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Constructing a Customer's Satisfactory Evaluator System Using GA-Based Fuzzy Artificial Neural Networks

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Abstract: In this paper, an important principle of economical survival in the business area has been studied. It has been considered by increasing the success rate in selling the products in order to overcome on other competitors. This can be achieved thereafter of taking suitable strategic decisions for the enterprise. It is while; the strategic decision determination is based on the quality analysis of the current organization. The analysis is based on the linguistic values received from the customers where the fuzzy modeling, as one of the possible ways, has been used to process these values. The customer's satisfaction has been considered as a key factor for the analysis based on his/her preference as the scope of the qualification for the organization service. In this paper, a new approach has been proposed to provide the reliability of the strategic decisions for an enterprise. This approach considers fuzzy artificial neural networks based on the genetic algorithm to construct a customer's satisfactory evaluator system in order to approximate the quality of the service. The proposed system is able to predict the quality values of the possible strategies according to customer's preference. Finally, the ability of this system in recognizing the customer's preference has been tested using some new assumed services.

Key words: Commerce % Service Impact Value % Linguistic Value % Evaluator System % Fuzzy Modeling % Fuzzy Artificial Neural Network % Genetic Algorithm

INTRODUCTION

The selling rate of the products for an enterprise, either be the business centers or the producer factories, is an important issue in the commercial competitions. The higher rate an enterprise gains the more merit for survival is proved. The earlier researches have shown that 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 the customers' satisfaction plays a key role for the enterprise survives, the analysis of his/her opinion is vital to make the next enterprise decisions. In general, the customer's satisfaction is not only a multi-variable issue but also is based on the linguistic values. On the other hand, the linguistic values, which have been used here, are intrinsically known as the vague values [3]. The two mentioned multi-variability and linguistic-variability make the problem more complex and the system evaluation would be more difficult. This is while; the strategic goals of the enterprises are determined according to the results of this analysis and thus, the evaluation of the customer opinion is an essential issue [4,5,2]. 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.

The customer's satisfaction is the 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 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 the indicator must be visible to the customers' view [5]. According to the literature, three basic aspects of independency, comparability and feasibility must be considered [1,2,4]. In this paper, indices have been used that supports the

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mentioned aspects employed by the other researchers. One of the ways to analyze the utilized indices, which is based on the linguistic values received from the customer, is the 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 paper. 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 the linguistic variables modeled by triangular fuzzy values [4,5].

Following aforementioned researches, this paper aim is to propose an evaluator system that would be able to recognize the customer's preference. Meanwhile, it uses the benefits of fuzzy modeling in the customer's satisfactory evaluation. This mentioned aim of constructing a system that recognizes the 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 the linguistic values is essential. This approach needs to follow the learning process based on the linguistic values, in addition of having the ability to learn from the customer's opinions. This task is carried out using the fuzzy artificial neural networks (FANNs), which are know as the soft computing techniques. FANNs are able to learn from the fuzzy values that are considered as linguistic terms. Meanwhile, the Genetic Algorithm (GA) has been used to obtain higher efficiency for FANN. The GA is able to find the optimum of the designed network. Finally, each enterprise will be able to have the benefits of using such constructed system as follows:

- To evaluate the possible strategies according to its current customer's tastes, in order to increase the 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 the business ethics, followed by the customer-orientation principle.

The organization of this paper, which aims at proposing such customer evaluator system using GA-based FANN, is as follows. First, in Section 2, the concept of customer evaluator system has been explained. Then, how to model the current problem using fuzzy modeling has been explained in Section 2.1. In the sequel, the proposed evaluator systems using GA-based FANN and its basic concepts have been explained in Subsection 2.2. The proposed system is implemented in the Section 3 and the results have been analyzed in the Subsections 3.1 and 3.2. In these two subsections, first the validation of the proposed system has been tested using the new inputs and then the ability of the system has been shown. Finally, a conclusion for the paper is given. Two datasets, which are used in this paper, are presented in appendix.

Customer Evaluator System: The Customer evaluator system defines the service quality of an organization based on the customer's satisfactory degree [4]. The structure of such evaluator system is shown in Fig. 1. The outcome of the system is based on the customer's opinion given to the system, which is represented by the parameters of some indicators.

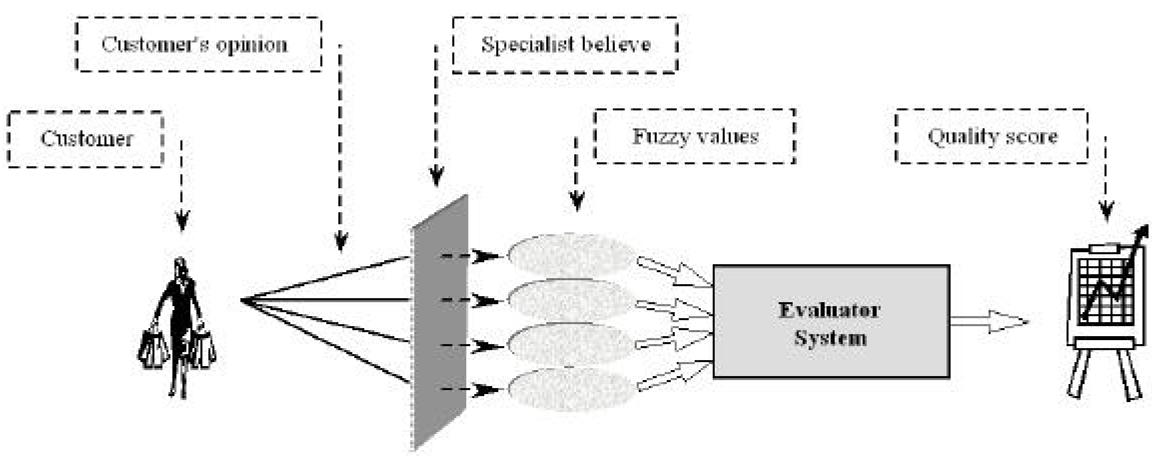

Fig. 1: The structure of the evaluator system

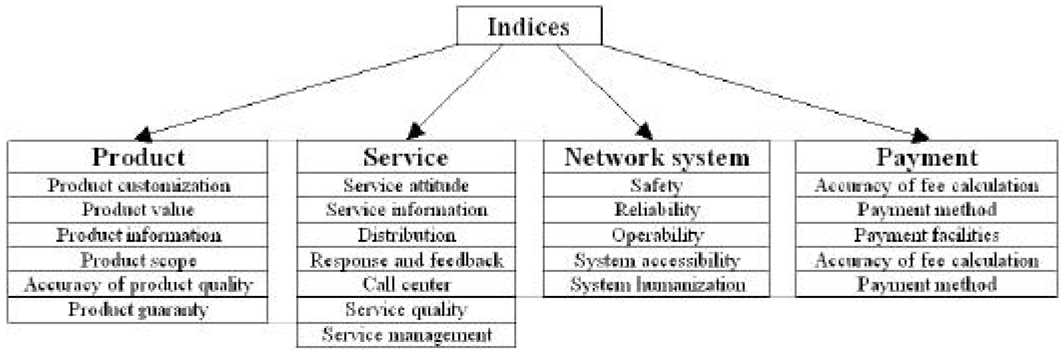

Fig. 2: A customer's satisfactory indices and its parameters

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

The parameters in Fig. 2 are represented in the form of the linguistic variables that are included as the vague values [3]. As these parameters are the inputs of the system, they are necessary to be prepared for processing. To this end, fuzzy modeling is utilized in such a way that first the input values are fuzzified and then they are fed to FANN system to be processed. More details of these procedures are described in the Subsections 2.1 and 2.2, respectively.

Fuzzy Modeling: The fuzzy set theory, which was proposed in 1965 [10], is utilized in many application areas by solving their corresponding problems [11-14]. This is due to the ability of the fuzzy logic, with its modeling, in facing the complex environments [16]. In such environments like agriculture, market prediction, risk assessment [17], image processing etc. [15], the linguistic variables can be used. Customer's satisfactory evaluation, the dealt issue in this paper, is among such environments. This is because the process of this evaluation is based on the information steamed from the linguistic terms. In addition, having many linguistic variables causes this problem to be as a multi-variable issue too. 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 paper, the fuzzy modeling is considered for processing the linguistic terms that are received from the customer in order to construct the evaluator system. The fuzzy variables, which are used in the evaluator system, are considered as the linguistic terms received from the customer. The evaluator system uses the fuzzy variables for the inputs and the parameters of the evaluator neural network. For the fuzzy values utilized in the input it is noticeable that; the transformation of these values depends on the experts' interpretation over the linguistic terms, which is done through the specialists' believes as illustrated in Fig. 1. However, the idea of this paper is concentrated on the evaluator system only and, thus; obtained fuzzy values have been used based on the other researchers' results [5]. For the fuzzy values utilized in the parameters of the evaluator system, this paper uses the fuzzy triangular values due to the simplicity of their calculations in the evaluation process. To be self-contained we quote some fuzzy arithmetic of fuzzy triangular values as special fuzzy sets of the real numbers *R*.

A triangular fuzzy value is shown as $\tilde{A} = (a_1, a_2, a_3)$ in which its membership function $m_{\tilde{A}} : R \to [0,1]$ is as the following:

$$m_{\tilde{A}}(x) = \begin{cases} 0 & x < a_1 \\ (x - a_1)/(a_2 - a_1) & a_1 < x < a_2 \\ (x - a_3)/(a_2 - a_3) & a_2 < x < a_3 \\ 0 & x > a_3 \end{cases} \quad (1)$$

Three basic operations of summation, subtraction and multiplication over triangular fuzzy numbers, which will be used in the proposed evaluator system, are defined as follows [18]:

$$\tilde{A}(+)\tilde{B} = (a_1, a_2, a_3) + (b_1, b_2, b_3) = (a_1 + b_1, a_2 + b_2, a_3 + b_3), \quad (2)$$

$$\tilde{A}(-)\tilde{B} = (a_1, a_2, a_3) - (b_1, b_2, b_3) = (a_1 - b_1, a_2 - b_2, a_3 - b_3), \quad (3)$$

$$\begin{aligned} \tilde{A}(\times)\tilde{B} &= (a_1, a_2, a_3) + (b_1, b_2, b_3) \\ &= \left[\min(a_1 \cdot b_1, a_1 \cdot b_3), a_2 \cdot b_2, \min(a_3 \cdot b_1, a_3 \cdot b_3)\right]. \end{aligned} \quad (4)$$

Evaluator Neural Network: The neural learning networks are among the soft computing techniques [18]. The learning networks of the fuzzy-type, so-called FANNs, were proposed after the crisp neural networks [19]. FANNs have attracted many researchers in consequent of acquiring improvements and knowing their abilities in solving the complex problems. In this paper, FANNs have been used as the main part of the customer's evaluator system. The outcome of the evaluation is resulted from the process of the system on the fed inputs. This network is able to learn the customer's preference by its training process. The training process is based on the fuzzy values resulted from the linguistic values transformation. Therefore, the trained networks will be able to predict the customer's satisfactory degree based on the current preference, which then it allows approximating the goodness of the new organizational changes to be applied. The steps of constructing such system are explained in Algorithm 1.

Algorithm 1: The steps of the evaluator neural network.

1	*Begin*
2	*initilize ()*
3	*x 7 create ()*
4	*While ¬ termination Criterion () do*
5	x_{new} *7 update (x)*
6	*If f* $(x_{new}) < f(x)$ *then x 7* x_{new}
7	*Return x*
8	*End*

Step 2 of Algorithm 1 initiates the indicators with the fuzzy values. Then, it creates the possible solutions by aiming to find a suitable network and x will be replaced with that. The 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;

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

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

Model Structure of Fuzzy Artificial Neural Networks (FANN): This section presents the structure of FANN [20]. Here, FANN of type-1 is used as the major part of the evaluator system, in which the input is fuzzy value and the output is crisp [15,21]. The input neurons

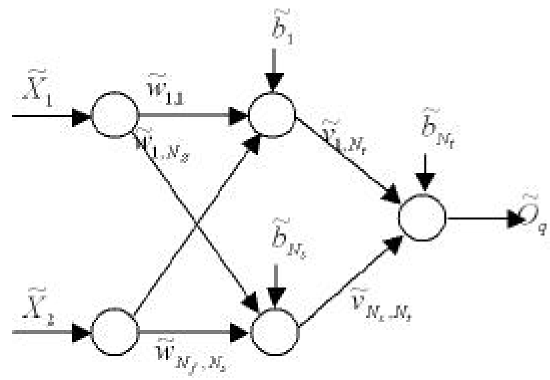

Fig. 3: A three-layer fuzzy neural network architecture

have been used to learn the customer's preference based on the "-cuts defined in [3]. The structure of such FANN, using two inputs a general architecture, is shown in Fig. 3.

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

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

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

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

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

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

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

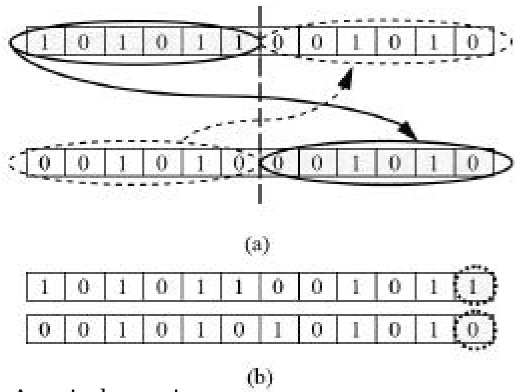

Fig. 4: **(a)** A typical crossover, **(b)**. A typical mutation

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

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

Genetic Algorithm Based FANN: Genetic algorithm (GA) was first proposed in 1975 [22]. It is categorized as an optimization and soft computing technique, which is based on the principles of the natural evolution [22,18]. Here, the optimization process holds on the defined generations. GA has been used toward improving the efficiency of a FANN. The idea of using GA for improving FANN was first proposed in 1994 [19]. Here, this idea, called GA-based FANN, is used as a validated method [23].

In the GA-based FANN, the genetic algorithm tries to find the network parameters in an optimized manner. Therefore, tuning the weights and the biases are an aim to find the suitable network through the optimization process of this algorithm. To this end, firstly, the parameters of the network are simulated as the genes on a genome. Then, the crossover and mutation functions, as a reproduction process, follow the optimization process in an evolutionary way. These two functions have been illustrated as in Fig. 4. The depicted (a) of this Figure illustrates the crossover function in which the gene of segmented parts of the genomes are replaced. The mutation, which holds after the crossover in GA optimization process, has been illustrated the part (b) of this Figure in which the values of some defined genes are changed randomly. Here in the implementations, heuristic and uniform models have been used for crossover and mutation, respectively. It is noticeable that here GA, as an optimization technique, is a lateral part of the major one of the evaluator system that is FANN.

IMPLEMENTATION AND RESULTS

Earlier, an approach were proposed to construct a customer's satisfactory evaluator system based on the frame of Fig. 1 by Algorithm 1. In this section, the proposed approach has been implemented to construct an evaluator system, where GA-based FANN has been used. Three layers consisting of seven neurons have been used to construct the evaluator system. The architecture of the network is designed such that the simplicity and less complexity is concerned. Two datasets have been used for testing the implementation. The utilized datasets have been generated based on the indicators data of [5], where the customer's opinions have been shown based on pre-assumed indicators. Then the computed gap as the difference between the expected value and satisfaction value of the customer's opinion from the current status has been computed. The results of the learning process are based on the generated error in each generation. Firstly, the validity of the proposed approach has been shown in Subsection 3.1 and then the ability of the proposed evaluator system has been shown using another dataset that is discussed in Subsection 3.2.

Validation of Proposed Evaluator System: In this section, the validity of the constructed system in a small-scaled environment is shown using the dataset of Table 1 in Appendix. The results of this small-scaled validation is supposed to be a direction of capability of this proposed evaluator system in a more complex environments, which has been presented in Subsection 3.2.

Table 1: The fuzzy values of the indicators for the test customers

	Indicator				
New Customer	Product	Service	Network	System	Expected Gap
1	(5.65, 5.1, 4.55)	(4.5,5.1,5.7)	(3.6,5.1,6.6)	(3.9,5.1,6.3)	5.1
2	(4.0, 5.0, 6.0)	(4.0,5.3,6.5)	(3.6,5.6,6.5)	(4.0,4.5,5.8)	. 5.1

Table 2: The test customers and predicted gaps using the obtained suitable evaluator system

	Indicator				
New Customer	Product	Service	Network	System	Gap
1	(2.1,3.0,4.1)	(3.1,4.5,5.7)	(2.3,2.6,5.1)	(3.3,5.8,6.4)	3.535
2	(5.5,7.0,8.1)	(6.7,7.3,7.6)	(4.8,8.0,8.1)	(3.5,4.2,7.7)	6.170
3	(3.6,4.9,7.3)	(3.7,6.4,6.6)	(2.6,5.6,6.5)	(3.3,3.8,5.8)	4.565

As shown in Table 1, the two customer's opinions, which are almost in contradiction to each other, have been considered. The data of this table has been plotted as shown in Fig. 5. Then, the neural evaluator system was trained in order to approximate from the new data. The populations of size 50 for 200 generations were used in the learning process. The average of the received error for this learning was 0.001 in terms of 100 times iteration.

Then, the trained network was tested for the validation. In order to do the test, two new customers who have had a middle opinion have been evaluated, as shown in Table 2. One of the customers has an exactly middle opinion, where the gap resulted from his/her opinion 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. Finally, the result of the trained system for the first customer is shown as Fig. 6 and for the second one is shown in Fig. 7.

As illustrated in Fig. 6 and 7, the values obtained from evaluating the new assumed customers are 5.1 and 5.2, which are as expected. Therefore, the results show the customer-preference orientation of the evaluator system in approximating the customer's opinion in a small-scaled environment works properly.

Ability of Evaluator System: In this section, the ability of the system in approximating the gap, as the outcome of the customer's opinion evaluation, has been analyzed in which more number of them exist in a more complex environment. The importance of this analysis is to show the ability of approximation for the evaluator system which is based on more available preferences. This makes the resulted outcome to be more reliable for the enterprise and, thus, more insure strategic decisions can be taken.

Here, the data of ten customers have been utilized, which are shown in Table 3 of the Appendix. The learning behavior has been analyzed, based on the variation percentage of the error decrease using different populations, in order to show the ability of the constructed system in learning the mentioned data. The results of the learning process, using 500 generation and three different population sizes of 50, 200 and 500, are shown in Fig. 8. It shows that the variation rate of the generated error keeps to its stability before the last generation just after achieving to its high value. This happens by passing a high decrement following its initial decrease. The starting point of this high decrement, which is a threshold of the convergence decrement to the optima, happens in the 80th generation at the 16% of the 500 training generations. The vertical dashed-line shows this threshold in Fig. 8. Therefore, according to the achieved threshold, it is possible to say that the ability of the constructed system in learning, the data of Table 3 and utilized populations, in terms of generated error is in the interval (0.001767- g <error<0.008492+ g). Since, initially, in the generations before the threshold, the general value of the suitable system is explored and afterward staking in the local minima is more possible to happen.

Three customers have been used to test the proposed system, which is trained based on Table 3. According to the indices, the opinions of these customers are shown in Table 4. The suitable system, which has been used for this test, is the case of the 500 populations in the 500 generations with the error of 0.0003 as in Fig. 6. It is worth mentioning that the

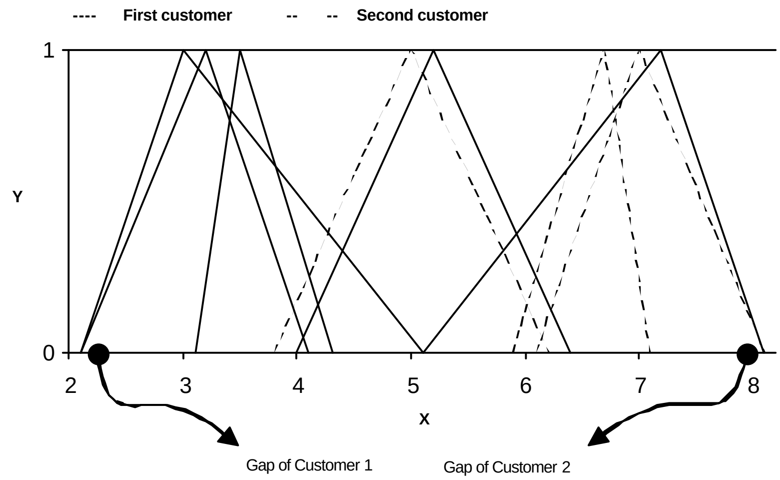

Fig. 5: The depicted opinions of the customers that are trained by the evaluator system

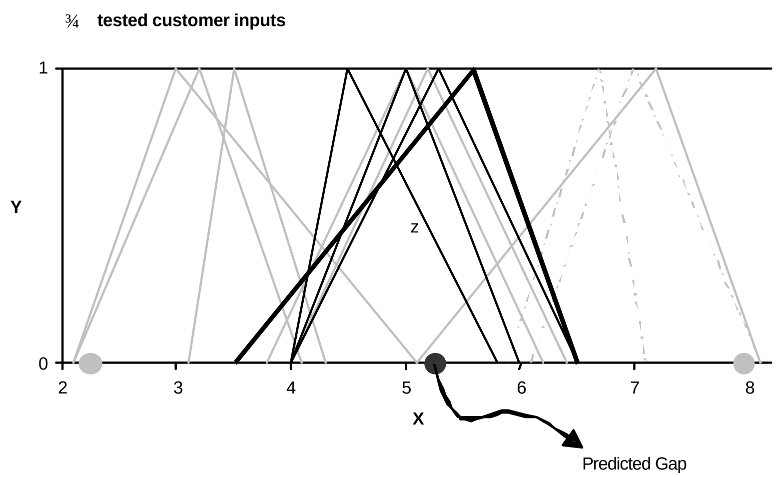

Fig. 6: The predicted gap for the first tested customer using the trained evaluator system

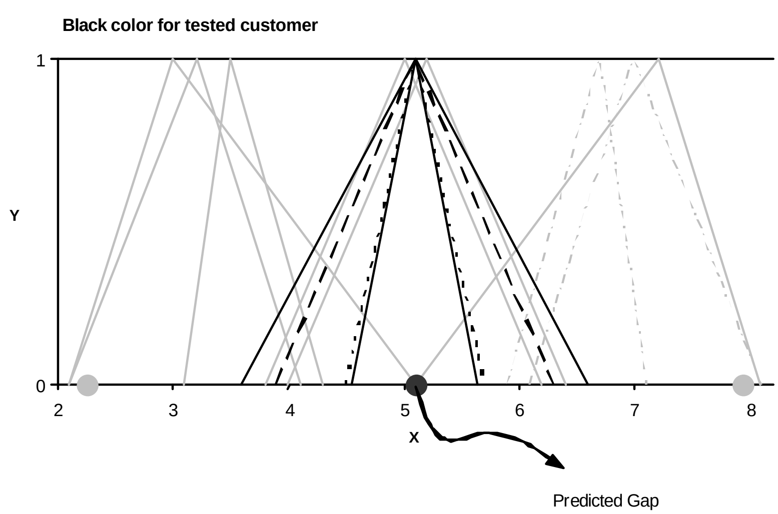

Fig. 7: The predicted gap for the second tested customer using the trained evaluator system

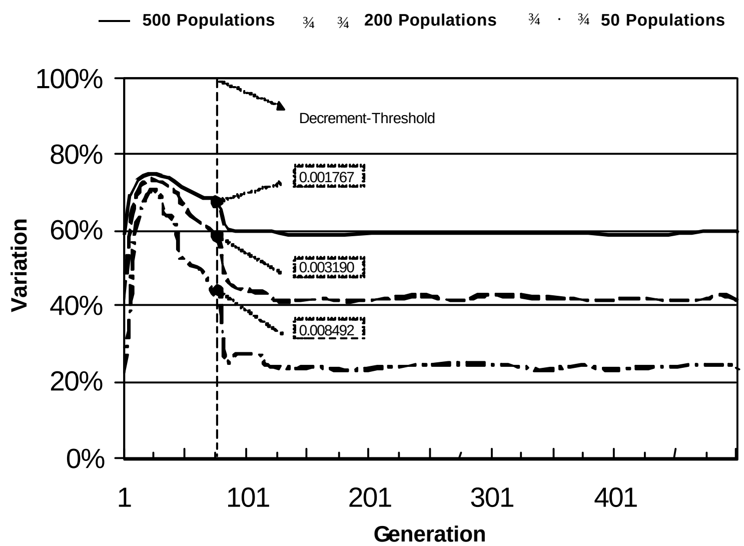

Fig. 8: The variation of the generated error by different populations in learning the dataset 2

Appendix

Table 3: Dataset 1

	Indicator				
New Customer	Product	Service	Network	System	Gap
1	(3.2, 4.1, 2.1)	(3.1,3.5,4.3)	(2.1,3.2,5.1)	(4.0,5.2,6.4)	2.25
2	(8.1, 6.1, 7.0)	(5.9,6.7,7.1)	(5.1,7.0,8.1)	(3.8,5.0,6.2)	7.95

Table 4: Dataset 2

	Indicator				
New Customer	Product	Service	Network	System	Gap
1	(2.0,2.5,4.0)	(3.1,3.5,4.3)	(1.9,1.9,3.5)	(4.0,5.2,6.4)	2.00
2	(6.1,7.8,8.1)	(6.0,7.1,8.0)	(7.0,8.2,8.2)	(3.8,5.0,6.2)	7.90
3	(4.5,6.0,7.7)	(4.7,5.3,6.5)	(5.5,6.7,8.1)	(2.4,3.7,5.2)	2.25
4	(2.0,2.3,4.1)	(2.3,3.4,3.7)	(1.9,2.8,3.5)	(3.1,4.1,7.5)	3.36
5	(3.7,7.3,7.8)	(6.0,6.4,8.0)	(5.3,6.4,8.1)	(4.2,4.5,6.2)	7.01
6	(4.8,5.8,7.7)	(2.6,3.9,5.1)	(5.4,7.7,8.0)	(2.2,2.6,6.3)	5.91
7	(2.6,3.3,4.5)	(2.8,6.0,6.7)	(2.0,2.6,4.6)	(3.1,4.2,6.7)	3.92
8	(5.7,7.0,7.2)	(6.0,8.0,8.1)	(4.3,6.4,8.0)	(4.7,5.2,7.0)	6.41
9	(4.2,4.7,7.7)	(2.6,3.9,5.3)	(5.2,5.3,6.9)	(3.0,7.7,8.0)	5.00

reason of using this case is the nature of the dealt problem, which aims at the strategic analysis for a higher quality output. Finally, the predicted outcomes have been presented in Table 4, which were received by obtained suitable evaluator system.

CONCLUSION

This paper, considered an approach to facilitate the analysis of strategic decisions for a business enterprise in order to find a suitable strategy. In this regard, the analysis of the customers' opinions, as one of the major issues, was considered for defining the business enterprises strategy. It assumed the customers' preferences as the major key, which is a new approach to solve the current problem. On the other hand, an approach was needed to analyze the customers' preferences as complex features. Therefore, this paper proposed a system that enables an enterprise, in any business level, to evaluate its new possible organizational changes. Using such system in a risky condition gives the beneficial consequences of the success rate as well as correct orientation to an enterprise. The ability of this proposed system, which is based on the genetic algorithm-based fuzzy artificial neural networks, was shown by some analysis. However, the broadness of customers' preferences and the ability of the proposed evaluator system, in approximation based on these preferences, are the issues that can be considered more in a future research.

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