilde{X}_d$, $\tilde{W}_1, \dots, \tilde{W}_d \in F_0(R)^d$ is fuzzy vectors; and, $\sigma: R \to R$ is a transfer function.

4 GA- and BP-Based Networks

GAs and BP approaches have been hybridized previously to enhance the performance of FANNs [23,24]. The advantage of GA-based FANNs is that they find a global optimum solution; in contrast, BP-based FANNs perform the local search to find a solution. However, the results are unexpected in different applications [31]. Besides that, taking the complexities to find a globally optimum solution is not always required for every application.

GAs perform based on principles of natural evolution. They gradually find the solution in generation based process, where each generation operates reproduction functions. The selection, crossover, and mutation functions operate on simulated genomes to replace the genes. Crossover function is known to be more effective; though, the result of optimization tightly depends on initial population. Thus, in practice, it hinders GAs to promise achieving global solution. In contrast, BP is based on strong mathematical fundamentals to backward the propagation of error when training a network. It calculates the gradient of loss function in respect to variables of network. BP is a local optimizer that is more likely to trap in local minima; however, theoretically, it finds the optimal value faster than GA [31]. Algorithm 1 proposes the evaluator systems constructed by BP and GA to probe the performance of each in hybrid with FANNs.

```
Begin
Initialize
(x1_ante, x2_ante) ← create random values(x)
While ≠ termination Criterion( ) do
   x1_post ← update GA(x1_ante)
   x2_post ← update BP(x2_ante)
   If f(x1_post) < f(x1_ante) then (x1_ante ← x1_post)
   If f(x2_post) < f(x2_ante) then (x2_ante ← x2_post)
Return(x1_ante, x2_ante)
End
```

Fig. 3. The steps of two evaluator systems

In Algorithm 1, the network is first initialized; and then, frequently, set the better solutions in terms of obtained errors by updating the outcome of each network. The updating procedure is continued until a method meets the stopping criterion (or criteria). Eq. (5) is a stopping condition used in this paper; where, f is fitness function, $\|.\|$ is the distance measure, and ε is an imperceptible positive error.

$$\left\|f(x_{post}) - f(x_{ante})\right\| < \varepsilon \tag{6}$$

5 Results and Analysis

This section provides the results of applying two algorithms to construct the evaluator systems, i.e., GA- and BP-based FANNs algorithms. The results are based on data set used by [35,36,37]; which consists of nine fuzzy instances, four predictor variables, and one response variable. We applied one-leave-out cross-validation on each fold to give the results by average in 100 runs. To build each FANN method, we designed two networks of fully-connected with four input and one output units in three layers. The outcome results are analyzed to find the effect of using GA- and BP-based FANNs. The analyses are carried out in terms of obtained error from the following aspects: (i) α-cuts of fuzzy numbers, (ii) predictor variables, and (iii) response variables. At the end, the results manifest the superiority of BP-based method to decrease the error rate of response variable.

Fig. 4 shows the obtained error on each α-cut of actual and target values. We applied one-leave-out validation to test each FANN method for predicting each variable of data set. The prediction abilities for each method are given in percentage. The error rate is computed by difference between actual and desired values of support and core boundaries of each fuzzy number.

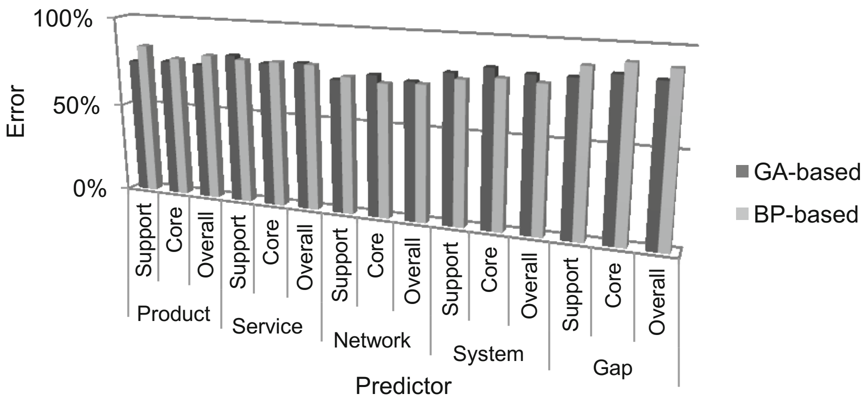

Fig. 4. Rate-Analysis for support and core α-cuts

Fig. 5 shows the analysis for each α-cut, which is based on portion of errors that support and core generates in compared to each other. We can find the superiority of a method by tracing the errors on each α-cut as they lead the overall error. In fact, the smaller size of an error we observe; the more ability of a method reveals to achieve the desired value.

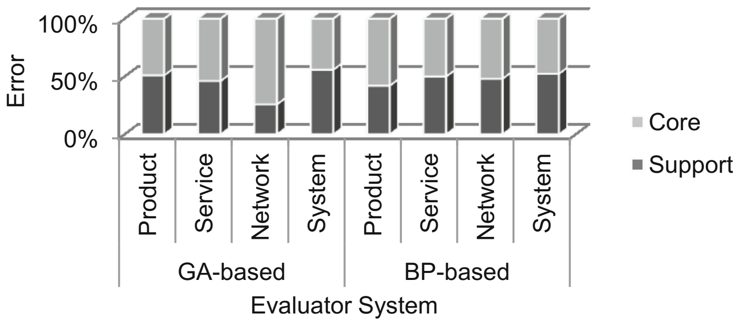

Fig. 5. Portion-Analysis for support and core α-cuts

Consequently, Fig. 6 gives the overall errors resulted by errors on each α-cut. The performance of a method depends on overall error on each predictor; obviously, the higher overall error we have on each predictor, the less performance we achieve for a method.

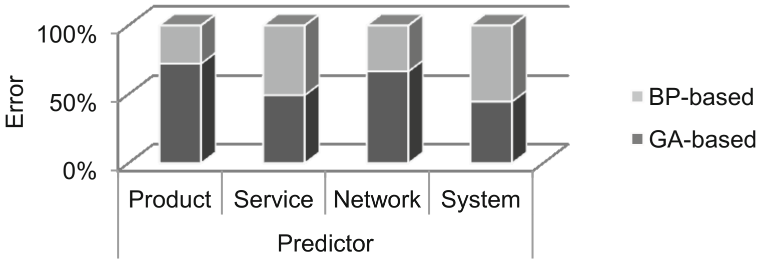

Fig. 6. Overall Input Errors

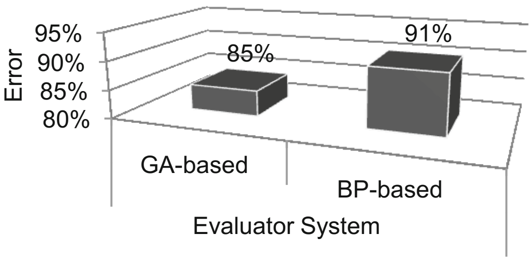

Fig. 7. Overall Output Error

Fig. 7 compares the final performance of two methods. We observe that the error rates on each α-cut of predictor affects on the response value; and thus, it reflects on performances of the applied methods. The obtained results show for FANNs that local optimizer BP is superior to global optimization GA. In other words, BP can better tune α-cuts of fuzzy variables for FANN by better finding the interconnections between input and target data. This achieved is possible only by avoiding the local minima. However, increasing the training iterations may change the performances of each method.

6 Conclusion

This paper proposed an evaluator system to predict the level of customer satisfaction. Keeping the originality of verbal opinions, expressed by customers, requires an evaluation system to process rich data; and therefore, linguistic terms demand a true representation. We used fuzzy artificial neural networks (FANNs) to process fuzzy-represented opinions, and consequently, FANNs carried the outcome in fuzzy-represented values. We applied genetic algorithm (GA) and back-propagation algorithm (BP) to find the best performance of FANNs. GA and PB were selected to find the effect of global and local optimization in performance of FANN evaluator. The results showed BP-based FANNs superior by 6% – though, analyzes on α–cuts showed that GA-based FANNs performs better in some parts. The reason is avoidance from traps of local minima, which directs the performances of each method to a rich or poor level. Future works can study whether BP-based FANNs will stand superior to GA-based FANNs with higher complex data. In addition, one can perform the attribute relevance analysis to increase the efficiency of evaluator system.

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