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Product lifecycle prediction using Adaptive Network-Based Fuzzy Inference System

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Abstract. The present article intends to develop a model for predicting product's lifecycle in the fuzzy environment using the neural network approach. To this end, parameters effective on production and sale processes are identified in the first step and then variables are categorized into four main sections and are regarded as inputs. Each variable is entered as fuzzy into the neural network and finally the product lifecycle is inferred from the system as the fuzzy output variable. In the neural network section, a fuzzy neural network with a multilayer feed forward leaner structure has been created through making product assessment models closer to human's actual performance assessment method. After the learning phase, outputs of the model come out from the fuzzy neural network as the number of sales in order to predict different phases of the product lifecycle with the least possible error.

Keywords: Adaptive-network-based fuzzy inference system, product lifecycle, neural network, fuzzy inference, prediction.

1. Introduction

Prediction is an issue which has long engaged human's mind. Generally speaking, one of the most important tasks of science in different fields is to find links between various phenomena in order to predict future. Production and service organizations are not exceptions. They should also predict future to sustain. Predicting lifecycle of the organization's product is one of the most important prediction cases in an organization. If an organization cannot identify its product and predict its lifecycle properly, it will die prematurely. To materialize this goal at each period of time, the organization should have the capacity to predict lifecycle of its product in order to be able to adapt production rate according to market conditions and compete in complicated and volatile markets (Tasure, 2002), (Raymond, 2008). Many organizations embark on solving the problem when their production is declined. This is while that in that certain production cycle, the ability to change is very low and a large number of loyal customers have been attracted by products of other organizations (Takata, 2004). Development of strategy and planning toward improving the product starts in the period that the product has passed its slow growth phase and has experienced rapid progress. In this period of time, the product's research and development project should be kicked off (Chang, 2007) & (Takata, 2004) and during the period in which the product has passed its development phase and is declining, the development and change project is carried out on the product (Mazher, 2004). The main challenge in prediction is the uncertainty of environment and dynamic conditions of markets (Tasur, 2009). Meanwhile,

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in order to actualize the targeted predictions, many methods have been tested. But, the error amount of methods determines their distance from actuality and actuality level (Kaebruick & other, 2007). Through modeling lifecycles of previous products, the present article intends to create a learning network which can offer the effective result with the least possible error. The model has been created through linking two fuzzy logic and neural network systems together. Fuzzy logic and neural networks have special arithmetic features. Linking the systems together makes calculations of special issues possible. In order to describe the case, it can be said that neural networks are capable to identify patterns, but they have many ambiguities regarding decision-making (Zhang, 2005). But, fuzzy systems are capable to analyze ambiguous information to describe the method of decision-making, but they are not capable to automatically create laws to adjust the system (Changa, 2006). The present article intends to develop a model for predicting product's lifecycle in the fuzzy environment using the neural network approach aiming to prepare strategies suitable for marketing, research and development in each period of the lifecycle. The article has been organized in the following way: in the second section the related problem will be defined. Then, in the third section, neural fuzzy network and mathematical algorithm are described, and in the fourth section empirical results gained from running the proposed algorithm will be analyzed. In the final section, conclusion and results will be outlined.

Sustainability is the most important priority of every organization. If an organization is not able to identify production processes and predict production volume, if will die prematurely. In order to materialize this goal at each period of time, the organization should have the capacity to predict lifecycle of its product in order to be able to adapt production rate according to market conditions and compete in complicated and volatile markets. Moreover, different strategies can be adopted during the production process in different places and times for improving changes on the production process. A certain product has a certain production cycle in different times and places considering the production process, based on the production cycle strategies are adopted. The production cycle is comprised of four phases, namely introduction and generation, growth, development, decline and death (Rose, 2000). As it can be understood from the abovementioned cases products follow a trend similar to living creatures. But, the difference comes out as living creatures die, but products can be revived through improving, re-designing, and developing into new products. But the question is at what time the product experiences death and decline and should be revived in order to remain in the growth and development phase? (Huang, 2009)

To identify the youngness and oldness of a product, there are different techniques, the most frequent of which are regression methods and ARIMA models. But these models are unsuccessful in practice to predict some series, because their structure is linear. Recent researches in the field of neural fuzzy network showed that the networks are able to learn non-linear complicated series as well as adapt with different statistical distribution functions (Raymond, 2008), (Rose, 2000), (Changa, 2006), (Yamagiva, 2001).

2. Fuzzy neural networks

Fuzzy neural network is a smart combined plan which has been emerged from two elements of fuzzy logic and neural networks. Neural networks have the ability to learn from data. This is while fuzzy logic solutions easily make modification and improvement processes possible (Tasi-chi, 2008). A neural network is basically used for predicting, categorizing, grouping and identifying patterns. The learning ability is the most important feature of neural networks which is possible through train network with some data for the past. Neuron is the first element in a neural network. Neuron K is mathematically formulated as follows:

$$U_k = \sum_{k=0}^{n} W_{kj} X_j \qquad (1)$$

$$Y_k = \varphi(U_K - \theta_K) \qquad (2)$$

In which X_j is synoptic weights, U_k is the output linear combination, Θ_k is the threshold figure, φ is the activation function, and Y_k is the output signal. Learning is carried out in two methods with supervisor and without supervisor. In learning with supervisor, the expected error between the expected output and the resulted output is calculated and then using minimization methods removing the error and adapting weights between the two connected layers is started from the output layer backward. The main issue in neural networks is the selection of suitable complication in the model such as the number of hidden layers or adjustment parameters. The number of hidden layers is dependent on the learning algorithm. In general, learning systems with supervisor are more flexible in designing hidden layers. In feed forward networks, sigmoid function is used in standard case to transfer function and different rules to stop the education process (Efendigil et al., 2009). But, applying neural networks has been limited due to some major reasons. The first, solutions which are resulted by neural networks are like black boxes, so it is not possible to describe, modify or change a specific behavior of a neural network manually. The second, voluminous calculations which are required are considered as a hindering factor for manufacturing most of product in large scale. And the third, selecting a proper network model and adjusting parameters of the learning algorithm is still an unknown knowledge and art and needs a lot experience (Zhang, 2005) & (Liya, 1999) & (Nikola, 2009). These problems are easily and to a great extent are resolvable through combining weak and strong points of neural networks with fuzzy logic. In fact, neural networks have the ability to learn from data, while fuzzy logic solutions can be easily modified and improved (Mazher, 2009). Systems which are incomplete in definition or uncertain in data can be easily modeled using fuzzy inference systems. The secret behind success of the fuzzy logic is in the possibility of describing the system's behavior using simple if-then relations and equations. This provides the opportunity for an easier solution and shorter time for designing the needed system (Yu, 2009). The fuzzy logic theory was invented to analyze systems in which relations among variables are very complicated. Such a complexity is common in different fields of science such as economy and many other fields. A general string which relates issues of this kind is the inaccuracy of categories, ambiguities and uncertainty of actualities (Zhou, 1998). This interesting and powerful possibility of the fuzzy logic is somehow a major limitation for it, as well, because in many sciences the knowledge of describing the system's behavior is hidden in its data set, and extracting the data manually from among lots of data needs much time and effort. Using a neural network can be promising for offering a solution in this regard, because neural networks have the ability to learn from the data set (Liya, 1999). The abovementioned limitations were the main motive force for actualizing the idea of establishing smart combined systems to merge two or more than two techniques in order to overcome limitations of each of the techniques (Nikola, 2009). The combined systems will be of high importance when the diverse nature of application fields is regarded (Liya, 1999) & (Nikola, 2009). Adaptive Network-Based Fuzzy Inference System (ANFIS) is a combined system which is able to create an input-output structure based on human knowledge in the form of if-then equations with proper membership functions. In this model neural networks are used to determine membership functions. This method plays a key role in creating the rules seen in the fuzzy logic (Efendigil et. al, 2009). The present article has used the Sugeno system for inference. In a grade one Sugeno system, the set of joint rules for two fuzzy if-then rules are as follow:

In which X, Y are the input variables, A_i, B_i are the linguistic quantifiers with the membership functions of $\mu(x)$, p_i, q_i, r_i are the parameters of the output function f(X,Y) which define the education period.

As it can be seen in the figure, initially the input variables are determined in the first layer. The second layer's output determines the amount of membership of the input's variables in the reference set.

$$O_i^1 = \mu_{A_i}(x) \qquad (3)$$

In which x is the input variable of the node I and Ai is the linguistic quantifier related to the node. Oi specifies the amount of membership of the input variable x in the Ai set. The membership function is usually in bell shape and is calculated using the below formula (Tuncer & Dandil, 2008) & (Efendigil et. al, 2009) & (Rashid & Ramerez, 1999) & (Abuzakhar & Manson, 2005).

$$\mu_{A_i}(x) = \frac{1}{1 + \left| \frac{x - c_i}{a_i} \right|^{2b_i}} \qquad (4)$$

In which $\{c_i, b_i, a_i\}$ are the parameters of the membership function and are applied to adjust the function's shape and are called the preferred parameters. The third layer indicates function of the fuzzy AND. The output of this layer multiplies input signals and transfers to the next layer. Each output node in this layer indicates the firing power of a regulation. Each node in the fourth layer calculates the firing power of the i^{th}

regulation proportional to the sum of powers of all the rules. The output of this layer is called the normalized value of the firing power.

$$O_i^3 = \mu_i = \mu_{A_i}(x)\times\mu_{B_i}(y) = \min(\mu_{A_i}(x),\mu_{B_i}(y)) \qquad (6)$$

Output of each node in the fifth layer indicates the output of the i[th] fuzzy regulation which is calculated as follows:

$$O_i^5 = \overline{\mu_i}\times f_i = \overline{\mu_i}.(p_i x + q_i y + r_i)$$

In which $\overline{\mu_i}$ is the output of the fourth layer and $\{p_i,q_i,r_i\}$ is the set of parameters of the output function. The parameters are trained using the back-transfer algorithm. The third, the fourth and the fifth layers indicate the inference process. Only the node of the six[th] layer calculates the general output as the sum of all the input signals. Only the node of this layer has the responsibility of defuzzying.

$$O_i^6 = \sum \overline{\mu_i} f_i = \frac{\sum \mu_i f_i}{\mu_i}$$

First and secondary parameters are among the most important factors in the algorithm. The used algorithm in the ANFIS structure constitutes the least square and declining gradient methods for learning membership functions in parameters. Also, the combined algorithm is comprised of two forward and backward transfers. In the forward transfer the output of nodes are transferred toward the front through keeping the first parameters fixed and are optimized using the least square method of secondary parameters. In the backward transfer, the output error is propagated backward using the back propagation learning algorithm and first parameters are modified using the declining gradient method. Through repeating this process, the error output is reduced and the propagated error is minimized (Abuzakhar & Manson, 2005).

3. Implementing proposed algorithm

In this section, the implemented steps in order to predict the lifecycle regarding television product which its related data has been collected from Pars Electric Company are described. In this stage, firstly variables which are effective on the lifecycle of television product have been identified and then through collecting data related to each variable, they are analyzed and it is specified that each variable can affect related outputs with how much weight and power. In the proposed model two fuzzy neural networks structure exist. The first network's output is used as one of the inputs for the second network.

- **First step: Identifying variables and collecting data**

The first step in designing a fuzzy neural network is to collect data, modifying and creating variables which define the system's behavior, so that each set of data includes a sample of output figures for each combination of input variables. In the create network, firstly 10 initial variables are combined together in order to create the expected output (product merits). These variables are: Beauty, Weight, Energy consumption, Size, Picture quality, Sound quality, Function quality, Receiving quality, Newness of product, Difference of product. The four main variables of the research are as follows. Combination of the variables creates the expected output (product life curve). Considering nature of variables in the research two fuzzy neural networks have been used in series: Product merits, Price, Advantages, Advertising. The product merits variable is the only output of the first network. It is regarded as the input for the next network. Figure 1 shows relations between the input and the output variables.

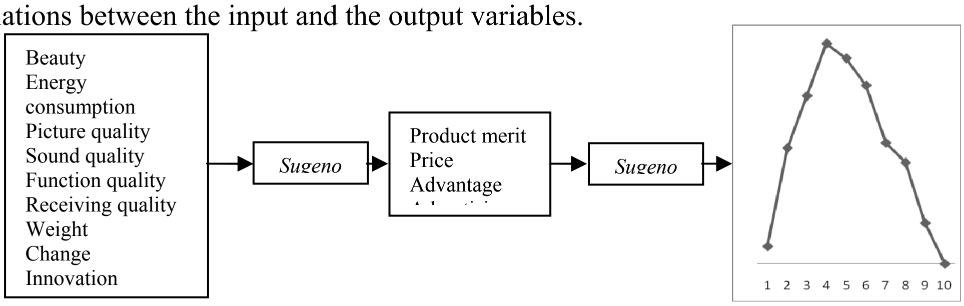

Fig. 1: relation between input and output variables

- **Second step: Creating a fuzzy logic system**

The train process of neural network starts with a fuzzy logic system. In this step, reference sets of each variable are turned into fuzzy variables considering results of determination and each of linguistic quantifier related to each index. In this stage, variables are turned from verbal into fuzzy using the bell shape function (equation 4). In this section, the Sugeno system has been used for inference. Due to the fact that the first network's output is used as the second network's input, the first network's output does not need defuzzying.

- **Third step: Definition of learning in fuzzy neural network**

The created ANFIS network has been established using a multilayer feed forward network which has not regressive feed relations and outputs are determined only sing current inputs and amounts of weights. It means that outputs of a layer will not expand toward inputs of the same layer or previous layers. Also, in this stage, the number of test, train and check data is specified in the related network. The check data are used in order to asses and control the system's capability and adapt data with actuality. Through creating test data it can be specified that the used fuzzy inference model can to what extent predict the data set output. In this network, 0.7 data are considered as train data (253 datum), 0.2 data as test data (74 datum), and 0.1 data as check data (43 datum). In order that data indicate the actual system, data have been selected randomly from among the existing data in each group. In order to define the number of layers and hidden neurons the Exhaustive Search method has been used simultaneously. All information related to the two networks is presented in the table 1.

Table 1: Information related to first ANFIS network

Neural fuzzy Network	
Architecture ***Multi layer Feed Forward Network*** ✓ Input Neurons : 10 ✓ Output Neurons : 1 ✓ Number of Linear Parameters : 550 ✓ Total Number of Parameters : 1550 ✓ Number of test Data Pairs : 74 ✓ Number of Fuzzy Rules : 55 ***Computation/Termination*** ✓ Max Epochs : 100 ✓ Step Size Increase Rate : 1.1 ✓ Fuzzy Inference : Sugeno	Hidden layers : 4 Number of Nodes : 1113 Number of Nonlinear Parameters : 1000 Number of Train Data Pairs : 253 Number of Check Data Pairs : 43 Error Goal : 1e-5 Initial Step Size : 0.1 Step Size Decrease Rate : 0.9 Training : Back Propagation rule

After defining the method of data categorization, the network is trained. When the program starts training, all its visual editors show the process of changing and modifying in membership laws and functions. So, the operator will be able to stop each stage of the learning process and re-analyze the system and make some manual changes or continue learning with the previous or new data sets. In addition, if the operator wants to handle the training process manually, the continuation or termination of the process can be automatically applied through defining termination conditions.

Table 2: Information related to second ANFIS network

Neural fuzzy Network	
Architecture ***Multi layer Feed Forward Network*** ✓ Input Neurons : 4 ✓ Output Neurons : 1 ✓ Number of Linear Parameters : 250 ✓ Total Number of Parameters : 650 ✓ Number of test Data Pairs : 74 ✓ Number of Fuzzy Rules : 50 ***Computation/Termination*** ✓ Max Epochs : 200 ✓ Step Size Increase Rate : 1.1 ✓ Fuzzy Inference : Sugeno	Hidden layers : 4 Number of Nodes : 507 Number of Nonlinear Parameters : 400 Number of Check Data Pairs : 43 Number of Train Data Pairs : 253 Error Goal : 1e-5 Initial Step Size : 0.1 Step Size Decrease Rate : 0.9 Training : Back Propagation rule

- **Fourth** step**: Optimizing and approving**

In this step, the structure is optimized using forward and backward transfer methods. In this stage, the network's weight coefficients are changed through comparing actual output with ideal output, so that the output is modified in next stages. In this line, the error function should be firstly defined in order to show the difference between actual and ideal outputs. If E_p indicates the network's pattern error, then t_{pj} will be the network's ideal error in the j^{th} node and o_{pj} will be the actual output in that node.

$$E_p = \frac{1}{2}\sum_j (t_{pj} - o_{pj})^2 \qquad (13)$$

And the error change can be defined as a function of net input of each unit as follows:

$$\delta_{pj} = f_j^{'}(net_{pj})(t_{pj} - o_{pj}) \qquad (14)$$

If δ_{pj} is the error reduction amount which has been taken place in the layer j is equal to net_{pj}, then the net input of the j^{th} unit multiplied by the difference between ideal and actual outputs will be a function for units in which the output layer's ideal and actual are specified. MSE and Network Error are calculated using equations 13 and 14. The amount and level of MSE basically show that to what extent actual and ideal outputs are close together. But, it does not specify that toward which direction the two sets are moving. Table 3 shows test and train data using ideal and actual inputs and their difference. Due to the reason that showing all the data will occupy much space, only 10 cases have been issued. In the first ANFIS network, after 100 training courses using back propagation algorithm and reaching the error level of 10-5 the mentioned network could offer the best possible learning cases.

Table 3: Difference between ideal and actual inputs

	Train target	Train Output	Difference	Test Target	Test Output	Difference
1	30	29.9959	-0.0041	30	24.5646	-5.4353
2	40	40.0017	0.0017	80	82.9965	2.9965
3	10	10.0165	0.0165	20	27.5582	7.5582
4	20	20.0012	-0.0012	40	31.5837	-8.4162
5	90	89.9992	-0.0008	50	54.6704	4.6704
6	80	80.0133	0.0133	80	74.5562	-5.4437
7	20	20.0046	0.0046	50	47.7709	-2.2290
8	30	29.9530	-0.0047	60	63.4781	3.4781
9	90	89.9962	0.0038	50	52.0585	2.0585
10	90	89.9945	0.0054	30	27.3916	-2.6083

The membership functions of the fifth variable (picture quality) after 100 times of training using the back propagation network are shown in the figure 2.

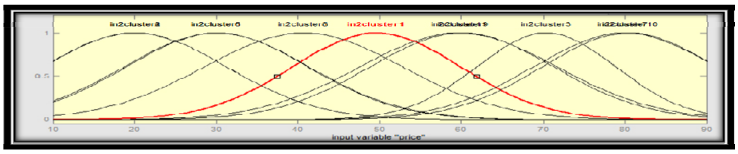

Fig.2: Membership functions of picture quality after being optimized

As it is seen in the figure, after 100 times of training, the related membership functions have been greatly changed and new functions adapt ideal and actual inputs with the least possible error.

- **Fifth step: Inputs of second fuzzy neural network**

The first fuzzy neural network structure and the second fuzzy neural network's structures after being combined have the ability to define the product's lifecycle. As it is seen in the figure, the 10 inputs of the first network determine the product's merit variable. This variable, along with the three variables of price, advantages and advertising, is the input for the second network to determine the product's lifecycle.

After 200 times of training by the back propagation algorithm, the networks have well managed to predict sales amounts in different months.

- **Sixth step**

After learn test was conducted on each network the number of sales can be predicted using linguistic quantifiers which are introduced in the fuzzy form. From the lifecycle the ability to identify research points in order to develop the product and carry out research are defined and using different identification cycles, various marketing strategies can be well implemented. The figure shows lifecycle of a new product which has been conducted by the abovementioned model. As it is seen in the figure, the utmost time for selling the product is only ten months after being supplied to the market due to offering new products by rival companies. Its maximum sale in the fourth months reached 1290 sets. Considering the figure, the research point for research and development is in the third months and the point for offering a new product is in the seventh month.

4. Conclusion

The present study intends to predict the product's lifecycle of a comprehensive prediction model based on combining the neural network and the fuzzy inference system. Meanwhile, using the fuzzy logic, different linguistic quantifiers for each index were defined and after specifying membership functions using the neural network a leaner system was created. To determine efficiency of the mentioned model in Pars Electric Factory case studies were conducted on a number of products. Results of the studies showed that the proposed model can easily and with the least possible error predict lifecycles of the studied products. Considering the studies and studying previous researches it can be said that the mentioned model was one of the initial studies in the field of predicting the product's lifecycle using combined artificial intelligent and can be used as a successful tool in supporting the decision. Regarding to the fact that the present study has considered only internal variables related to the product for modeling, it is suitable to consider environment factors such as rivalry, loyalty of customer and so on in other researches in this field. Also, the model can be used for other products and other combined smart systems, such as the fuzzy genetic algorithm, in future researches for designing models.

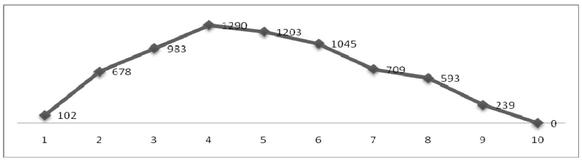

Fig.3: New product life cycle forecasting

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