Modeling the Customer Outage Cost; Introduction of New Fuzzy Modeling in Comparison With Customary Average Modeling

IMAN NASSERI, MAHMUD FOTUHI-FIRUZABAD
Department of Electrical Engineering,
Sharif University of Technology
Azadi Ave, Tehran, P.O.Box 11155-9363
IRAN
imannasseri@alum.sharif.edu, fotuhi@sharif.edu, http://ee.sharif.edu

Abstract: **-** One of the problems that every power industry deals with is choosing a suitable reliability and security level and this can be done through reliability cost/worth evaluation. Since estimation of value of reliability by customers is difficult, most power industries have just considered the factor of investment in specifying reliability level. The reliability cost is usually known and measured by the outage cost. After a brief introduction to the common methods in customer outage cost assessment, this paper discusses the modeling of customer outage cost evaluation. Finally, the fuzzy modeling is introduced as a new method of outage cost modeling and compared with the average outage cost modeling as an old method.

Keywords: Reliability, Outage Cost, Modeling, Fuzzy Modeling, Neuro-Fuzzy, ANFIS

1 Introduction

Outage is an unpleasant event that imposes inevitable damages on society. Outage has various social, economical and even mental outcomes. Regardless of different aspects related to its harmful effects, extravagant economic damages resulting from outage is enough motivation for studying and estimation of outage costs. Here, we do not intend to discuss about importance of power, rather studies on outage cost answer to the question of "What outcomes does power interruption has?". Obviously, answering to the above question will show the importance of electric power.

The first attempts on estimation of outage cost carried out in industrial developed countries and these attempts have been developing gradually. Although outage costs have been considerable in developing countries, a few studies have been carried out in this connection. Study and estimation of outage costs are of less consistency in developing countries in comparison with industrial developed countries. It can be said that studies on outage cost in the third world countries have been carried out at least one decade upon carrying out the first studies in the industrial developed countries.

Estimation of outage cost encounters many problems on one hand in applying economic theories and calculation techniques and on the other hand in accessing to a suitable data base. In fact, accuracy of computation of outage cost is limited due to two main reasons: Firstly, the main part of computation depends on subjective concepts, thus there is no unanimity in applying the theories. Therefore, the results of computations may change in the same conditions just because of using different theories and methods. Secondly, accuracy of computations is limited to the accuracy of collected statistical data.

In this paper, after a brief introduction to the common methods of customer outage cost assessment, we discuss the modeling of the results of customer outage cost evaluation. Finally, the fuzzy modeling is introduced as a new method of outage cost modeling and compared with the average outage cost modeling as an old method.

2 outage cost evaluation

In general, there is no special rule or formula in choosing reliability level of power systems. This depends on the preceding conditions and work experiences to a great extent and one of the problems that every power industry deals with is choosing a suitable reliability and security level. Though choosing such level can be theoretically obtained through comparison of manufacturing and distribution expense with customers' interests in different levels of reliability. Thus, any power industry requires estimation of its service expenses in different reliability levels apart from estimation

of reliability value. In fact, the selected reliability level is responsible for making balance between power generation cost and customers' benefit (customers outage cost) as shown in Figure 1 [3].

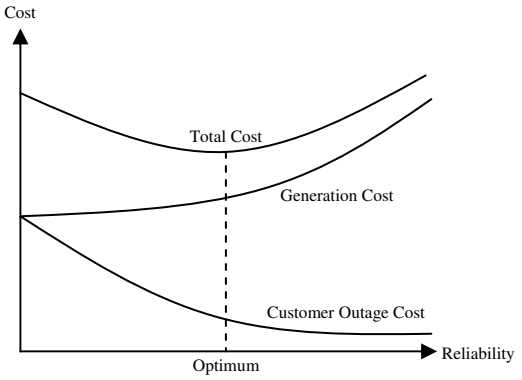

Fig.1 Cost vs. Reliability

Since estimation of value of reliability by customers is difficult, most power industries have just considered the factor of investment in specifying reliability level. Reliability value is usually evaluated indirectly. Value of reliability is usually known as outage costs and can be evaluated through statistical data obtained from using components of system for specifying Interrupted Energy Assessment Rate (IEAR) or Value of Lost Load (VOLL). Therefore, we need to identify customers' damages while outage, in order to estimate outage cost. Outage cost can be also applied as unreliability index and is analyzed as reliability value in planning and exploitation of the system in future. Outage can lead to both direct and indirect damages and costs. Lost production, lost raw materials and damages incurred to life and assets are among direct effects while the facts such as crimes, dislocation of factories or offices and dispensing with ordering goods due to delay in delivery are considered as indirect damages of outage. Consequences and damages resulting from outage shall be computed as tangible value, even though this is practically impossible. For instance, it may be possible to estimate expense of consequences and effects of outage on the damaged primitive material but estimation of expenses of damages resulting from this event on life and disturbance in its progress is very difficult. This is because the viewpoint of each customer regarding the outage is different considering his/her purpose of using power. Thus, in estimation of outage cost, we should consider cases such as type of subscription, amount of energy consumption, outage activities, outage period and frequency of outage in existing conditions. [1]

Economic loss incurred by the customers due to outage can be shown through Customer Damage Function (CDF).

The dependent variable of outage cost is defined as financial amount of damage against per outage, per kw/h of unsupplied energy or per kw/h annual consumption of energy. This equation predicts outage cost regarding the factors affect it. Outage parameters include outage period, season and weekday of occurrence, outage time and the like. Customers' specifications also include issues such as annual consumption (kw/h), level of demand (kw), type of usage, existence and number of equipment sensitive to outage (rate of dependency on electrical energy), existence of support equipment and other demographic specifications and ultimately geographic characteristics including temperature, moisture, storm frequency and other geographic conditions affecting the economic loss due to outage. [2]

To determine outage cost from the customers' viewpoint, there are two theories: [8] The first one is based on customers' desire to pay extra amounts for increase in reliability of power supply and the second one assumes power as a mediator which makes the customers satisfied through production of goods and services.

2.1 Outage cost evaluation methods

Common methods for evaluation of outage costs are:

1- Proxy Method
2- Market-based Method
3- Case Study Method
4- Direct Survey Method

Proxy method uses marginal data for measuring willingness to pay. This method aims at measuring customers' satisfaction that is a quality factor with quality criteria (e.g. money). In market-based method, the observed behavior of customers is used for inference of outage costs. In direct survey, people are asked to reveal how much they give value to assumed goods that are not priced in market; and finally, case study method that used upon a particular outage is just limited to wide-spread outages such as outage of New York in 1977.

3 Modeling outage cost

Outage cost collected data through one of the above-mentioned methods can be classified

through Standard Industrial Classification[1], power tariff, voltage level, geographic region or other parameters. Then, the classified data is used in development of outage cost model that actually describes the relationship between outage length and outage cost.

3.1 Average outage cost model

One of the simplest approaches of modeling input/output data is graphical average model. In this method, against every input point, average of output points is computed and is considered as typical output against that special input. Then, in providing results, graphical method is used to show how the input variable is related to the output variable. Most of outage cost researches have used this model in providing the results of research. [3]

In this method, upon clustering outage cost data for different types of customers, a separate model is used for outage cost. This method that is applied for development of outage cost model is summarized in three steps:

Step 1: To normalize outage costs of all units of the statistical society so that the results of computation of outage cost can be compared with power consumption by customers using other related parameters such as the annual maximum demand of the unit (in the base year of computations) or the total annual energy consumption of the unit (in the base year).

Step 2: To compute average outage cost of all the customers' units of a particular section and/or industrial standard subgroups for customers of industrial section.

More simply, if $C_{D,i}(d_j)$ is the normalized outage cost of the ith customer against outage length of d_j, we will have:

$$C_{D,k}(d_j) = \frac{\sum_{i=1}^{n} C_{D,i}(d_j)}{n} \qquad (1)$$

where $C_{D,i}(d_j)$ is the average normalized outage cost based on the maximum demand against outage length of d_j in group k of the customers (customers of a special section such as household section or customers who are subgroups of industrial standard of industrial section). Meanwhile, in the above relation, n is the typical number of units of statistical society in group k.

Step 3: This stage will be just carried out in case of grouping the customers of a special sector into the standard subgroups such as SIC subgroups for industrial customers and in case of willingness to have a general model for the customers of that particular section (but not in a separated form). In this case, average normalized outage cost in each group shall be computed by a suitable weight coefficient against outage lengths.

If normalizing the data has been carried out by the parameters such as total maximum demand, the same parameter will be also selected as weight coefficient that is total maximum demand. Thus, the following equation can be used for computation of the normalized outage cost based on the maximum demand for customers of each section for *ns* subgroup:

$$C_{D,S}(d_i) = \frac{\sum_{k=1}^{ns} C_{D,k}(d_j).D_k}{\sum_{k=1}^{ns} D_k} \qquad (2)$$

where D_k is total maximum demand of the existing units in group k.

3.2 Fuzzy modeling

Fuzzy modeling is a new subject for identification of non-linear systems. In addition, fuzzy models are sort of dynamic models. In comparison with traditional black box modeling methods, whether linear or non-linear, that can just use a number of numerical data, fuzzy modeling method is a unique method in capability of using both quality and quantity data. The actual power of fuzzy modeling is well shown through numerous applications that this modeling method has so far had.

A trend that is growing in visibility relates to the use of fuzzy logic in combination with neuro-computing and genetic algorithms. More generally, fuzzy logic, neuro-computing, and genetic algorithms may be viewed as the principal constituents of what might be called soft computing.

Among various combinations of methodologies in soft computing, the one that has highest visibility at this juncture is that of fuzzy logic and neuro-computing, leading to so-called neuro-fuzzy systems. Within fuzzy logic, such systems play a particularly important role in the induction of rules from observations. An effective method developed by Dr. Roger Jang for this purpose is called ANFIS (Adaptive Neuro-Fuzzy Inference System).

3.2.1 Fuzzy models structure

Fuzzy structure can be used as one of the verbal structures for modeling. Modeling operations are carried out through a system called "Fuzzy

[1] SIC

Inference System" (FIS). Actually, FIS changes numerical data into verbal variables. To this end, three steps containing fuzzification, data processing using fuzzy rules and finally, defuzzification in order to convert the fuzzy results into numerical values, are used. [5]

Fuzzy inference systems are also known as fuzzy rule-based systems, fuzzy models, fuzzy associative memories (FAM), or fuzzy controllers when used as controllers. Basically a fuzzy inference system is composed of five functional blocks (See Fig. 2):

- a rule base containing a number of fuzzy if-then rules;
- a database which defines the membership functions of the fuzzy sets used in the fuzzy rules;
- a decision-making unit which performs the inference operations on the rules;
- a fuzzification interface which transforms the crisp inputs into degrees of match with linguistic values;
- a defuzzification interface which transform the fuzzy results of the inference into a crisp output.

Usually, the rule base and the database are jointly referred to as the knowledge base.

The steps of fuzzy reasoning performed by fuzzy inference systems are:

1. Compare the input variables with the membership functions on the premise part to obtain the membership values of each linguistic label (Fuzzification).
2. Combine the membership values on the premise part to get firing strength (weight) of each rule.
3. Generate the qualified consequent (either fuzzy or crisp) of each rule depending on the firing strength. Aggregate the qualified consequents to produce a crisp output. (Defuzzification.)

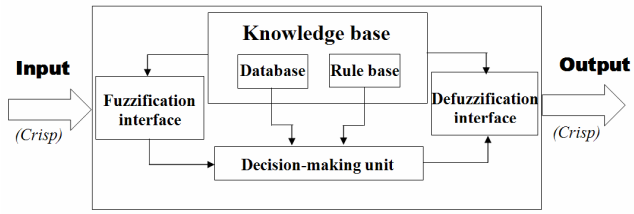

Fig.2 Fuzzy Inference System

FISs are tools with capability of comprehensive estimation of continuous functions on a limited range and certain accuracy. Comprehensive estimation characteristic in fuzzy models is not the only superior characteristic of them. Fuzzy models give a new aspect to the results obtained from modeling, which is verbal aspect that provides us with conceptual and verbal explanation of the modeled system behavior.

3.2.2 Fuzzy modeling using input-output data

Fuzzy models can be used for representation of behavior of each continuous function. In fact, fuzzy modeling is the process of specifying parameters such as location, form and distribution of membership functions, structure of fuzzy principles, selection of fuzzy logic operations and the like. High freedom degrees in choosing these parameters have caused that providing a single procedure for selection of all parameters become a difficult and complicated task. A common solution is to choose a logical operations and membership functions based on special conditions (differentiability, verbal integration, implementation capability, etc.) before conducting the process of specifying parameters. Other parameters can be specified using input-output data with the aid of different methods, though all the methods are generally based on one goal that is minimizing estimation error between output figures and the figures obtained from fuzzy model. One of the methods of specifying parameters is model of using fuzzy nervous device. [6]

3.2.3 Structure of fuzzy inference system (FIS)

A network structure can be used for interpretation of input/output record like neuro system that records inputs to outputs through membership functions and output membership functions and the parameters related to each of them.

Parameters that deal with membership functions vary in using learning process. Computing these parameters is used by gradient vector that is a measurement for modeling utility of input/output data against a set of design parameters. [7]

Once gradient vector obtained, each of the common methods of optimization can be applied for determination of parameters in line with reduction of measuring error, which is usually defined as total squares of difference between true outputs and the expected ones.

In MATLAB, structure of fuzzy inference system has been defined as an object that includes all data of fuzzy inference structure. All the existing data in fuzzy inference system including name of variables, definitions of membership functions, etc. have been defined in fuzzy inference system. This

structure can be considered as a hierarchy of structures, as shown in Figure 3. [7]

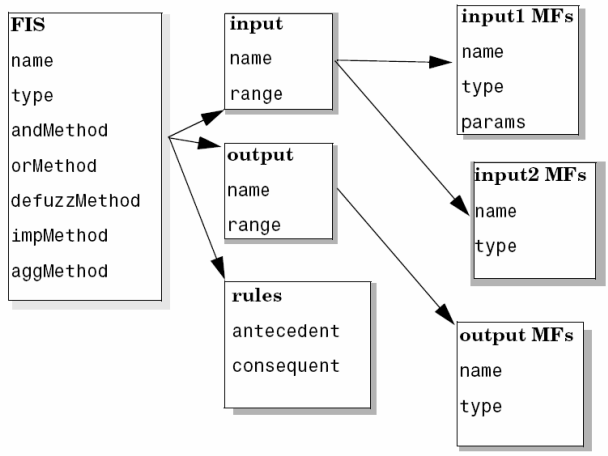

Fig.3 Hierarchical structure of FIS

3.2.4 ANFIS architecture

For simplicity, we assume that the fuzzy inference system under consideration has two inputs x and y and one output z. Suppose that the rule base contains two fuzzy if-then rules of TS[2] type [11].

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$,

Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$.

Then the fuzzy reasoning is illustrated in Fig. 4(a), and the corresponding equivalent ANFIS architecture is shown in Fig. 4(b).

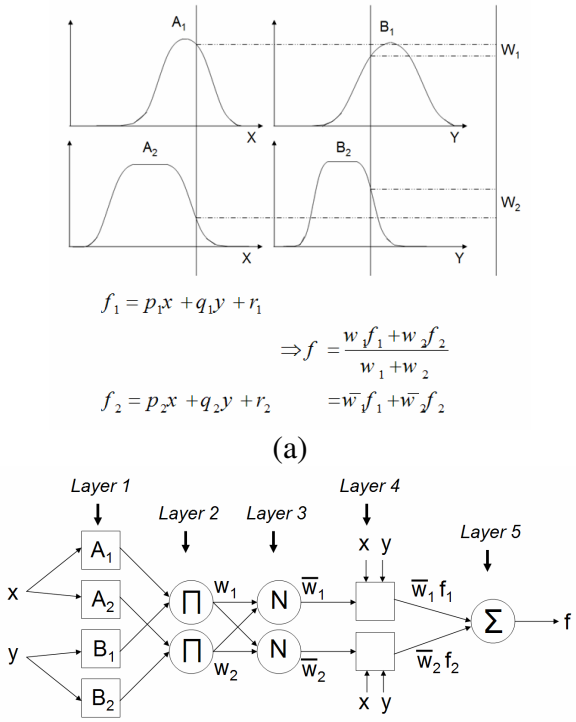

Fig. 4. (a) fuzzy reasoning. (b) Equivalent ANFIS

[2] Takagi and Sugeno

The node functions in the same layer are of the same function family as described below:

Layer 1: Every node *i* in this layer is a square node with a node function

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

where *x* is the input to node *i*, and A_i is the linguistic label (small, large, etc.) associated with this node function. In other words, O_i^1 is the membership function of A_i and it specifies the degree to which the given *x* satisfies the quantifier A_i. Usually we choose $\mu_{A_i}(x)$ to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as

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

or

$$\mu_{A_i}(x) = \exp\left\{-\left(\frac{x - c_i}{a_i}\right)^2\right\} \tag{5}$$

where $\{a_i, b_i, c_i\}$ is the parameter set. As the values of these parameters change, the bell-shaped functions vary accordingly, thus exhibiting various forms of membership functions on linguistic label A_i. In fact, any continuous and piecewise differentiable functions, such as commonly used trapezoidal or triangular-shaped membership functions, are also qualified candidates for node functions in this layer. Parameters in this layer are referred to as premise parameters.

Layer 2: Every node in this layer is a circle node labeled Π which multiplies the incoming signals and sends the product out. For instance,

$$\omega_i = \mu_{A_i}(x) \times \mu_{A_i}(y), \quad i = 1, 2. \tag{6}$$

Each node output represents the firing strength of a rule. (In fact, other *T-norm* operators which perform generalized AND can be used as the node function in this layer.)

Layer 3: Every node in this layer is a circle node labeled N. The *i*th node calculates the ratio of the *i*th rule's firing strength to the sum of all rules' firing strengths:

$$\bar{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2}, \quad i = 1, 2. \tag{7}$$

For convenience, outputs of this layer will be called *normalized firing strengths*.

Layer 4: Every node *i* in this layer is a square node with a node function

$$O_i^4 = \bar{\omega}_i f_i = \bar{\omega}_i (p_i x + q_i y + r_i) \quad (8)$$

where $\bar{\omega}_i$ is the output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer will be referred to as *consequent parameters*.

Layer 5: The single node in this layer is a circle node labeled Σ that computes the overall output as the summation of all incoming signals, i.e.,

$$O_i^5 = overall\ output = \sum_i \bar{\omega}_i f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i} \quad (9)$$

Thus an adaptive network is constructed which is functionally equivalent to a fuzzy inference system. [12]

3.2.4 Using ANFIS

ANFIS is one of the important components of the Fuzzy Logic Toolbox in MATLAB. Using a given input/output data set, the toolbox function ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a back-propagation algorithm alone, or in combination with a least squares type of method. This allows your fuzzy systems to learn from the data they are modeling. ANFIS can be used either through GUI or by using the anfis command in the MATLAB command line. The command anfis, which we have used to make our model in this paper, takes at least two and at most six input arguments. The general format is:

[fismat1,trnError,ss,fismat2,chkError] =anfis…
(trnData,fismat,trnOpt,dispOpt,chkData,method);

where trnOpt (training options), dispOpt (display options), chkData (checking data), and method (training method), are optional. All of the output arguments are also optional. [7]

3.3 Fuzzy outage cost model

Before development of the fuzzy model, it is worth considering that the existing data have been developed by processing the questionnaires obtained from customers' survey project, done by the Iran Power Research Institute. Also, since the ultimate objective of the said project has been to specify and draw a graphic model of average customers' cost through the method explained in section 3.1, processing the questionnaires has been carried out by crisp, and not fuzzy, approach (outage cost against different periods of outage that is one of the parameters of questionnaire design). means that for all questionnaires, figures have been taken into account as outage cost only for certain periods such as 1 hr., 4 hrs., etc. However, being more accurate and making some changes in designing the questionnaire and even processing the answers given to the existing questionnaires, we can specify the results of outage cost of every customer as fuzzy figures based on outage period.

3.3.1 Data preparation

The method of fuzzy model development that has been provided in this article, similar to many other approaches in outage cost modeling, is a method for achieving the outage cost model of customers which has been separated by type of customer (SCDF). Thus, hereafter, data means separated data, based on type of customer. However, sometimes there is a considerable scattering among data of a special type of customers and particularly industrial customers who has generally different behavior in using electricity. Therefore, the data related to this special type of customers has been provided by separation of different industrial standard categories.

Since, through the method that will be introduced below, model parameters are estimated using neuro-fuzzy structure, numbers of input-output data which are used in learning of neuro system are effective in better operation of the model and making the output error smaller. Since the existing data, upon omission of the faraway and altered data, belong to 280 users in different industrial groups, in case of dividing these data into industrial standard group, number of data in each group for learning the neural network and testing them will be too few and development of the model will accompany with higher error. Therefore, we intend to consider the whole industrial customers society as an integrated society of customers and develop fuzzy model of customers' outage cost for the whole society which are industrial customers.

Paying some attention to all the existing data and studying their behavior for every customer, the increasing trend of outage cost against outage periods could be observed with a rather similar gradient for all customers but what caused non-convergency of model output and its high error in estimation of the system function was observing different levels of outage cost for all the outage periods among the existing data. In other words, some customers give more value to reliability than

others. Thus, it does not seem logical to find a model for expressing outage cost of all customers without considering the reliability worth. Therefore, we looked for a criterion for separating customers based on reliability worth and in other words, the extent of dependence of customers' activities on electrical energy using outage cost data. Reviewing the data, we considered average outage cost of the customers in different outage periods as an ideal criterion for classifying customers based on reliability worth or value of electrical energy for their activities. Finding this index was aimed at data clustering based on degree of dependence on electrical energy.

Assuming *n* clusters for the customers based on degree of dependency of customers of each cluster on the electrical energy, the above-mentioned theory can be implemented with the following algorithm.

1- Specifying the total average for outage cost
2- Specifying the location of the clusters such that the total index of each cluster be equal to *1/n* of the total, where *n* is number of clusters.

Assuming four groups of customers for the existing data, number of customers' data is obtained in this study as follows: the first cluster 195, the second cluster 50, the third cluster 25, and the forth cluster 10 data. Thus, according to the above explanations, we divided data related to one particular type of customers into four groups with *very little dependency*, *little dependency*, *much dependency* and *very much dependency* on the electricity.

The important issue that should be considered in the last phase of data preparation is that in every group of customers, in each of input-output data sets, the input variable is available only in four definite amount (special periods of outage). However, in estimation of parameters of fuzzy model, not only we need to rather many points for education of estimator network but also these points should be distributed in input fuzzy sets. Assuming four input fuzzy sets of very short period of outage, outages about 1, 2 and 4 hours, the input points of our existing data are placed only in one point of each data set and all the outputs of this data set are evaluated against that one point. To resolve this problem, and reduction of estimation error and simulation of input-output data to the data which have been collected for a fuzzy study, we express the data by a statistical distribution (such as normal distribution, etc.) in total range of every input set.

However, the reason of performing this stage in this study, as discussed earlier, is existence of only available data which have been collected for another purpose.

3.3.2 Development of fuzzy outage cost model

Here, assuming availability of the suitable input-output data, we take actions to develop fuzzy model of the customers' outage cost.

To this end and using ANFIS as described in 3.2, we have developed a fuzzy model of TS type with the features descried earlier, using 280 input-output data related to four periods of momentary outage, 1 hour, 2 hours and 4 hours.

As explained before, in order to use ANFIS for estimation of fuzzy model parameters, first we should determine the structure of fuzzy model. In this article, *Genfis1* function has been used to specify the structure of the model. In fact, this function uses TS type model with one output for production of the primary structure and since our model has just one output, and of course one input, this function can help us to a great extent to form the primary structure of fuzzy model. In the general block diagram of TS fuzzy model, Fuzzification, Fuzzy Inference and Defuzzification are regarded as the main components. In this structure, fuzzification uses the singleton fuzzy sets. Fuzzy inference system is also a system of TS fuzzy inference that is produced by *Genfis1* function. Defuzzification is also of type of weighted average or the centroid defuzzifier.

As explained in the previous section, four clusters of customers have been considered in this model. Due to service importance and outage cost a separated model has been developed for each group of customers.

Before providing the results, we should refer to a number of parameters that is provided to developer of the model in each model so that we can achieve to an ideal model as well as a model with less error through making changes based on the available data.

Number of customers' clusters and criterion of data clustering of customers' outage cost (in the section of data preparation), form of membership functions, number of membership functions, number of learning points, step size, step size increase/decrease rate are some of the parameters that can be changed.

In the following results, four clusters of customers with average criterion of outage cost in all periods and bell-shaped membership functions are used. The results have been provided in three groups with 10, 50 and 70 input membership functions. Also, variable number of learning points has been

used upon demand. We have considered step size in two amounts of 0.1 and 0.0001 and have also considered the default value of step size increase/decrease rate.

An outage cost model has been developed and provided for the first group of customers who are called the users whose electrical energy importance is less than activities of others or the cost of their outage is lower than others. Figures 5 and 6 show the results of this model.

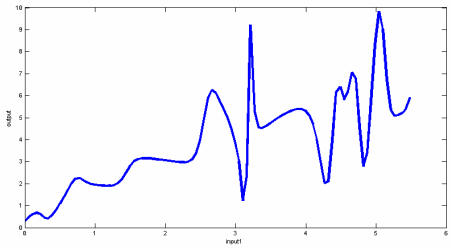

Fig.5 result of input-output model for group 1, 10 bell-shaped membership functions, 300 learning steps with step size of 0.1

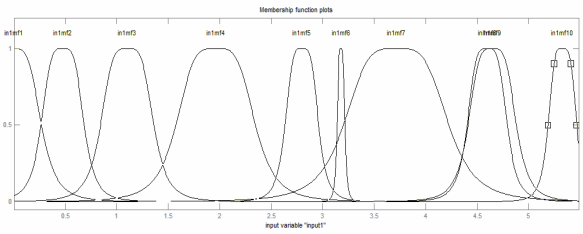

Fig.6 input membership functions for model of figure 2

Figures 7 to 12 show the results of fuzzy model of outage cost which have been also obtained for customers of other groups through changing some parameters.

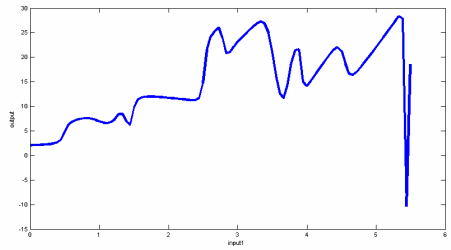

Fig.7 result of input-output model for group 2, 10 bell-shaped membership functions, 500 learning steps with step size of 0.1

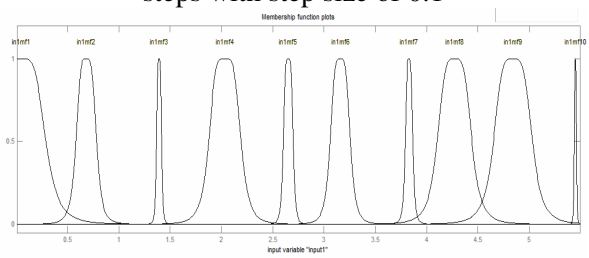

Fig.8 input membership functions for model of figure 4

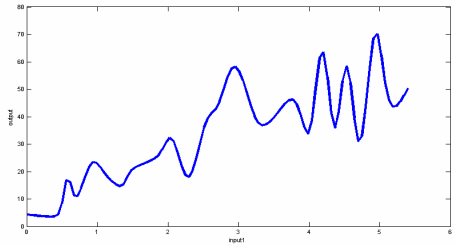

Fig.9 result of input-output model for group 3, 10 bell-shaped membership functions, 300 learning steps with step size of 0.1

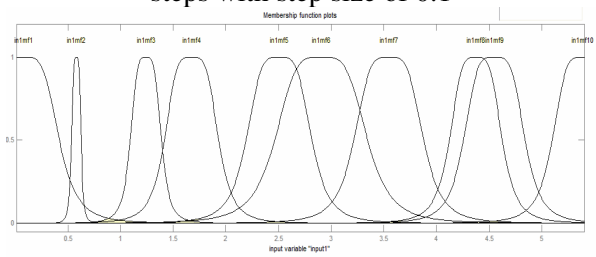

Fig.10 input membership functions for model of figure 6

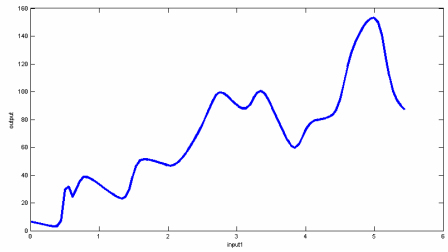

Fig.11 result of input-output model for group 4, 10 bell-shaped membership functions, 200 learning steps with step size of 0.1

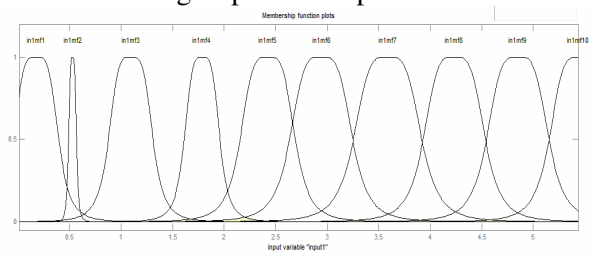

Fig.12 input membership functions for model of figure 8

Meanwhile, by changing two important parameters of step size and number of input membership functions, the following results as sample model output for customers of the first and forth groups have been shown in figures 13 to 16.

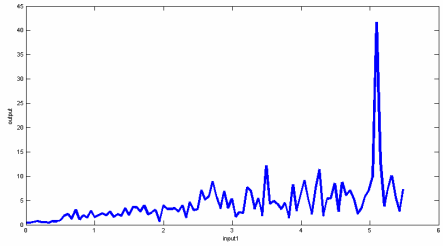

Fig.13 result of input-output model for group 1, 50 bell-shaped membership functions, 500 learning steps with step size of 0.1

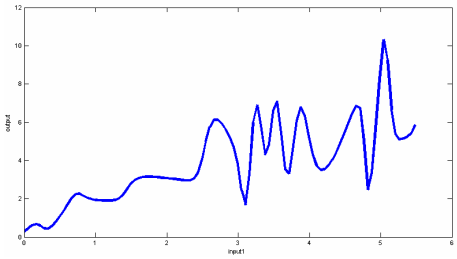

Fig.14 result of input-output model for group 1, 10 bell-shaped membership functions, 1000 learning steps with step size of 0.0001

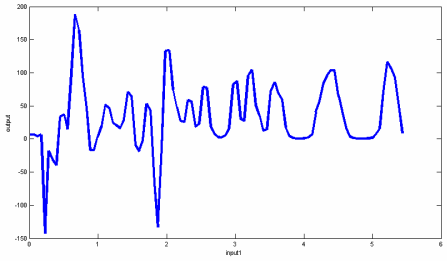

Fig.15 result of input-output model for group 4, 50 bell-shaped membership functions, 500 learning steps with step size of 0.1

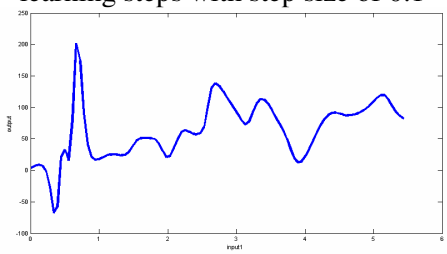

Fig.16 result of input-output model for group 4, 10 bell-shaped membership functions, 2500 learning steps with step size of 0.0001

Paying more attention to the outputs of different models (with different parameters and for different groups of customers), we can conclude that in case of more similarity (less scattering) of data of each group, this feature was more observable in the forth group, the model output was more similar to real data. Also, number of input fuzzy sets affects directly on reduction of learning error and model output improvement. But, we should not forget that this number shall not be increased too much. Number of learning stages affects this to the extent that it is possible to reduce error. Through changing the first step and rates of change in step size, we can help reducing learning error.

The important point that should not be forgotten while reviewing the model outputs is that our data have not been suitable for development of this model and we have scattered the data artificially at the range of input variable (outage period); otherwise, i.e. innate scattering of data, we should expect better results of this model.

3.4 Comparison with the results obtained from average outage model

The graphic display of fuzzy model, according to the method explained in the previous section, has been obtained for each of four groups of customers with 10 input membership function and in this section, it will be compared with the graphic display of the average model for the similar data that has been obtained through the method shown in part 3.1.

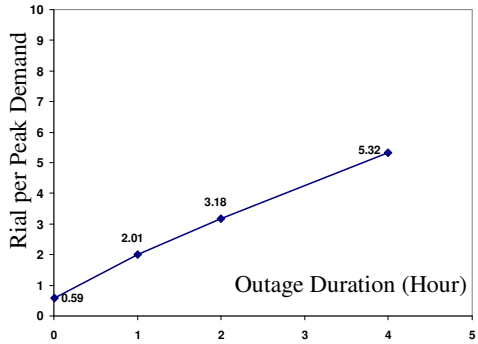

Fig.17 Graphical Representation of Average Model for Customers Group 1

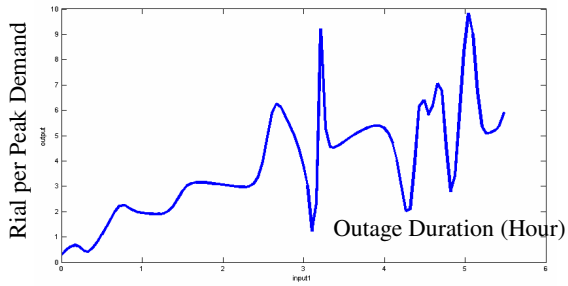

Fig.18 Graphical Representation of Fuzzy Model for Customers Group 1

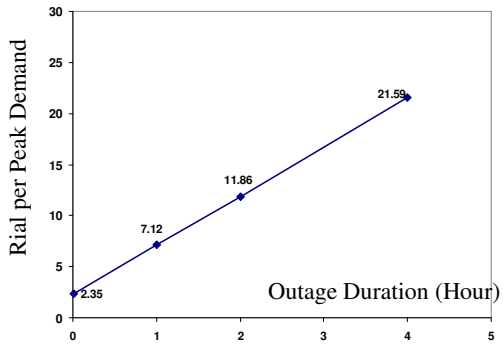

Fig.19 Graphical Representation of Average Model for Customers Group 2

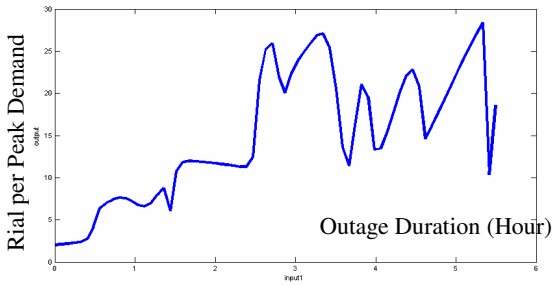

Fig.20 Graphical Representation of Fuzzy Model for Customers Group 2

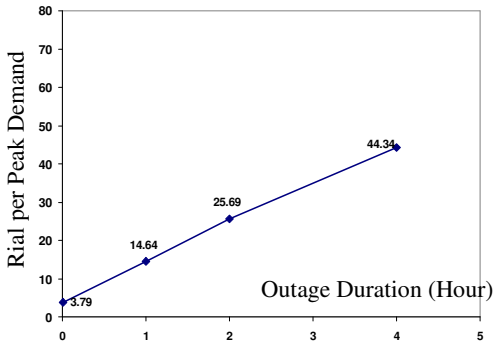

Fig.21 Graphical Representation of Average Model for Customers Group 3

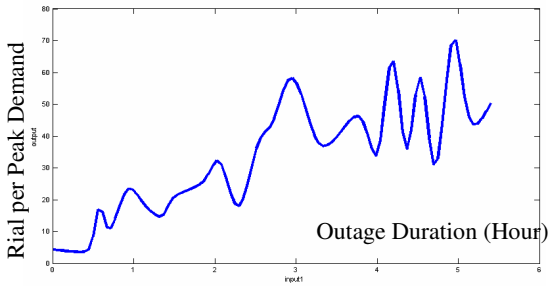

Fig.22 Graphical Representation of Fuzzy Model for Customers Group 3

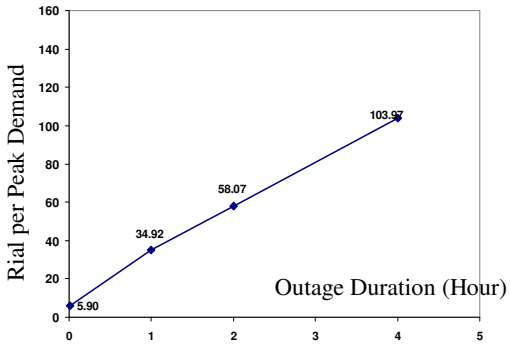

Fig.23 Graphical Representation of Average Model for Customers Group 4

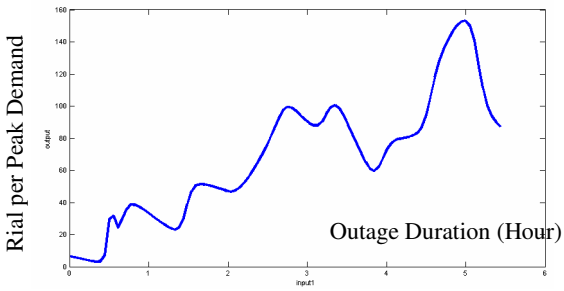

Fig.24 Graphical Representation of Fuzzy Model for Customers Group 4

As seen in the above results, there is a good similarity between the general behaviors resulted from fuzzy model and the result of average model. We did not expect anything else, but the difference is non-linear fuzzy model and linear average model that was mentioned earlier. Meanwhile, the resulted fuzzy model that is a software model can predict output for the inputs other than the considered range of data with some error in case the parameters are chosen properly. In fact, in output of fuzzy model, we will have a non-linear function which is capable of estimating the output for the inputs other than learning data in addition to showing an ideal display of the output for the total range of learning input data.

3.5 Conclusion

The fuzzy model that has been provided in this article is a flexible model towards the resulted input-output data. Average model just uses the average of total data. Existence of even one very remote input can change it and in order to almost completely remove this effect, we need a very high number of input points. Using a fuzzy model and specially taking advantage of a neuro system for optimizing the model and specifying its parameters, due to using a non-linear model instead of the linear average model, makes it possible to more accurate prediction of output for the range of the input whose output does not exist among the available data, in addition to making the model function closer to the real data behaviors and removing the problems due to input data (although high number of input data is needed for the learning process in fuzzy model, but this high number is yet less than what we need to remove the problem in the average model). One of the important issues that is clearly revealed by observing the output of the fuzzy model is that for achieving a suitable model and outputs with a behavior according to reality, the input data should be fuzzy or in other words, the input and output

variables should be fuzzy variables. Since the data applied in this study and specially the input variable, i.e. outage period, have been crisp and they have artificially modified in order to be similar to fuzzy data through an algorithm, the output has some differences with reality that has been exactly resulted from this issue.

In case the questionnaires of direct survey project is designed and processed by fuzzy approach and in line with achieving scattered points on the axis of period of time by considering uncertainty, the results obtained from this method of modeling will be definitely better and much closer to the reality.

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