JOURNAL OF APPLIED INTELLIGENT SYSTEMS & INFORMATION SCIENCES

VOL. 1, ISSUE 1, PP. 1-10, FEBRUARY 2020.
Available at: www.journal.research.fanap.com
DOI:10.22034/jaisis.2020.99358

AN ADAPTIVE NEURO-FUZZY SYSTEM TO ANALYZE THE COST OF QUALITY

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ABSTRACT

Many companies consider the cost of quality as a core value for promoting customers satisfaction to steer towards competitive advantages. A balance must be provided between the features of a product and its resultant quality on the one hand and the return on investment on the other hand. The desirable level of quality is assessable in terms of maintenance costs, and thus it paves the way for the balance to be achieved. In the industrial environment, regardless of information availability, the reasonable classification of such costs is vital to optimize the subsequent maintenance expenses which are the primary concern of our research. Here, an Adaptive Neuro-fuzzy Inference System (ANFIS) is presented to analyze the cost of quality in order to investigate the effectiveness of investment in the different types of costs. To implement the proposed methodology and demonstrate its applicability, a simulation in industrial enterprises is studied and the results are analyzed. The results show that the input component combinations that cause the minimum amount of error have proven effectiveness in the output.

KEYWORDS: Adaptive Neuro-fuzzy Inference System, Neural Networks, Cost of Quality.

1. INTRODUCTION

Nowadays, cost, quality and their relationship, are among the most important issues to be considered when dealing with services and industrial activities. The importance of studying cost and quality can be a competitive advantage in such environments. Determining how the lack of quality can affect the cost of products and consequently the organization's income and recognizing the amount of money that should be spent to reach a desirable quality, have made the cost of quality a special tool in the quality control (Modarress & Ansari, 1987).

The cost of quality is a novel topic in management and enables the company to assess its performance in different aspects such as cost accounting, quality control, maintenance, supply chain, production management, warehouses, safety and hygiene, learning, optimization and etc. It also helps the company to control and improve the cost of quality by creating quality balance sheets and comparing the cost of quality trends. However, how one should use this information after cost identification to improve the technique structure, has been neglected in the cost of quality literature. As a matter of fact, the results include raw data and cannot help the management to make the right decisions. The proposed method in this research discusses the matter that not all of the costs of quality have the same effect on the product's final quality; therefore the first question that needs to be answered is that how these costs should be different. There is no common definition for cost of quality (COQ) in this field. Usually, costs of quality are defined as the sum of costs of conformance (COC) and the costs of non-conformance (CONC). Costs of conformance are those costs that the company pays to prevent low quality

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RECEIVED: 25 NOVEMBER, 2019; ACCEPTED: 21 DECEMBER, 2019; PUBLISHED ONLINE: 21 DECEMBER, 2019

appraisal and quality assessment are an example of these costs. Costs of non-conformance includes the costs caused by low-quality products and service errors i.e. costs of rework or return of products.

Most of the proposed methods in literature are focused on classification and identification of costs. Some of the more famous models are Juran model, Crosby model, the intangible cost of quality, Process model and ABC costing analysis (Machowski & Dale, 1998). Many companies introduce costs of quality as a value for the customer and it has become a critical success factor in order to obtain a competitive advantage. Whenever serious efforts are made to improve quality, the costs of reaching that quality level naturally increases. This is because the goal of an improvement plan must be achieved at the lowest cost to meet customer needs. This cost reduction can only be achieved by reducing the expenses of obtaining that quality level. In turn, this reduction can only be achieved when these costs are identified and measured. Therefore, measuring and reporting the costs of quality should be discussed as an important factor among the managers. The main goal behind the cost of quality methods is obtaining a desirable level of quality while minimizing the sum of all costs of quality. Although most of the applied methods to measure costs of quality are process/activity-based, traditional cost measuring methods focus on expenses rather than activities. Therefore, most of the costs of quality need to be estimated using other methods (Feigenbaum, 1956).

The American Society for Quality Control (ASQC, 1970) defines the costs of quality according to the following four categories. The internal failure cost implying the expenses of completed activities to prevent error or defect in the product before it is delivered to customers includes costs of? reworks, wastes, re-appraisal, corrective activities, redesign, sales, and similar errors. The external failure cost considers expenses of the completed activities to prevent any error after the customer receives the product. These costs include warranty, repairing, product liability and resale. Further, appraisal costs are imposed on the company when any analysis, test or other planned activities are performed to ensure the software and hardware proper performance. These costs include the first appraisal, tests, supplier's supervision, receipt inspection, and all similar expenses. Finally, preventive costs include all activities that are performed in order to inhibit any error and minimize the number of appraisals and failures.

There is a great deal of uncertainty in today's world, and making the right decisions largely depends on the viewpoint of the experts. Given this, different systems have been proposed to increase the accuracy of decisions. With the advancement of science and technology, expert systems and artificial intelligence are widely used for decision making. Neural networks are among the most important branches of artificial intelligence in engineering sciences. In this field, researchers and engineers use artificial intelligence and specifically fuzzy-based and neural network systems to solve extremely hard problems or the problems that are impossible to solve using traditional methods. Considering their ability to deduce results from complicated data, neural networks can help extract patterns and identify different orientations that are too hard for humans and computers to find. Some of the neural networks' important features are the ability to restore and review the data, map the input set onto the output set, approximate and estimate functions, recognize patterns, optimize and find the solution in the presence of several constraints, and conduct data mining including knowledge extraction from new attribute big data. In this research, we innovatively propose a Neuro-fuzzy system in order to analyze the costs of quality.

2. Theoretical Aspects and Literature Review

Feigenbaum (1956) developed a novel Dollar-based reporting system and also, introduced a cost of the quality analysis system. The included costs of quality are prevention, appraisal, internal and external failure. Juran (1951) introduced three other aspects of the cost of quality analysis which are the cost of quality, quality economics, and graphical form. The prevention cost is a function of all activities that are performed to ensure the quality of products and services. The cost of appraisal is a function of the quality of the process as well as the cost of the failure to ensure the quality and accuracy of the products and services before and after the customer receives them. In this model, the balance among the sum of prevention, appraisal costs and failure costs is discussed and most of the cost of quality methods are based on P-A-F classification (Prevention-Appraisal-Failure). The main assumptions in P-A-F models are (1) the money spent on prevention and appraisal activities, reduces the failure costs and (2) enhancing the fund spent on prevention activities reduces the appraisal costs. P-A-F model is based on the traditional view that optimal COQ is a solution in which cost of quality causes more profit than the cost of improving quality. This aspect is quite challenging and the fact that there is no economical level of quality is open to discussion. One must also consider that spending money on the prevention phase is usually justified, and in fact, the optimum level of quality is equal to zero error.

Classification of the Crosby model is quite similar to P-A-F model. Crosby defines quality as conformance to requirements. So in this point of view, the cost of quality is equal to the sum of the cost of conformance (COC) and the cost of non-conformance (CONC). Cost of Conformance is spent to ensure that the products function properly for the first time and it includes the costs of prevention and appraisal. Cost of non-conformance is the money that is spent when activities do not conform to the customers' requirements and it is usually calculated by quantifying reconstruction, rework and waste costs that correspond with actual failure costs. This model has been used in companies that measure the cost of quality (Fine, 1986).

By reviewing the results of the cost of quality simulations, it is clear that both Juran and Crosby models can be covered in a single model. The balance of traditional models like Juran and Crosby may give a correct static view of the cost of quality economics, but in a dynamic multi-periodic environment. Failure costs can move towards reduction without conforming to the increase in prevention and appraisal costs. There is a global method to allocate overhead elements to the cost of quality, while there is no appropriate method to determine the cost of quality for resources. Therefore, considering the experts' knowledge in the organization, the exact expenses for each cost function can be derived by finding the specific cost sources of each activity and cost of quality for each cost function. This approach can be considered as a selective structure to help identify, quantify and allocate the costs of quality among products and finally to manage the costs of quality effectively. To achieve this goal, a hybrid Neuro-fuzzy system is presented to estimate the effectiveness of each element of COQ, so the long-term goal of the system is to estimate worthless activities and to continuously improve the ongoing processes, activities and quality of the products without any error.

In fact, despite all the requirements that some data may have, each classification should have a logical goal, and in our case, the goal here is to improve costs as long as the same level of quality is maintained. An important point to note is that costs in an industrial environment depend on the amount of production and the type of industry you are dealing with. These costs can be very high, so any improvement, even a small amount, can be costly. Considering the issues mentioned, the costs that are considered in the cost of quality are very sensitive because they are directly related to the final quality of the product, so an improvement plan cannot be considered without scientific design. In the real world, some activities are done to reduce quality costs, but the question remains: which activities are the best answer to the current quality costs. This research seeks to provide an efficient approach to service or industrial environments that can be used in most case studies with potential limitations, while at the same time maintaining and even improving the quality level, and effectively reducing quality costs. The approach should also determine the effectiveness of each of the four quality costs.

In Fahimifard et al. (2009), the application of Adaptive Neuro-fuzzy Inference System (ANFIS) and auto-regressive integrated moving average (ARIMA) pattern are compared to estimate retail prices of agricultural products. In this research, a novel adaptive-neuro fuzzy-inference system is introduced and its applicability is compared to ARIMA, as the most common linear method for predicting econometrics, to estimate the retail price of rice, chicken, and eggs within three time-horizons of one, two and four weeks. To achieve this purpose, weekly data were gathered from Iran State Livestock Affairs Logistics and Refah chain malls across the country (between 23/9/2002 and 03/01/2009), and some efficiency inspection criteria such as R^2, mean absolute deviation (MAD), and root mean square error (RMSE) were used. The results of analyzing the mentioned criteria showed that the estimated data from the designed structure tests of ANFIS pattern are more similar to the actual data compared to the estimated data from the out-of-sample dataset using ARIMA model. Therefore the nonlinear pattern of ANFIS model is more efficient for the estimation of the agricultural products retail price in the specified time horizons. Chen (2011) discussed the applicability of a hybrid ANFIS model to estimate the failure of a business using particle swarm optimization and subtractive clustering. The author estimated a business plan using the particle swarm optimization technique in order to find the appropriate parameter settings for subtractive clustering and data integration based on the adaptive Neuro-fuzzy-inference system. In this research, the data of 160 electronic companies in Taiwans' stock market were used. This approach yielded promising results for estimating the potential financial crisis in those companies. Teli et al. (2013) assessed the different costs of quality analysis techniques in the automotive industry. Hajipour et al. (2014) designed an approach based on the balanced scorecard model and Fuzzy logic to increase the effectiveness of funding in the cost of quality. As shown in the literature on the cost of quality, there have been few pieces of research using the Fuzzy approach. Moreover, no research has been found to use the adaptive Neuro-Fuzzy-inference system in this field.

Schmidt & Pearson (2019) provide some models to estimate COQ associated with analytical error in clinical area. They suggest a general and a simplified model for estimating the cost of analytical errors in patient results and a separate model for estimating costs due to QC failures. Makhanya et al. (2018) investigated the factors that prevent the successful implementation of COQ. They conducted a systematic literature review as the research methodology. Their findings including suggestion of 20 key factors were identified with measurement and improvement, return on investment, management support, awareness, and strategic alignment as the most listed contributors to poor COQ implementation. Mantri & Jaju (2015) discussed new trends in cost of quality practices, especially by use of advanced technologies, computers, information technology infrastructure and innovative methodologies. They also provide a general framework for quality cost management system (QCMS) and the interaction of it with other organizational elements is discussed as well.

3. Research Methodology

Statistical process control techniques are widely used in manufacturing centers in order to control the value of the mean and variance of qualitative characteristics of the product. As discussed in the literature on the cost of quality, there have been few pieces of research using the fuzzy approach. Moreover, no research has been found to use the adaptive Neuro-fuzzy-inference system in the cost of quality. The adaptive-neuro-fuzzy-inference system was first introduced by Jang (1993) as an adaptive neural network using fuzzy inference system training. ANFIS belongs to a family of the hybrid systems, called 'Neuro fuzzy networks' inheriting the properties of both neural networks and fuzzy logic. Neural networks can easily learn from the data. However, it is difficult to interpret the knowledge acquired by it, likewise meaning associated with each neuron and each weight is quite complex to comprehend. In contrast, fuzzy logic itself cannot learn from the data. But fuzzy-based models are easily understood as they utilize linguistic terms rather than numbers or the structure of IF-THEN rules. Linguistic variables are defined as variables whose values are words or sentences in a natural language with associated degrees of membership. A fuzzy set containing linguistic variables is an extension of a 'crisp' set where an element could have full or no membership. However, fuzzy sets allow partial membership as well, which implies that an element may partially belong to more than one set (Nedjah & de Macedo Mourelle, 2005). In other words, for a crisp set, the membership level of an element x in set A can be expressed by a characteristic function $\mu_A(x)$, such that:

$$\mu_A(\chi) = \begin{cases} 1 \;\; \text{if } \chi \in A \text{ implying full membership} \\ 0 \text{ if } \chi \notin A \text{ implying non-membership} \end{cases} \tag{1}$$

But for a fuzzy set A, the membership function $\mu_A(x)$ can take values in the interval [0, 1]. The basic structure of the developed ANFIS controller for the prediction of residual limb skin temperature consists of four parts, which are fuzzification, rule base, inference engine and the defuzzification blocks as seen in Fig. 1.

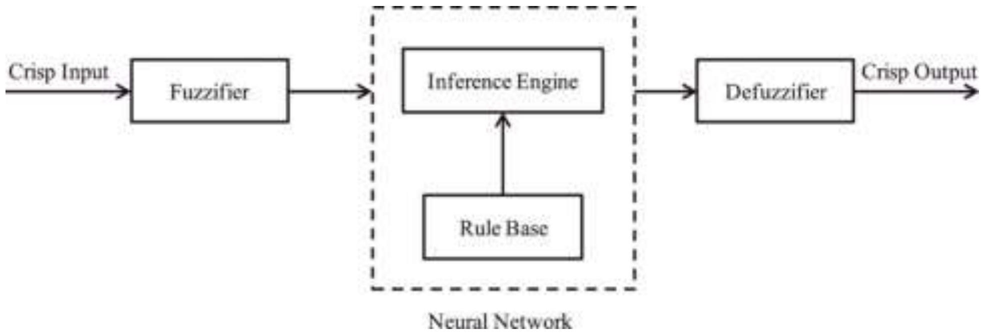

Fig. 1. Block diagram of a Neuro-fuzzy (ANFIS) controller

In the ANFIS controller, the crisp input signal (liner temperature in our case) is converted to fuzzy inputs by the membership function. The membership function pattern used in our ANFIS model is Gaussian. The fuzzy inputs along with the Gaussian membership function are then fed into the neural network block. The neural network block consists of a rule base which is connected to the inference engine. Back propagation algorithm is used to train the inference engine for the proper selection of rule base. Once the training is over, proper rules can be generated and fired from the neural network block to yield optimal output. The linguistic output from the neural network block is then converted into crisp output (residual limb skin temperature) by the defuzzifier unit (Sugeno & Kang, 1988). The structure of the Neuro-fuzzy model consists of different adaptive layers. Each of these layers has nodes with an associated network of transfer functions through which the fuzzy inputs are processed. The output from these nodes is then combined to generate a single crisp output when the ANFIS configuration allows only one output of the model. This crisp output is feedback on the input of the model and compared with the set value. If there is any deviation, the generated error signal becomes the input for the ANFIS controller, thereby maintaining system stability (Sugeno & Tanaka, 1991).

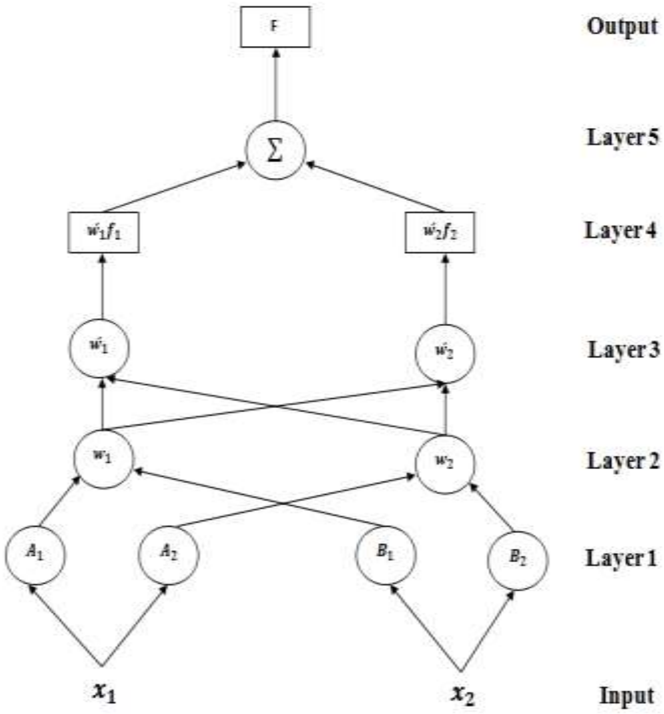

Fig. 2. Architecture of a first-order two rule Takagi–Segno type ANFIS (Takagi & Sugeno, 1985)

ANFIS supports the Takagi-Sugeno based systems. The structure of the adaptive network is composed of five network layers i.e. layer 1 to 5 (with nodes and connections) as shown in Fig. 2. Assuming that the system is defined to have two inputs x_1 and x_2, one output z and fuzzy sets A_1, A_2, B_1 *and* B_2; then for a first order Takagi-Sugeno fuzzy model, having two If-Then rules in the common rule set, can be written using the following Eqs. (2-3)

$$Rule\ 1:\ if\ \ \chi_1\ is\ A_1\ and\ \chi_2\ is\ B_2\ then\ f_1 = p_1\chi_1 + q_1\chi_2 + r_1 \tag{2}$$

$$Rule\ 2:\ if\ \ \chi_1\ is\ A_2\ and\ \chi_2\ is\ B_2\ then\ f_2 = p_1\chi_1 + q_1\chi_2 + r_2 \tag{3}$$

Layer 1: This layer is called the fuzzification layer. Here, the crisp input signal is fed to the node *i* which is associated with a linguistic label A_i or B_{i-2}. Thus, the membership function $O_{1,i}(x)$ determines the membership level (full, none or partial) of the given input. The output of each node is calculated using Eqs. (4-5). $O_{1,i}(x)$ is the generalized Gaussian shaped membership function used in our model development.

$$O_{1,i} = \mu_{Ai}(\chi_1)\ for\ \ i = 1,2 \tag{4}$$

$$O_{1,i} = \mu_{Bi}(\chi_2)\ for\ i = 3,4 \tag{5}$$

Layer 2: The nodes in this layer are fixed and labeled as $O_{2,i}(x)$. The output of each node is the product of all the incoming signals as Eq. (6).

$$O_{2,i} = w_i = \mu_{Ai}(\chi_1)\mu_{Bi}(\chi_2)\ for\ \ i = 1,2 \tag{6}$$

The output of each node represents the firing strength of a rule. This layer, also known as the membership layer, acts on the input variables from layer 1 as membership functions to represent them in their fuzzy sets.

Layer 3: Each node in this layer calculates the ratio of the individual rule firing strength to the sum of all rules firing strength as Eq. (7).

$$O_{3,i} = \varpi_i = \frac{w_i}{w_1 + w_2} \quad for \;\; i = 1,2 \tag{7}$$

Here, ϖ_i represents the normalized firing strength. Hence, this layer is also known as the rule layer. Since, each node in this layer calculates the normalized weights, the output signal can be thought as the normalized firing strength of a given rule.

Layer 4: This layer is known as the defuzzification layer. It calculates the individual output values *y* from the inference from the rule base. Individual nodes of this layer are connected to the respective normalization node in layer 3 and also receive the input signal. Each node in this layer is compatible with the function of the node given in Eq. (8) where p_i, q_i, r_i are sets of consequent parameters of rule *i*.

$$O_{4,i} = \varpi_i f_i = \varpi_i (p_i x_1 + q_i x_2 + r_i) \tag{8}$$

Layer 5: This layer is known as the output layer. It has only one node and it calculates the sum of all the outputs coming from the nodes of the defuzzification layer to produce the overall ANFIS output as shown in Eq. (9).

$$Overall \;\; output = O_{5,i} = \sum_i \varpi_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{9}$$

This architecture of the adaptive network is used to develop the ANFIS model to analyze the cost of quality and is discussed in the next section.

4. Simulation and Analysis of the Results

In order to implement the proposed methodology and prove its efficiency, a case study has been performed. The chosen data were derived from the product development program that was conducted in Niru-Moharekeh Company to manufacture the gearbox of a Kia car in 2009 and after performing the simulations, the results were thoroughly analyzed.

4.1. Input and output parameters

Here, we deal with four input parameters including prevention, appraisal, internal failure and external failure costs denoted as input 1-4, respectively. The single output of the problem is the cost of quality.

4.2. Problem simulation

One of the most important applications of ANFIS is to estimate complicated nonlinear functions. In this algorithm, a fuzzy system is trained to minimize the mean square error using a neural network. The overall structure of this method is as follows. In order to solve the mentioned problem, MATLAB software was used. The overall structure of the problem is to have four input parameters and each of them is assigned with three fuzzy numbers, as shown in Fig. 3.

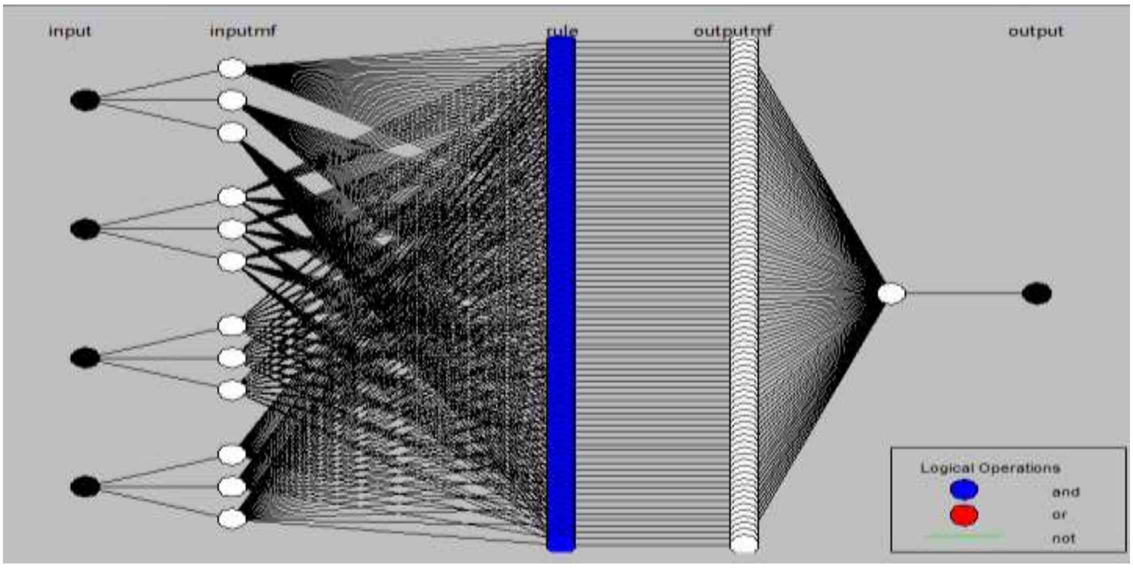

Fig. 3. The structure of the neural network with three fuzzy numbers for each input

4.3. Information and data classification

To evaluate the neural network generalization and to compare the efficiency of different structures, at first, the given data are divided into three data sets, namely training, validation and testing data. From all 120 samples in our data set, the first seventy samples are used for training and the other fifty samples are set aside to check the network performance.

The next step is to add the testing data and form the structure of FIS within ANFIS, and then the neural network is trained. Using the hybrid algorithm and zero fault tolerance, and considering that each input has three membership functions and the output can only be one of the two states of constant or linear, all the membership functions are tested and finally, the function with minimum error estimation is chosen as the final membership function. The results are presented in Table 1. As the model becomes more complex, the fuzzy system error in the training dataset decreases, and the error in the testing dataset increases.

As shown in Table 1, the ANFIS models in the second and sixth rows have the minimum square error. The final ANFIS structure has four inputs each of which has three membership functions, so there will be 81 fuzzy rules. Membership functions should have a triangular or trapezoidal shape (both shapes result in the same amount of error). The dataset has a total number of 120 samples, 70 of them are used as training data and 50 of them as testing data. A number of 100 iterations were chosen for the training session. Figure 4 shows the change in input behavior and its effect on output. For example, in the right bottom picture, by increasing input #2 (appraisal costs) and input #4 (external failure costs), the output (costs of quality) shows an increasing trend.

In order to analyze and determine the costs' components that have the biggest effect on the costs of quality, different combinations were performed in ANFIS and the amount of error for testing and training data were measured. At the end, the combination that causes greater error reduction or the one that has the biggest impact on the output is reported. Figures 5-7 show different combinations of input variables. Figure 6 indicates that focusing on internal failure costs has the biggest effect on the costs of quality. If we focus on dual cost components that have the biggest effect on the output, the fourth input (external failure cost) combined with any other input that would be the most efficient choice, as shown in Fig. 6. Finally, as depicted in Fig. 6 the combination of first, third and fourth inputs is the best triple combination of input parameters, meaning that the main focus should be on appraisal, internal and external failure costs.

Table 1. Computational results after performing ANFIS using different settings

No.	Number of membership functions	Type of membership function	Type of output	Training error	Testing error
1	3	Triangular	Constant	466	74600
2	3	Triangular	Linear	9873	11087
3	3	Gaussian	Constant	381	130504
4	3	Bell-shaped	Constant	202	83213
5	3	Trapezoidal	Constant	3536	60472
6	3	Trapezoidal	Linear	9873	11087

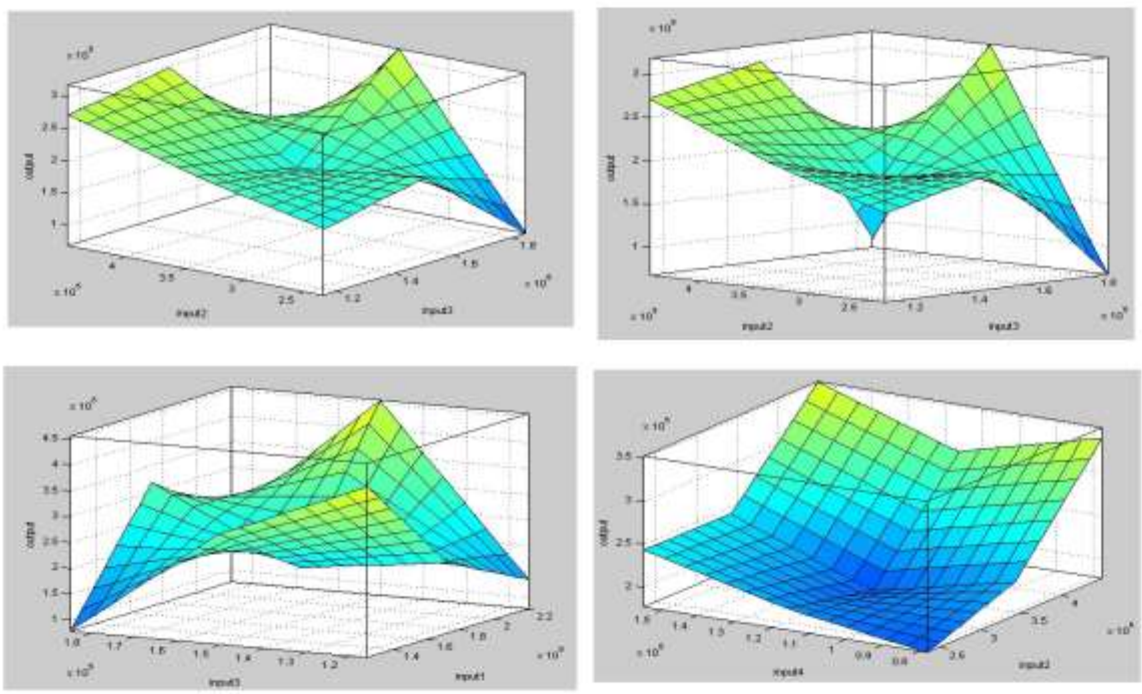

Fig. 4. Costs of quality behavior in accordance with changes in input parameters

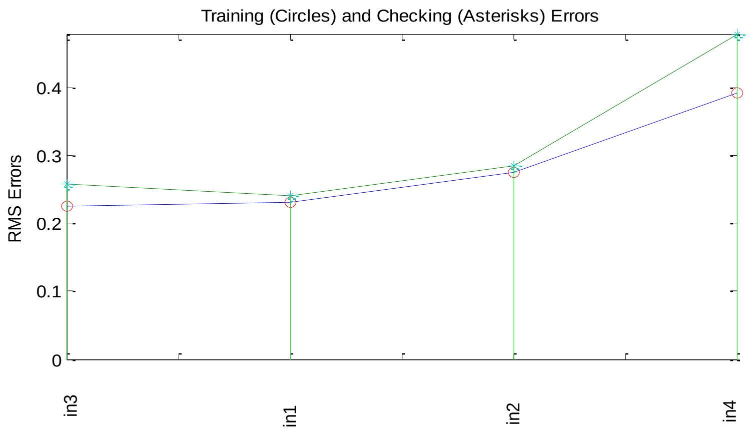

Fig. 5. The effect of each input cost variable on the cost of quality

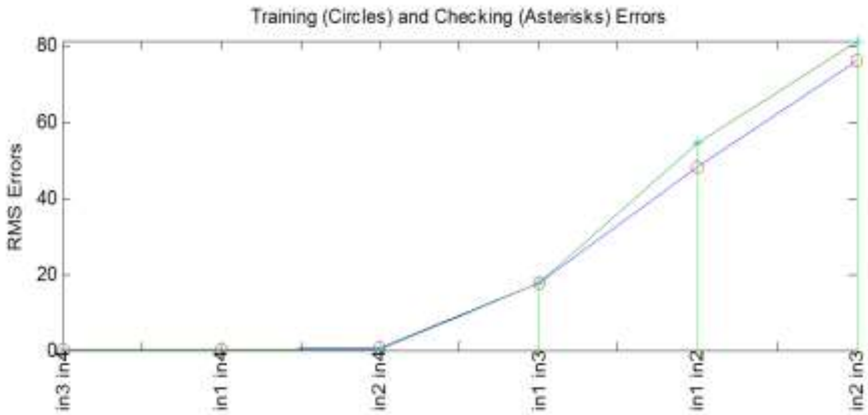

Fig. 6. The effect of dual combinations of input cost variables on the cost of quality

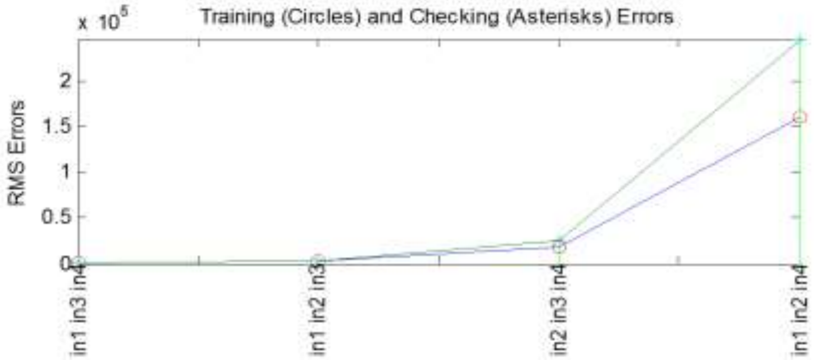

Fig. 7. The effect of triple combinations

5. Conclusion

The advances in science and technology have caused smart computer-based systems and artificial intelligence in general, to be more important than ever. Neural networks, in fact, is to tackle NP hard problems that are intractable by the traditional methods. The main applicability of such approach is to extract useful pattern from convoluted data. Here, an adaptive-neuro-fuzzy system is proposed to analyze the costs of quality and determine the effectiveness of investment in any of its components. In order to implement the proposed methodology and prove its applicability, a case study of Nirou Moharekeh Company has been performed and the results were analyzed. The results demonstrate that the input component combinations that cause the minimum amount of error have the greatest effectiveness in the output. In the single component case, internal failure costs have the biggest effect on the costs of quality. On the other hand, if we intend to focus on dual components, the fourth input (external failure costs) combined with any of the other three inputs have the biggest effect on the costs of quality. Finally, the best triple component would be that of appraisal costs, internal and external failure. As the future research, it would be valuable to justify the performance of the proposed algorithm by the employment of Levenberg-Markvrt and Evolutionary approaches.

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