Measuring Customer Service Satisfactions Using Fuzzy Artificial Neural Network with Two-phase Genetic Algorithm

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Abstract

In this chapter, we propose a new method based on genetic algorithms (GAs) for fuzzy artificial neural network (FANN) learning to improve its accuracy in measuring customer service satisfaction for establishing a principle of economical survival in business area. The analysis is based on linguistic values received from customer service satisfactions index where fuzzy modeling, as one of possible ways, has been used to process these values. Here, customer's satisfaction is considered as a key factor for the analysis based on his/her preference as the scope of qualification for organization service. In the proposed method, we have introduced two-phase GAs-based learning for FANNs. In the neural network, inputs and weights are assumed to be fuzzy numbers on the set of all real numbers. The optimization ability of GA is used to tune alpha-cuts boundaries of membership functions for fuzzy weights. Here, five alpha-cuts are used for tuning as other researchers have used, which in two-phase method; two of them are for first phase and three of them for second phase. This leads to obtain better results for FANN. Comparisons are included with another method using two data sets to give some analyses to show the superiority of proposed method in term of generated error and executed time. From the experiments, the proposed approach has been able to predict quality values of possible strategies according to customer's preference. Finally, the ability of this system in recognizing customer's preference has been tested using some new assumed services.

Key words: Weight adjusting; placement definition; shape definition.

1. Introduction

Selling rate of the products for an enterprise, either be a business centers or producer factories, is an important issue in the commercial competitions. The higher rate an enterprise gains the more merit for survival is proved. Earlier researches have shown that the increase or decrease of this rate highly depends on customers' view to that commercial enterprise [1,2]. Such that; the more ability of satisfying the customer an enterprise has, the more success in competition with other competitors it will achieve. As customers' satisfaction plays a key role in an enterprise survival, the analysis of his/her opinion is vital to make the next enterprise decisions. In general, customer's satisfaction is not only a multi-variable issue but also is based on linguistic values. On the other hand, linguistic values, which have been used here, are intrinsically known as vague values [3]. The two mentioned multi-variability and linguistic-variability make the problem to be more complex and system evaluation would be more difficult. This is while; strategic goals of the enterprises are determined according to the results of this analysis, and thus, the evaluation of customer opinion is an essential issue [2,4,5]. A suitable evaluation significantly helps an enterprise to emerge its defined strategic goals. This needs to have a well understanding of customer's opinion in order to be able of approximating his/her satisfactory degree.

Customer's satisfaction is satisfactory degree of the customer, which he/she is purchasing commodities [4]. Some indicators measure this degree. The indicators and its parameter are non-standard, and thus, each enterprise has been established an index according to its own customer's view [4,5]. Some indices, which are well known among the others, are American Customer Satisfaction Index (ACSI), Swedish Customer Satisfaction Index (SCSI), European Customer Satisfaction Index (ECSI) and Korean Customer Satisfaction Index (KCSI) [4,5]. It is worth mentioning that the parameters of indicator must be visible to customers' view [5]. According to the literature, three basic aspects of independency, comparability and feasibility must be considered [1, 2, 4]. In this chapter, indices have been used that supports the mentioned aspects employed by other researchers. One analysis ways of utilized indices, which is based on linguistic values received from the customer, is fuzzy modeling [3]. It is used in many papers for evaluation of the customer's satisfaction in the e-commerce, where the data of this area is utilized in this chapter. Various methods have been considered based on this modeling. Some researches have been used AHP [6-8] or either fuzzy cognitive maps [9]. Recently, some literatures have been appeared based on the combination of linguistic variables modeled by triangular fuzzy values [4,5].

Following aforementioned researches, this chapter aims to propose an evaluator system that would be able to recognize customer's preference. Meanwhile, it uses the benefits of fuzzy modeling in customer satisfactory evaluation. This mentioned aim of constructing a system that recognizes customer's preference has not been considered by the other authors. This is the difference of this research with the others'. In order to construct such a system proposing an approach, as the major part of the system, that can consider two terms of the learning and linguistic values is essential. This approach needs to follow learning process based on linguistic values in addition of having the ability to learn from customer's opinions. This task is carried out using Fuzzy Artificial Neural Networks (FANNs), which are know as soft computing techniques. FANNs are able to learn from fuzzy values that are considered as linguistic terms. Meanwhile, the Genetic Algorithm (GA) has been used to obtain higher efficiency for FANN. GA is able to find the optimum of designed network. Finally, each enterprise will be able to have the benefits of using such constructed system as follows:

- To evaluate possible strategies according to its current customer's tastes, in order to increase success rate;
- To analyze a strategy, regardless its business level, using the least number of the customers;

- To decrease the risk exists behind the decision making for its next organizational changes;
- To emerge the importance of business ethics, followed by customer-orientation principle.

It is necessary to have an evaluator system with a higher accuracy to decrease strategic decision risks and increase the success rate by evaluating possible strategies based on the preferences of the least customers. Such that; the higher accuracy of the system there is, the better organizational changes are obtained. Thus, it increases the success rate while emerges the business ethics. Knowing that an enterprise needs organizational changes to be adaptable with customer preferences, having a higher accuracy system rises to be necessity as listed below:

- to have more effective participation from customer side;
- to have more participant customers;
- to decrease the computational costs of evaluator system

Each enterprise needs to consider more effectively customers' opinion to have better understanding of their preferences, and thus, having a precise data is necessary for organizational evaluation. This is while; having variety opinions are necessary in covering broader preferences to have an assured organizational evaluation. Thus, the evaluator system is able of better approximation for new possible preferences. However, obtaining to points 1 and 2 comes with increase of the complexity, such that; the increase of data preciseness causes less accuracy for evaluator system, while the increase in number of data being processed causes less accuracy too. Therefore, a system that is able of dealing with such data environment is necessary. However, the ideal is such an evaluator system that is able to increase the accuracy while complexity increases. Such system, which this chapter proposes, enables an enterprise to have more assured evaluation in less time.

Based on previous research [10], this chapter follows to improve the last results. Therefore, the aim of proposed system is to improve the previous one using two phases for evaluator system. This system, called two- phased GA-based FANN, utilizes the abilities of GA to find a suitable status of evaluator system in order to improve the accuracy [11]. The first and second phases are called place-definition and shape-definition, respectively. Alpha-cuts (α-cuts), which here the fuzzy numbers are processed based on them, are defined and applied in each phase separately. The abilities of such evaluator, relative to complexity increase, on overcoming aforementioned complexities are:

- to decrease the predicted outcome error;
- to increase the processing speed;

Finally, using such system will enable an enterprise to:

- Have the ability of processing more realistic data received from the customer;
- Have more precise evaluation and suitable strategy approximation to increase the success rate in less time;

- Decrease the risks behind the organizational changes in terms of increasing preferences reality;
- Survive ethical principle of customer-orientation by customer participation.

The organization of this chapter, which aims at proposing such customer evaluator system using GA-based FANN, is as follows. First, in next section the concept of customer evaluator system has been explained. Then, how to model the current problem using fuzzy modeling has been explained in its first subsection. In the sequel, proposed evaluator systems using GA-based FANN and its basic concepts have been explained in its second subsection. Proposed system is implemented in following section and the results have been analyzed in its two subsections. In these subsections, first, the performance validation of proposed system has been tested using new inputs and then the ability of system has been shown. Finally, a conclusion for the chapter is given. Two datasets, which are used in this chapter, have been presented in appendix.

2. Customer Evaluator System

Customer evaluator system defines service quality of an organization based on customer's satisfactory degree [4]. The structure of such evaluator system is shown in Figure 1. The outcome of system is based on customer's opinion given to the system, which is represented by the parameters of some indicators. The preciseness of outcome exploration depends on the preciseness of modeled opinion expressed from the customer and the processing ability of evaluator system based on them.

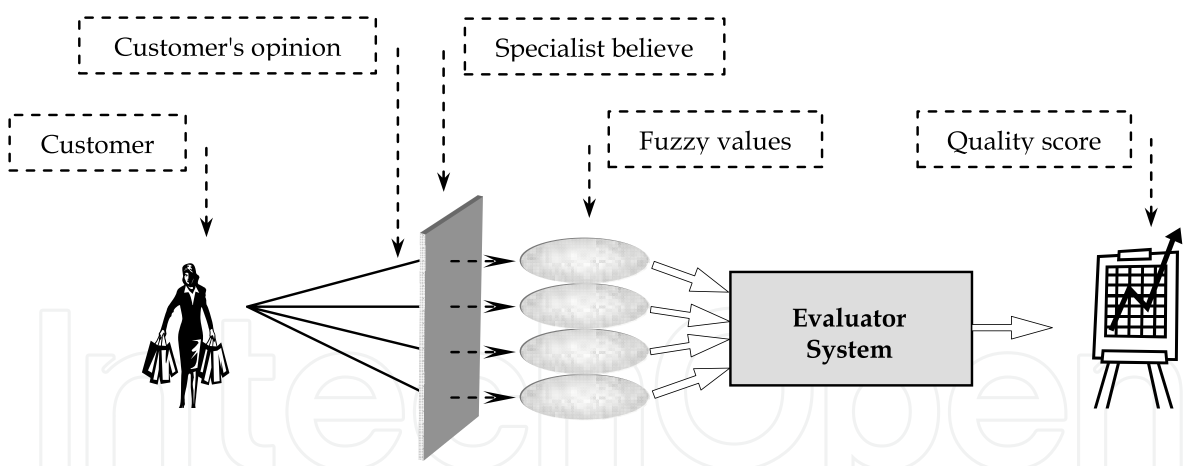


Fig. 1. The structure of the evaluator system

Hence, it is essential to have the parameters for evaluator system. They are presented by some indicators indices so-called customer satisfactory indices [4,5]. As aforementioned, these indices are not standard and this chapter uses the one that has been employed in [4]. The parameters of these indices are shown in Figure 2.

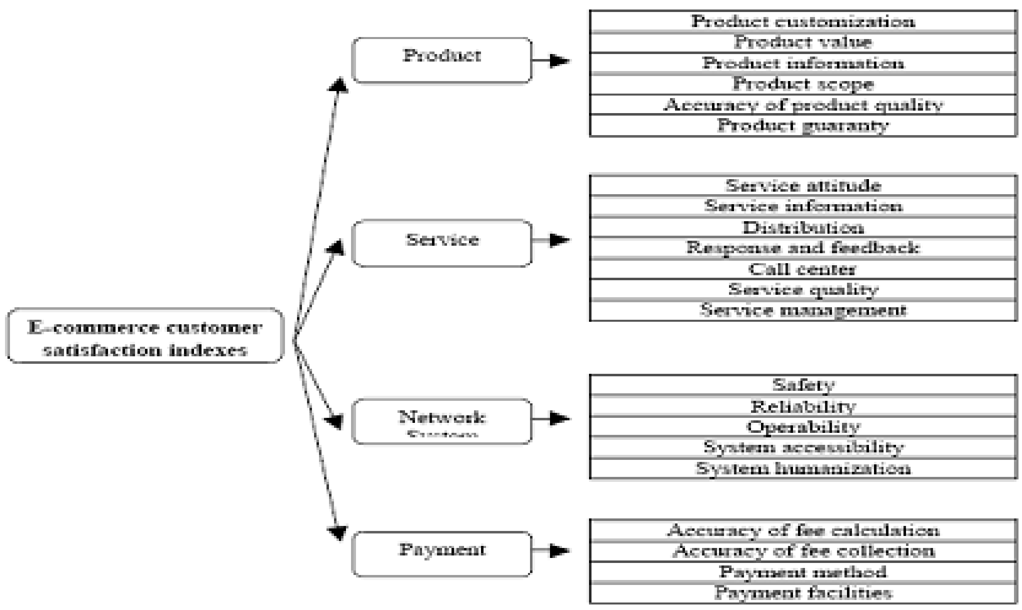


Fig. 2. A customer satisfactory indices and its parameters

The parameters in Figure 2 are represented in the form of linguistic variables that are accounted as vague values [3]. As these parameters are the inputs of system, they are necessary to be prepared for processing. To this end, fuzzy modeling is utilized in such way that first; the input values are fuzzified, then they are fed to FANN system to be processed. More details of these procedures are described in the following subsections, respectively.

Fuzzy modeling: Fuzzy set theory, which was proposed in 1965 [12], is utilized in many application areas by solving their corresponding problems [13,14,15,16]. This is due to the ability of fuzzy logic, with its modeling capability, in facing with complex environments [17,18]. In such environments like agriculture, market prediction, risk assessment [19], image processing etc. [16] the linguistic variables can be used. Customer satisfactory evaluation, the dealt issue in this chapter, is among such environments; this is because the process of this evaluation is based on information steamed from linguistic terms. In addition, having many linguistic variables causes this problem to be as a multi-variable issue. The latter one makes the problem to be more complex and, thus, a suitable modeling is much more needed for a better problem solving. Therefore, in this chapter, fuzzy modeling is considered to process linguistic terms that are received from the customer in order to construct evaluator system. Fuzzy variables, which are used in the evaluator system, are modeled linguistic terms received from the customer. Modeling a fine linguistic term needs more α-cuts as the preciseness of a fuzzy value depends on them. On the other hand, increasing the number of α-cuts causes the evaluation process to be more complex. However, the proposed approach in this chapter, which has a particular view to fuzzy modeling, considers this issue solvable.
The evaluator system uses the fuzzy variables for the inputs and parameters of the evaluator neural network. It is noticeable for the fuzzy values utilized in the input that; the transformation of these values depends on experts' interpretation over linguistic terms,

which is done through specialists' believes as illustrated in Figure 1. However, the idea of this chapter is concentrated on evaluator system only and, thus; obtained fuzzy values have been used based on other researchers' results [5]. Here, five α-cuts are used for fuzzy valued parameters of evaluator system to explore fuzzy numbers in its evaluation process. To be self-contained, we quote some fuzzy arithmetic on fuzzy numbers where a fuzzy number, $\widetilde{A}$, defined as below: $\widetilde{A} = \{(x, \mu_{\widetilde{A}}(x)) \mid x \in \Re, \mu_{\widetilde{A}} : \Re \to [0,1]\}$

$$\widetilde{A} = \{(x, \mu_{\widetilde{A}}(x)) \mid x \in \Re, \mu_{\widetilde{A}} : \Re \to [0,1]\} \tag{1}$$

such that $\mu_{\widetilde{A}}$ is a continues function and $\Re$ is set of all real numbers. A-cuts zero, one and middle of fuzzy number $\widetilde{A}$ are deified as below:

$$\widetilde{A}_1 = Core(\widetilde{A}) = \{x \in \Re \mid \mu_{\widetilde{A}}(x) = 1\}, \tag{2}$$

$$\widetilde{A}_0 = Support(\widetilde{A}) = \{x \in \Re \mid \mu_{\widetilde{A}}(x) > 0\}, \tag{3}$$

$$\widetilde{A}_\alpha = middle_\alpha(\widetilde{A}) = \{x \in \Re \mid \mu_{\widetilde{A}}(x) \geq \alpha\},\ \alpha \in (0,1). \tag{4}$$

Henceforth, all fuzzy numbers are assumed convex, such that all $middle_\alpha(.)$ are intervals in $\Re$ and their $Support(.)$ are bounded. Two basic operations of the summation and multiplication over triangular fuzzy numbers, which are used in proposed evaluator system, are defined as follows [18]:

$$\begin{aligned}\widetilde{A}_\alpha(k) + \widetilde{B}_\alpha(k) &\equiv \left[\widetilde{A}_\alpha^L(k), \widetilde{A}_\alpha^R(k)\right] + \left[\widetilde{B}_\alpha^L(k), \widetilde{B}_\alpha^R(k)\right] \\ &= \left[\widetilde{A}_\alpha^L(k) + \widetilde{B}_\alpha^L(k), \widetilde{A}_\alpha^R(k) + \widetilde{B}_\alpha^R(k)\right]\end{aligned}$$

$$\begin{aligned}\widetilde{A}_\alpha(k) \cdot \widetilde{B}_\alpha(k) &\equiv \left[\widetilde{A}_\alpha^L(k), \widetilde{A}_\alpha^R(k)\right] \cdot \left[\widetilde{B}_\alpha^L(k).\widetilde{B}_\alpha^R(k)\right] \\ &= \left[\min\left((\widetilde{A}_\alpha^L(k).\widetilde{B}_\alpha^L(k), \widetilde{A}_\alpha^L(k).\widetilde{B}_\alpha^R(k)\right), \max\left(\widetilde{A}_\alpha^R(k).\widetilde{B}_\alpha^L(k), \widetilde{A}_\alpha^R(k).\widetilde{B}_\alpha^R(k)\right)\right]\end{aligned}$$

Evaluator neural network: Neural learning networks are among soft computing techniques [20]. Learning networks of the fuzzy-type, so-called FANNs, were proposed after crisp neural networks [21]. FANNs have attracted many researchers in consequent of acquiring improvements and knowing their abilities in solving the complex problems. In this chapter, FANNs have been used as the main part of customer evaluator system. Evaluation outcome is processing result from the system based fed inputs. This network is able to learn customer's preference by its training process. Training process is based on the fuzzy values resulted from linguistic value transformations. Therefore, trained networks will be able to predict customer's satisfactory degree based on current preference, such that; it allows to approximate the goodness of new organizational changes to be applied. The steps of constructing such system, as a general case of customer evaluator neural network, are explained in Algorithm 1.

Algorithm 1: The steps of the evaluator neural network

```
1 begin
2    initialize ( )
3    x ← create ( )
4    while ¬ terminationCriterion( ) do
5       x_new ← update (x)
6       if f(x_new) < f(x) then x ← x_new
7    return x
8 end
```

Step 2 of Algorithm 1 initiates the indicators with fuzzy values. Then, it creates possible solutions by aiming to find a suitable network and x will be replaced with that. Reproduction process, as the update function and finding the better solution, is repeated until it meets the termination criterion. A criterion for a near-optimal solution is;

$$\|f(x_{new}) - f(x)\| < \varepsilon \tag{5}$$

where f is fitness function, $||\cdot||$ is distance norm and ε is a given pre-assumed positive small number as error bound.

Model structure of Fuzzy Artificial Neural Networks (FANN): This subsection presents the structure of FANN [22]. Here, FANN of type-1 is used as the major part of evaluator system, in which the input is fuzzy value and the output is crisp [17,23,22,11]. Input neurons have been used to learn customer's preference based on the α-cuts defined in [3]. The structure of such FANN, using two inputs a general architecture, is shown in Figure 3.

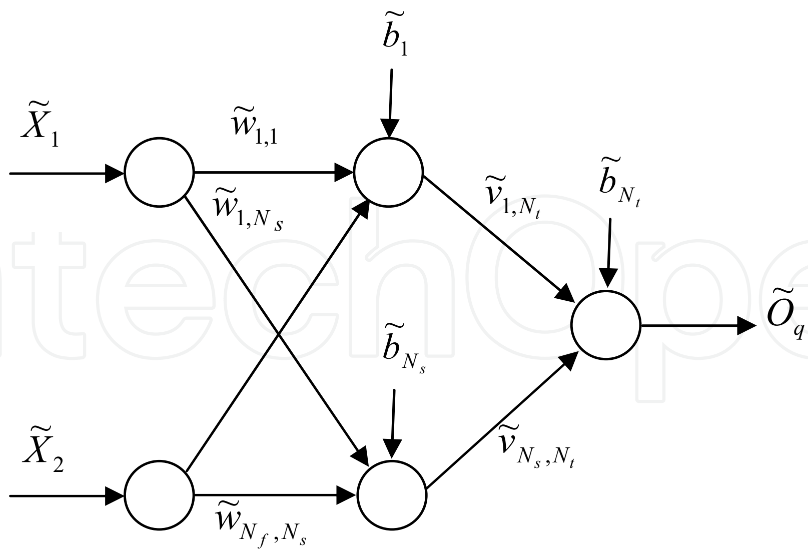


Fig. 3. A three-layer fuzzy neural network architecture

The first layer is input layer which does not have any computational unit. In the second layer, the matrix of fuzzy weights, $\tilde{w}_{N_f,N_s}$, shows fuzzy weights connecting neuron N_f in the first layer to neuron N_s in the second layer. The vector of fuzzy biases, $\tilde{b}_{N_s}$, shows fuzzy bias of the neuron, N_s, in the second layer. Similarly, in the third layer, fuzzy weight matrix, $\tilde{v}_{N_s,N_t}$, shows fuzzy weights connecting neuron N_s in the second layer to the neuron N_t in the third layer. The form of activation function of the neurons in the first and second layers, which is utilized in this chapter, is sigmoid function given as below:

$$f(x) = \frac{1}{1+e^{-x}} \tag{6}$$

Fuzzy output of $In\tilde{t}er_{N_s}$, for the second layer of this architecture is as follows:

$$In\tilde{t}er_{N_s} = f(A\tilde{g}g_{N_s}), \qquad N_s = 1,2...,n \tag{7}$$

where N_s is the number of neurons in the second layer and $A\tilde{g}g_{N_s}$ is defined as follows:

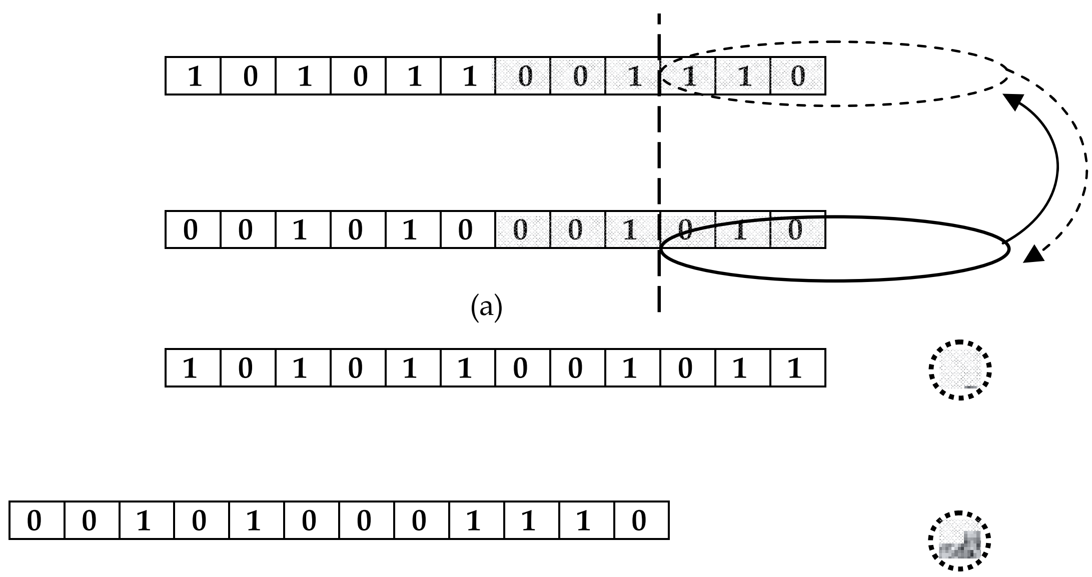
$$A\tilde{g}g_{N_s} = \sum_{i=1}^{N_f} \tilde{X}_i \cdot \tilde{w}_{ij} + \tilde{b}_j, \qquad j = 1,2...,N_s \tag{8}$$

where N_f is the number of neurons in the first layer and $\tilde{X}$ is fuzzy input. The third layer receives the $A\tilde{g}g$ values from the neurons in second layer through their fuzzy weight $\tilde{v}$. Therefore, the output is given by:

$$\tilde{O}_q = \sum_{j=1}^{Ns} A\tilde{g}g_j \tilde{v}_{jq}, \qquad q = 1, 2..., N_t \tag{9}$$

where N_t is the number of neurons in the third layer and $\tilde{O}_q$, is fuzzy outcome. Then, the outcome is considered as a crisp value when the distance is measured with the ideal.

Genetic algorithm based FANN: Genetic algorithm (GA) was first proposed in 1975 [24]. It is categorized as an optimization and soft computing technique, which is based on the principles of natural evolution [20,21]. Here, optimization process holds on defined generations, where GA is used toward improving the efficiency of FANN. The idea of using GA for improving FANN was first proposed in 1994 [21].



(b)

Fig. 4. (a) A typical crossover, (b) A typical mutation

Here, this idea, called GA-based FANN, is used as a validated method [25]. In GA-based FANN, genetic algorithm tries to find network parameters in an optimized manner. Such that tuning the weights and biases is an aim to find suitable network through optimization process of this algorithm. To this end, firstly, the parameters of network are simulated as the genes on a genome, then crossover and mutation functions, as a reproduction process, follow optimization process in an evolutionary way. These two functions have been illustrated as in Figure 4. Depicted (a) of this figure illustrates crossover function in which the gene of segmented parts of genomes are replaced. The mutation, which holds after the crossover in GA optimization process, has been illustrated in part (b) of this figure; in which the values of some defined genes are changed randomly. In this chapter, an improved case of previously used GA-based fuzzy neural network in last research is used as major part of the system as shown in Figure 5 [11]. In comparison, the previous system was using one phase GA-based FANN abbreviated as 1P-GBLM-ES; while this system uses two phase GA-based FANN abbreviated as 2P-GBLM-ES shown in Figure 6.

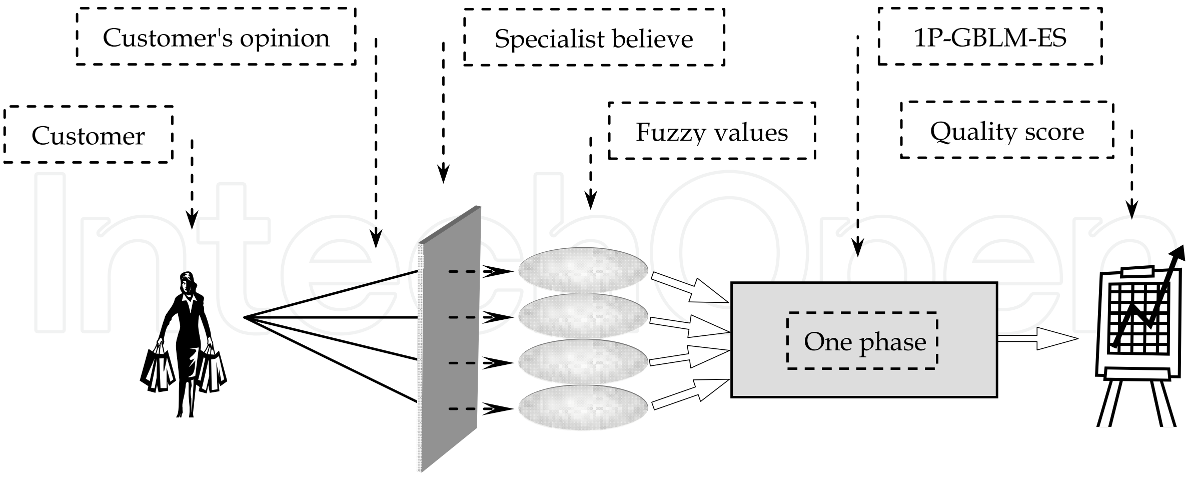


Fig. 5. general structure of 1P-GBLM-ES

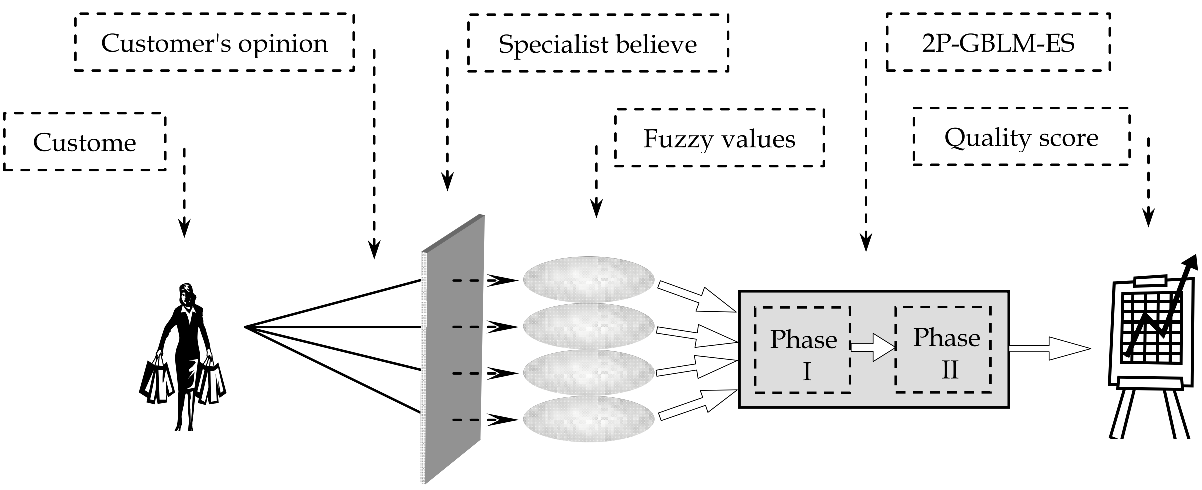


Fig. 6. general structure of 2P-GBLM-ES

Figure 5 explains the steps of constructing 2P-GBLM-ES. This system is designed in two phases of place-definition and shape-definition; in which a suitable place for fuzzy value is obtained in steps two to eight using support and core of the fuzzy numbers and a suitable shape using $middle_{\alpha}$ in steps nine to sixteen [11].

Algorithm 2: The steps of the 2P-GBLM-ES

$$
\begin{array}{l}
\textit{begin } 2P-GBLM \\
\quad \textit{begin phase I} \\
\qquad \textit{initialize } (\,) \\
\qquad x_1 \leftarrow \textit{create } (\,) \\
\qquad \textit{while} \neg \textit{ terminationCriterion } (\,) \textit{ do} \\
\qquad x_{new} \leftarrow \textit{update } (x_1) \\
\qquad \textit{if } f(x_{new}) < f(x) \textit{ then } x_1 \leftarrow x_{new} \\
\qquad \textit{return } x_1 \\
\quad \textit{end phase I} \\
\quad \textit{begin phase II} \\
\qquad \textit{initialize } \text{using } x_1 \textit{ boundaries } (\,) \\
\qquad x_2 \leftarrow \textit{create } (\,) \\
\qquad \textit{while} \neg \textit{ terminationCriterion } (\,) \textit{ do} \\
\qquad x_{new} \leftarrow \textit{update } (x_2) \\
\qquad \textit{if } f(x_{new}) < f(x) \textit{ then } x_2 \leftarrow x_{new} \\
\qquad \textit{return } x_2 \\
\quad \textit{end phase II} \\
\textit{end } 2P-GBLM
\end{array}
$$

Here in the implementations, heuristic and uniform models have been used for the crossover and mutation, respectively. It is noticeable that; here GA as an optimization technique is a lateral part of major FANN in evaluator system.

3. Implementation And Results

Earlier, an approach were proposed to construct a customer satisfactory evaluator system based on the frame of Figure 6 using Algorithm 2. In this section, proposed approach is implemented to construct this evaluator system; a three-layer GA-based FANN with seven neurons are used to construct 2P-GBLM-ES. In order to have a higher accuracy for 2P-GBLM-ES, suitable allotments of learning generations for first and second phases are found. To emerge the superiority of proposed system in comparisons, another customer satisfactory evaluator system has been constructed based on the frame of Figure 5 using Algorithm 1. In this order, a three-layer GA-based FANN consisting of seven neurons have been used to construct 1P-GBLM-ES. The architecture of the networks are designed such that considers the simplicity and less complexity for the network. Two datasets are used to test the implementation; utilized datasets have been generated based on indicators data of [5], where customer's opinions have been shown based on pre-assumed indicators. Then, computed gap has been computed as the difference between expected value and satisfaction value of customer's opinion from current status. The comparisons results for 1P-GBLM and 2P-GBLM are in terms of generated error and executed time; initially, the first subsection shows the validity of proposed approach by comparison, then the ability of proposed evaluator system has been shown in the second subsection using dataset of Table 4.

Validation of Proposed Evaluator System: This subsection shows performance validity of constructed 1P-GBLM-ES and 2P-GVLM-ES for approximating the gap in a small-scaled data environment using the dataset of Table 3 in Appendix. The results are supposed to be a direction of showing the capability for these systems in a more complex environments to show the superiority for 2P-GBLM-ES, which is presented in the next subsection. Regarding the validation test, two customer's opinions are considered that are almost in contradiction to each other as shown in Figure 7 based on Table 3. Then, neural evaluator system is trained to approximate the gap based on new data. The learning processes were done in the same conditions for initial population using size 50 for 200 generations, while the average of received errors were obtained in terms of 100 times iteration. In order to construct 2P-GBLM-ES, suitable allotments of learning generations for first and second phases were obtained as shown in Figure 10. Then, trained networks were tested for the validation; two new customers who had a middle opinion were evaluated, as shown in Table 1. One of the customers has an exactly middle opinion, where the gap resulted from his/her is exactly 5.1. The other customer has almost a fair opinion, where the gap resulted from his/her is a value around 5.1.
Regarding the validation for 1P-GBLM-ES, the average of generated error for trained system was 0.03 in 16-second time. The results of approximation for this training were obtained as shown in figures 8 and 9 for first and second test customers, respectively.

Customer / Indicator	#1	#2
Product	(4.55,4.67,4.76,4.89,5.1,5.3,5.44,5.53,5.65)	(4,4.21,4.4,4.61,5,5.37,5.6,5.77,6)
Service	(4.5,4.61,4.74,4.85,5.1,5.35,5.46,5.58,5.7)	(4,4.28,4.54,4.8,5.3,5.77,6.02,6.23,6.5)
Network	(3.6,3.91,4.2,4.5,5.1,5.7,5.99,6.29,6.6)	(3.6,4.02,4.43,4.88,5.6,6.04,6.19,6.32,6.5)
System	(3.9,4.15,4.39,4.62,5.1,5.59,5.81,6.04,6.3)	(4,4.09,4.16,4.24,4.5,4.96,5.25,5.51,5.8)
Expected Gap	5.1	$\approx$ 5.1

Table 1. Fuzzy values of the indicators for validation test.

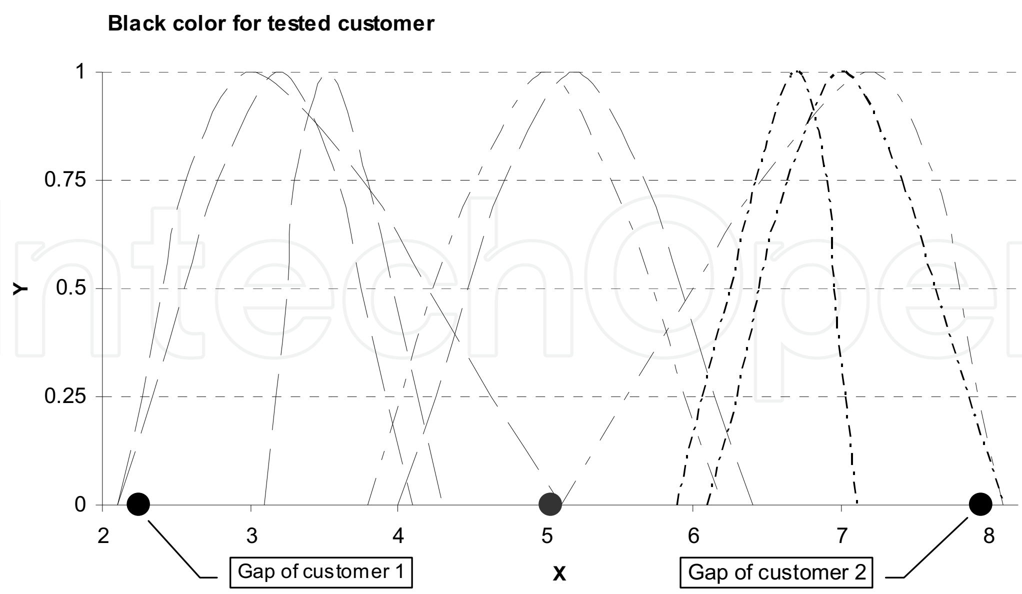


Fig. 7. Depicted opinions of the customers trained by evaluator systems

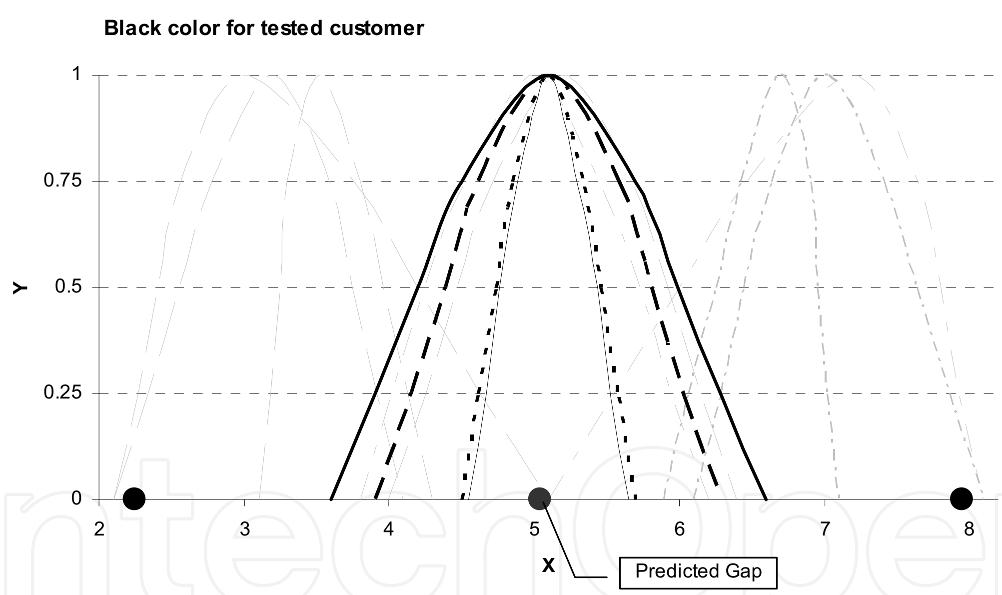


Fig. 8. Predicted gap for the first test customer using trained 1P-GBLM-ES

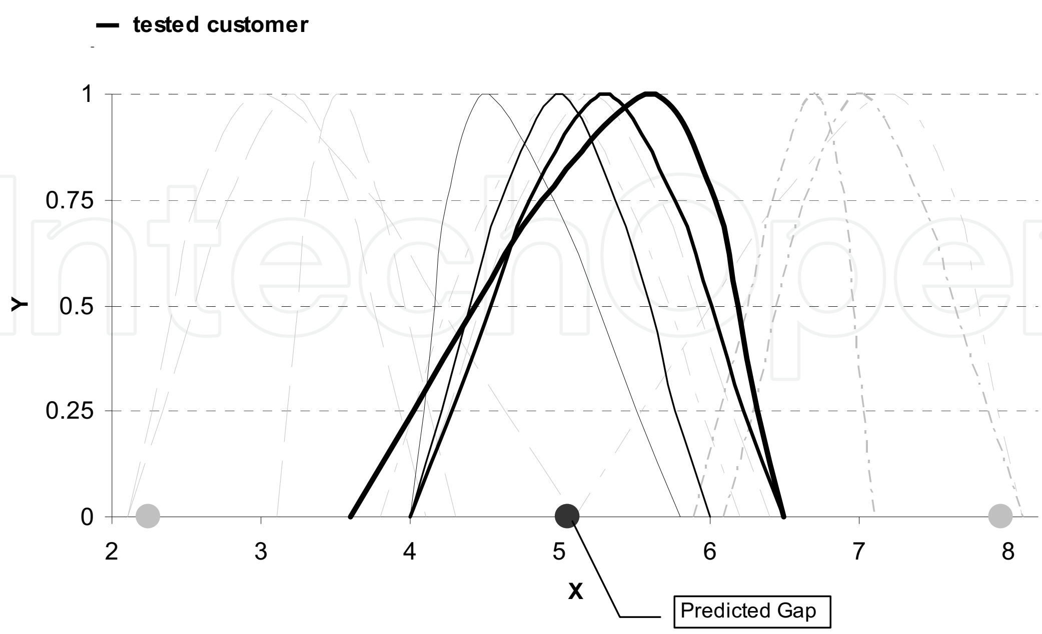


Fig. 9. Predicted gap for the second test customer using trained 1P-GBLM-ES

Figures 8 and 9 shows the values obtained from evaluating new assumed customers are 5.04 and 5.05, which are as expected. Therefore, the results show that customer-preference orientation of 1P-GBLM-ES in approximating customer's opinion works properly for a small-scaled environment. Then, regarding the validation for 2P-GBLM-ES, the same initial population was used to train the system as for 1P-GBLM-ES. In order to have a suitable accuracy for this system, different cases of allotments were tested to find a suitable case for each phase of the system. The result in Figure 10, which is the average of 100 iteration, shows the best-case belonging to 90% and 10% for the first and second phases, respectively. Then, 2P-GBLM-ES was trained using best-case allotment, where the average of overall generated error for the trained system obtained 0.002 in 11-second time. Figures 11 and 12 shows the outcome received form trained 2P-GBLM-ES using best-case allotment in evaluating new assumed customers that is 5.1 and 5.25 as expected.

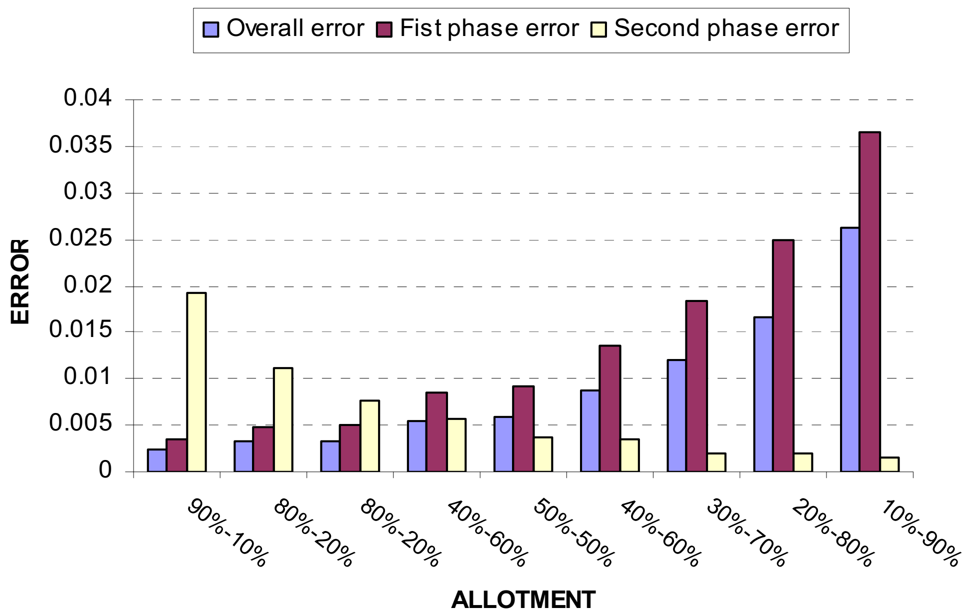


Fig. 10. Different cases of allotments for first and second phases of 2P-GBLM-ES using dataset of Table 3.

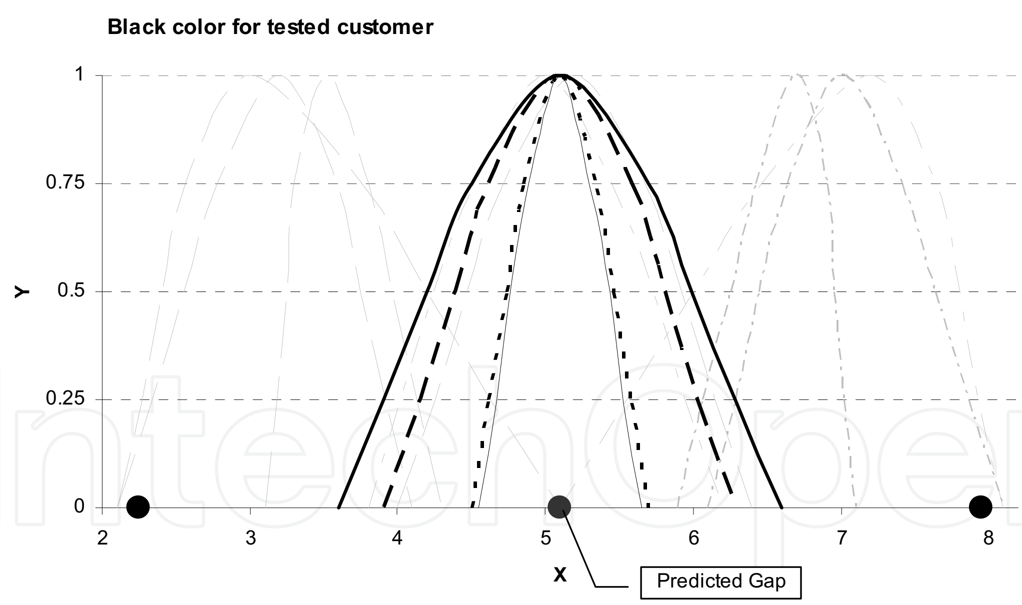


Fig. 11. Predicted gap for the first test customer using the trained 2P-GBLM-ES

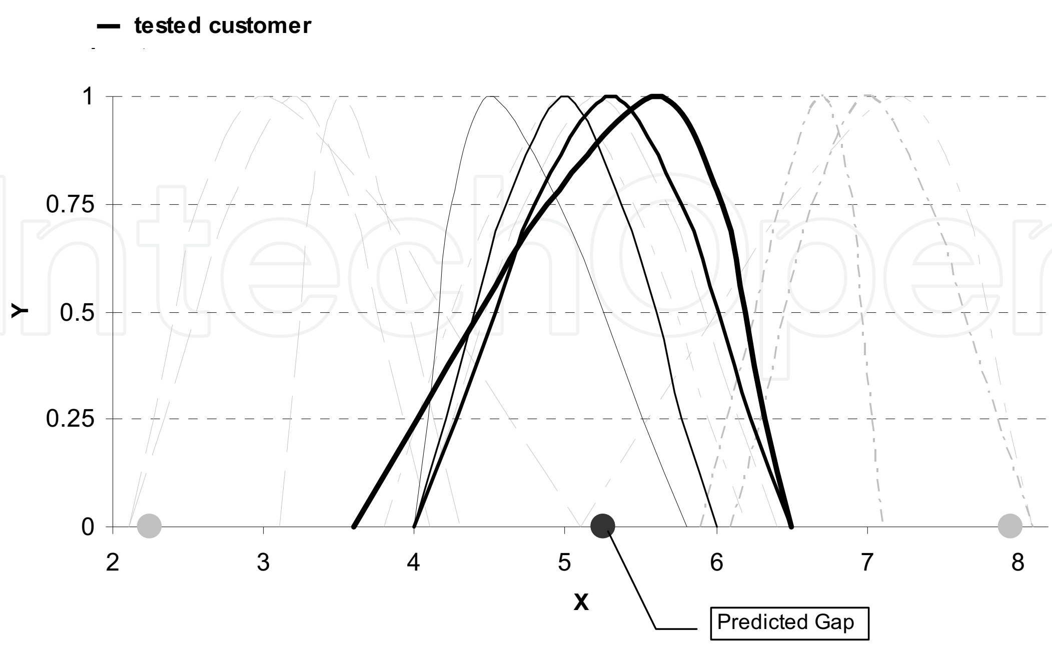


Fig. 12. Predicted gap for the second test customer using the trained 2P-GBLM-ES

The obtained results of figures 8, 9, 11 and 12 in this subsection, validate the performance of both 1P-GBLM-ES and 2P-GBLM-ES in approximating the gap. However, 2P-GBLM-ES showed to have less error in a less execution time.

Ability of evaluator system: In this subsection, the ability of 1P-GBLM-ES and 2P-GBLM-ES are analyzed in approximating the gap based on customer's opinion, in which more of them are exist in a more complex environment. The importance of this analysis is to show the approximation ability of both evaluator systems which are based on more available preferences. This makes resulted outcome to be more reliable for the enterprise and, thus, more assured strategic decisions could be taken. Here, ten customers data are utilized, which have been shown in Table 4 of Appendix. Learning behaviors are analyzed based on variation percentage of error decrease using different populations, in order to show the ability of constructed systems in learning data.

The results of learning process for 1P-GBLM-ES and 2P-GVLM-ES, using 500 generation and three different population sizes of 50, 200 and 500, have been shown in figures 13 and 15. Figure 11, which illustrates the learning behavior of 1P-GBLM-ES, shows that the variation rate of generated error keeps to its stability before the last generation just after achieving to its high value; this happens by passing a high decrement. Starting point of this, which is a threshold of convergence decrement to the optimum, happens in the 51st generation at the 10% of the 500 training generations. Vertical dashed-line shows this threshold in Figure 11, which the general status of suitable evaluator system is found. However, suitable evaluator system is defined after the threshold that needs ability of learning method in finding precise values. According to achieved threshold, it is possible to say in a pessimistic way that the ability of constructed system in learning the data of Table 6 and utilized populations is in the interval (0.0054-ε <error<0.0263+ ε).

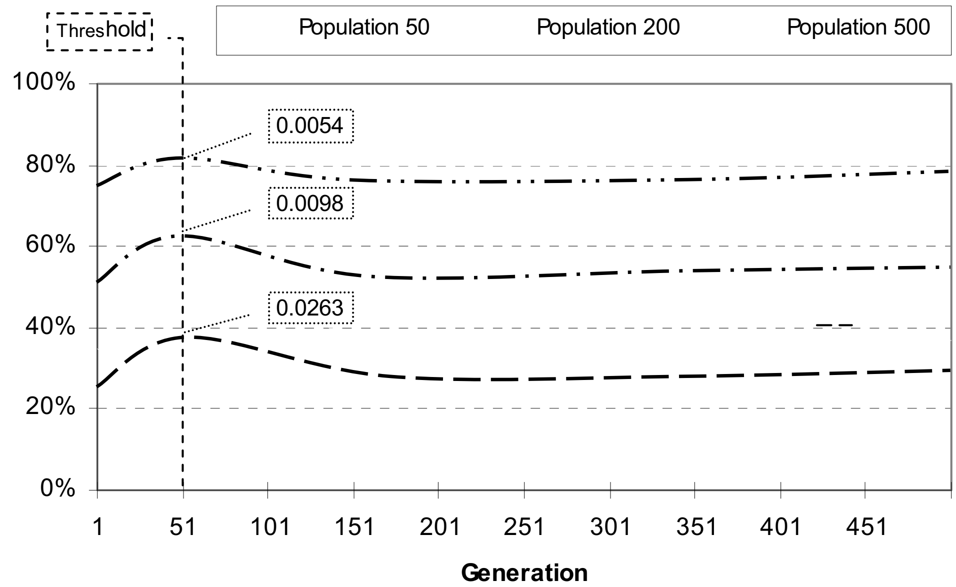


Fig. 13. The variation of generated error in different populations using 1P-GBLM-ES

Regarding 2P-GBLM-ES, different allotment cases of learning generations for its first and second phases was obtained using dataset of Table 6; so that the best-case allotment found in terms of generated error. Figure 12 shows the best-case allotment belonging to 90% of generations for first phase and 10% for second phase.

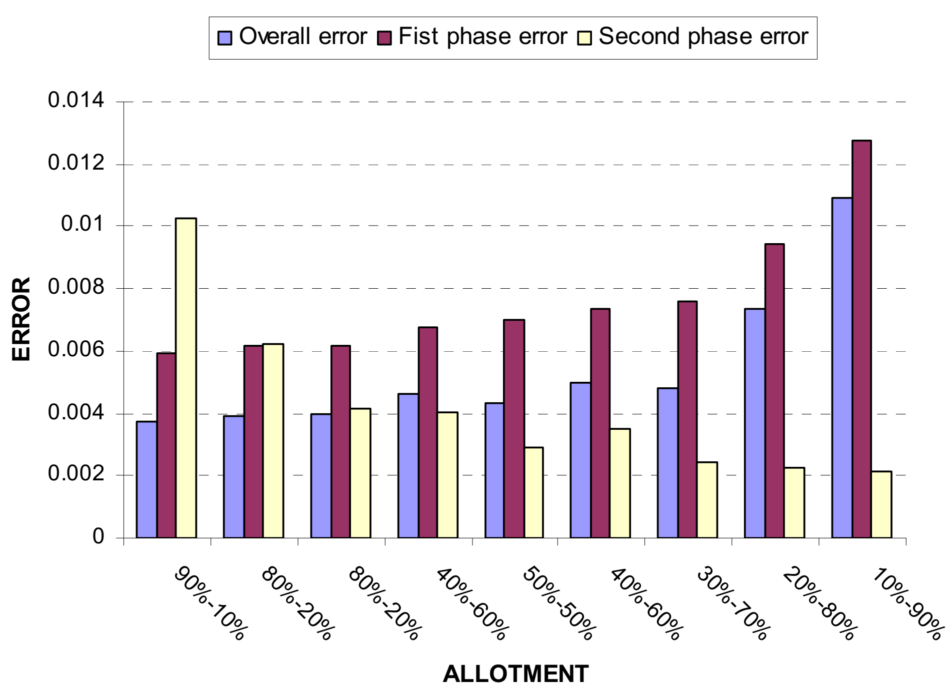


Fig. 14. Different cases of allotments for first and second phases of 2P-GBLM-ES using dataset of Table 4

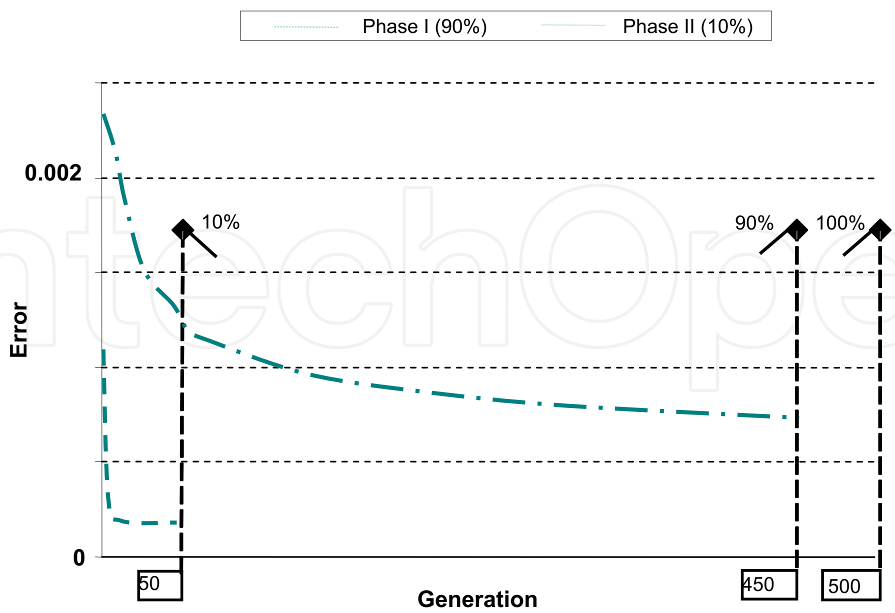


Fig. 15. The variation of generated error using 2P-GBLM-ES

Accordingly, Figure 15 shows the learning behavior of 2P-GBLM-ES using the based-case allotment. Here, the general suitability of the system is obtained in the first phase, where the second phase finds its precise status. Three customers have been used to test trained 1P-GBLM-ES and 2P-GBLM-ES based on Table 4. The suitable systems that has been used for this test is the case of 500 populations in 500 generations; while the error of 0.0263 for 1P-GBLM and 0.00371 for 2P-GBLM were obtained in 1518 and 1104 second-time respectively. Table 2 shows related outcomes received from obtained suitable evaluator systems based on the opinions of these customers. It is worth mentioning; the reason of using this case is the nature of dealt problem, which aims at strategic analysis for a higher quality approximation. Obtained results in this subsection, shows that both 1P-GBLM-ES and 2P-GBLM-ES has the ability of dealing with a precise customer data. However, 1P-GBLM-ES has less ability in the convergence, where it decreases after a threshold on learning generations. The threshold in Figure 13, showed that having the beneficial of 10% of learning generation, in which general suitable system is found, other remained 90% are most possible to be trapped in the local-minima. This shows disability of 1P-GBLM-ES in tuning the $middle_{\alpha}$, which is after 51st generation. This is while; 2P-GBLM-ES more avoiding to be trapped in the local-minima by separating the learning generations into two phases. Such that as the best-case allotment; 90% of learning generations are used to find the general suitability of the system, which was lost to be effectively used in 1P-GBLM-ES, and other remained 10% find precise status of the system. In addition, the separation of learning generations caused the speed of system to be faster in converging to suitable system. Therefore, 2P-GBLM-ES is superior in comparing with 1P-GBLM-ES in both terms of generated error and executed time.

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5. Conclusion

This chapter considered an approach to facilitate a better analysis of strategic decisions to find a suitable strategy for a business enterprise; defining business strategy held on precise analysis of customers' opinions. It assumed customers' preferences as the major key in analysis, which is a new approach to solve the current problem. Regarding high complexity of customers' preferences in precise case, organizational analyze needed an approach being capable of obtaining an assured results. Therefore, this chapter proposed a system to enable an enterprise evaluating new possible organizational changes, in any business level. The superiority of this proposed system, which uses two phase genetic algorithm based fuzzy artificial neural network, was shown in comparison with one phase genetic algorithm based fuzzy artificial neural networks by some analysis. This was due to the ability of this system in finding general status of suitable evaluator system and more avoidance from trapping into the local-minima to find a precise status. This is while; this ability were based on fuzzy obtained best-case allotment for each phase of evaluator system. Finally, valid performance and the ability of system assure an enterprise to have beneficial consequences of using it for a risky condition in correct orientation as well as success rate in less time. However, its ability in dealing with more precise data and number of them may be found in a future research.

Customer / Indicator	#1		2#		
Product	(2.1,2.34,2.5,3,3.59,3.84,4.03,4.3,5.1)		(5.5,5.77,5.99,6.37,7,7.59,7.8,7.93,8.1)		(3.6,3.79,
service	(3.1,3.28,3.48,3.76,4.5,4.74,5.07,5.36,5.78)		(6.7,6.8,6.83,6.97,7.3,7.49,7.57,7.58,7.6)		(3.7,4.27,4.
Network	(2.3,2.35,2.41,2.44,2.6,2.69,4.2,4.6,5.1)		(4.8,5.77,6.13,6.71,8.0,8.05,8.08,8.09,8.1)		(2.6,3.23,3
System	(3.3,3.48,3.93,4.74,5.8,6,6,6.15,6.19,6.4)		(3.5,3.74,3.88,3.99,4.2,5.7,6.45,7,7.7)		(3.3,3.43,3
Gap/ System	**1P-GBLM-ES**	**2P-GBLM-ES**	**1P-GBLM-ES**	**2P-GBLM-ES**	**1P-GBLM**
	2.743	3.625	5.819	6.758	5.261

Table 2. Test customers and predicted gaps using 1P-GBLM-ES and 2P-GBLM-ES

6. Appendix

Customer / Indicator	#1	2#
Product	2.1,2.27,2.41,2.56,3,3.76,4.2,4.63,5.1	6.1,6.3,6.45,6.64,7,7.41,7.64,7
service	3.1,3.18,3.25,3.3,3.52,3.8,3.96,4.13,4.3	5.9,6.07,6.26,6.43,6.7,6.9,6.95,
Network	2.1,2.34,2.55,2.78,3.2,3.59,3.75,3..92,4.1	5.1,5.55,6,6.46,7.2,7.65,7.8,7.
System	4,4.26,4.47,4.72,5.2,5.67,5.92,6.15,6.4	3.8,4.02,4.24,4.53,5,5.45,5.73,5
Gap	2.25	7.95

Table 3. Dataset 1

Customer / Indicator	#1	#2	
Product	(2,2.1,2.14,2.24,2.5,2.9,3.2,3.51,4)	(6.1,6.54,6.82,7.17,7.8,7.8,7.9,7.97,8.1)	(4.5,4.98,5.32,5.58
service	(3.1.3.19,3.27,3.36,3.5,3.75,3.91,4.07,4.3)	(6,6.24,6.43,6.68,7.1,7.24,7.38,7.6,8)	(4.7,4.8,4.95,5.07,5
Network	(1.9,1.9,1.9,1.9,1.9,2.3,2.62,2.95,3.5)	(7,7.24,7.5,7,7.78,8.2,8.2,8.2,8.2,8.2)	(5.5,5.9,6.13,6.32,
System	(4,4.31,4.56,4.81,5.2,5.73,5.94,5.15,6.4)	(3.8,3.9,4.07,4.37,5,5.3,5.58,5.91,6.2)	(2.4,2.71,2.94,3.2,3
Gap	2	7.9	2
Customer / Indicator	**#4**	**#5**	
Product	(2,2.08,2.15,2.17,2.3,2.89,3.16,3.59,4.1)	(3.7,5.02,5.72,6.4,7.3,7.47,7.58,7.7,7.8)	(4.8,5,5.16,5.37,5
service	(2.3,2.61,2.81,3.05,3.4,3.46,3.53,3.59,3.7)	(6,6,6.09,6.16,6.4,6.72,7.09,7.49,8)	(2.6,2.92,3.48,3.
Network	(1.9,2.06,2.24,2.8,3.02,3.07,3.18,3.5)	(5.3,5.49,5.72,5.95,6.4,6.6,6.91,7.28,8.1)	(5.4,5.86,5.24,6.8
System	(3.1,3.31,3.53,3.7,4.1,5.11,5.76,6.38,7.5)	(4.2,4.2,4.28,4.35,4.5,4.74,5.07,5.51,6.2)	(2.2,2.2,2.29,2.4
Gap	3.36	7.01	5
Customer / Indicator	**#7**	**#8**	
Product	(3.1,3.32,3.53,3.67,4.2,4.69,5.06,5.64,6.7)	(4.7,4.76,4.8,4.9,5.2,5.66,5.82,6.17,7)	(3,5.13,5.95,6.76,
service	(2,2.21,2.14,2.26,2.6,3,3.27,3.74,4.6)	(8.3,5.8,5.45,5.87,6.4,6.56,6.72,7.09,8)	(5.2,5.22,5.24,5
Network	(2.8,3.74,4.37,4.97,6,6.28,6.36,6.45,6.7)	(6,6.86,7.23,7.53,8,8,8,8,8.1)	(2.6,3.01,3.15,3.4,3
System	(2.6,2.74,2.81,2.96,3.3,3.6,3.84,4.07,4.5)	(5.7,6.1,6.25,6.56,7,7.04,7.07,7.07,7.2)	(4.2,4.28,4.34,4.4,4
Gap	3.92	6.41	

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