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Electrical Load Forecasting using Adaptive Neuro-Fuzzy Inference System

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Abstract

Electrical load forecasting is well-known as one of the most important challenges in the management of electrical supply and demand and has been studied extensively. Electrical load forecasting is conducted at different time scales from short-term, medium-term and long-term load forecasting. Adaptive neuro-fuzzy inference system is a model that combines fuzzy logic and adaptive neuro system and is implemented in time-series forecasting. First, ANFIS structure is decided using subtractive categorization; next, ANFIS premise and consistent parameters are identified using hybrid algorithm; finally, some factors affecting future daily electrical load such as weather and population become inputs of ANFIS to forecast daily electrical load on the following day. The membership function used is Gbell membership function. The forecasting result shows that the forecasting model is considered valid with an RMSE score of 0,0298.

Keywords: *Electrical load forecasting, ANFIS, Gbell membership function, RMSE.*

1 Introduction

Electric energy distribution should efficiently meet the public need of electricity. A problem arises when electricity supply produced by a power plant is higher than electricity demand since it causes waste of energy. On the other hand, electricity supply that is lower than the demand for electricity will result in overload and eventually electricity blackouts. Accurate balance between electricity supply and demand is vital in order to fulfill customers' need of electricity. Hydroelectric and geothermal power plants that generate 1000MW of electricity are considered as the most economical power plants and once became the most preferable type of power plant to use. These two types of power supplies have not yet been able to fulfill customers' need of electricity. Therefore, natural gas and petroleum power plants are built in order to meet electricity demand of customers. Effective strategies and methods to create a balance between electricity supply produced by power plants and electric demand of the customers are required. Public consumption patterns of electricity that are influenced by the environment and weather should be taken into account. So that electricity supply meets electricity demand, stakeholders should have accurate information on electricity load and demand for several years ahead through electrical load forecasting.

Several previous studies on electrical load forecasting have been successfully conducted. Electric load forecasting studies conducted by Fan and Hyndman [1] as well as Friedrich and Afshari[2] show that electrical load forecasting using Autoregressive Integrated Moving Average (ARIMA) results in the smallest percentage of MAPE; the percentage is 2.68%. Based on previous studies on electrical load forecasting using ARIMA, it was revealed that ARIMA could not account for electricity fluctuations whether in the increase or decrease of electrical load.

Fuzzy Inference System (FIS) is able to overcome the weaknesses of conventional forecasting methods such as ARIMA since fuzzy inference system is able to translate knowledge from experts as well as some issues and historical data into the form of a linguistics ratio. Khosravi and Nahavand [3], Tseng et al. [4], and Huamani et al. [5] have successfully carried out electrical load forecasting using FIS. However, there are some disadvantages of FIS, namely cyclical data and inaccurate levels of FIS. The Neural Network (NN) method is the suitable method to overcome issues of cyclical data. Ye et al. [6] conducted short-term electrical load forecasting for modes of transportation with irregular interval using ARIMA, NN and genetic algorithm. Sugeno states that the NN method can make more accurate predictions of electric load than the state electricity company in Indonesia, Perusahaan Listrik Negara (PLN). NN has the ability to predict non-linear variables and creates smaller errors, but it takes longer to conduct training for the method [7].

In order to solve the aforementioned problems, Adaptive Neuro-Fuzzy Inference System (ANFIS) can be implemented. The method is an adaptation of neural networks that functionally is equivalent to the Fuzzy Inference System (FIS). In a distribution system, electrical load forecasting is a sophisticated procedure because the available information is limited to the consumption of electricity. The effect is that the system produces inconsistent or biased, inaccurate and random estimation of consumer's demand. Adaptive neuro-fuzzy is the approach used in the study. Inaccurate and unreliable data input is analyzed using the fuzzy membership function. The fuzzy membership function is used to describe input where actual data is used as training data set in the study. The samples of actual data are electricity load within a year. Adaptive Neuro-Fuzzy Inference

System (ANFIS) is a combination with the Fuzzy Inference System that is described with a neural network system architecture [8].

Electrical load forecasting based on time scales can be categorized into three classifications: long-term electrical load forecasting that refers to electrical load forecasting of a time scale of more than 1 (one) year, medium-term electrical load forecasting that refers to electric load forecasting of a time scale of between one month up to one year, and short-term electrical load forecasting that refers to electrical load forecasting of a time scale of several hours in one day up to one week.

The study focuses on ANFIS for short-term electrical load forecasting. The analysis used is time-series analysis because electrical load data has time interdependence. Time-series predictions are very important because based on them past events can be analyzed to understand possible patterns of future events so that preventive or corrective decisions can be taken to prevent unwanted circumstances. Electrical forecasting is conducted every one hour due to the high fluctuations per hour. ANFIS is a non-linear method that combines the two systems of fuzzy logic and adaptive neuro system. ANFIS based on trained fuzzy inference uses a learning algorithm derived from the adaptive neuro system. Therefore, ANFIS has all the advantages of both fuzzy inference and adaptive neuro system.

The study aims at developing a predictive model with the ability to conduct short-term electrical load forecasting that facilitates scheduling in power plant operations using 2 (two) external factors. It is expected that the model enhances accuracy of electrical load forecasting.

2 Related Works

Takagi Sugeno Kang introduced the fuzzy model where the antecedent and consequent of fuzzy set becomes a crisp set. A new terminology is coined from the process: fuzzy adaptive. One fuzzy adaptive model is the Adaptive Neuro Fuzzy Inference System (ANFIS) developed by Roger Jang [9]. Adaptive Neuro Fuzzy Inference System (ANFIS) is one of the systems of the neuro-fuzzy set that is classified as a hybrid system in soft computing. The hybrid system is a match or combination of between at least two soft computing methods of which the purpose is to create a more perfect algorithm. The neuro-fuzzy system is based on the fuzzy inference system that is trained using a learning algorithm which is derived from neural network systems. Therefore, the neuro-fuzzy system has all positive traits of the fuzzy inference and neural networks systems.

Adaptive neuro fuzzy inference (ANFIS) or adaptive system network based fuzzy inference system or neuro fuzzy is a combination of adaptive neuro system and fuzzy logic. For a linguistic-based system, the adaptive neuro system technique will give the abilities of learning and adaptation to extract the parameters (premise and consequences) of fuzzy rules from a group of numerical data. In particular, a neuro-fuzzy network eliminates the deficiencies in conventional fuzzy system design where the designer must download tuning (tune) by trial-error membership function of fuzzy sets defined on the input and output of the universe of discourse. In ANFIS, the parameter is the premise of membership functions and consequences [10]. Learning ANFIS can use the back-propagation algorithm or hybrid algorithms. The hybrid algorithm is a combination of the back-propagation algorithm with the least squares method (Least Squares Estimate). The Least Squares Estimate is used to determine the consequences parameter while the back-propagation algorithm is used to renew the weights premise.

2.1 Adaptive Neuro Fuzzy Inference System (ANFIS)

One of the ANFIS structures that have been widely recognized is described in Figure 1. In the structure, the fuzzy inference system being implemented is the first order of Takagi Sugeno Kang's fuzzy inference model. The ANFIS described in Figure 1 consists of 5 (five) layers; the layers represented with squares are adaptive while ones represented with circles are non-adaptive. The output from each of the layers are represented with $O_{l,i}$ where i represents the node and l represents the order of the layers.

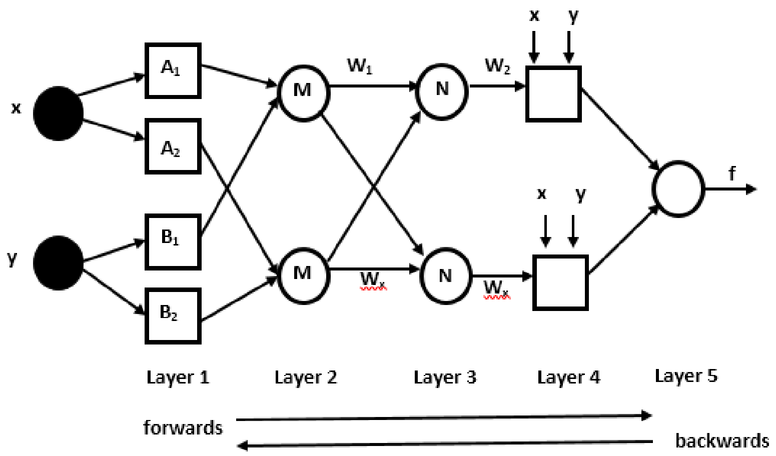

Fig.1: Architecture of ANFIS

From the theory of fuzzy systems, different fuzzification and defuzzification mechanisms with different rule-based structures can result in various solutions to a given task. ANFIS is a technique for automatically tuning first-order Sugeno type inference systems based on training data. It can be applied in different domains such as traditional forecasting with time-series analysis [11] [12], ARIMA [13], linear regresion [4], and fuzzy controller design [14]. We consider that the fuzzy inference system under consideration has two inputs x and y, and one output f. We consider that for a first-order Sugeno fuzzy model of base rules with two fuzzy, the if-then rules can be expressed as:

Rule 1 : IF x is A1 and y is B1 then $f_1 = p_1x + q_1y + r_1$
Rule 2 : IF x is A2 and y is B2 then $f_2 = p_2x + q_2y + r_2$

Figure 2 describes the analysis mechanism of the Sugeno model [10]. x and y represent input and f represents output [15]. A1, A2, B1, and B2 are input membership functions, W1 and W2 represent firing strength rules, and {pi, qi, ri} is the parameter set.

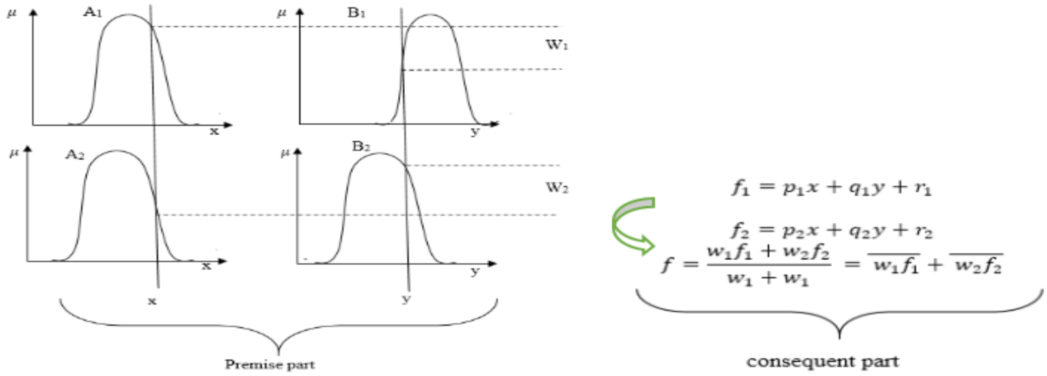

Fig. 2: Two-input first order Sugeno fuzzy model

The steps of inference operations for the above fuzzy if-then rules completed by fuzzy inference systems are:

1. *Premise part:*

The input is compared to membership functions to obtain the membership ratio of each linguistic label (this step is widely recognized as fuzzification). Membership function is combined in order to obtain the firing strengths (weights) of each rule.

2. *Consequent part:*

The qualified consequent is selected from each rule which relies upon the firing strength. The qualified consequents are aggregated to produce a crisp output. This step is called deffuzzification.

In the structure described in Fig.2, the antecedent of rules contains fuzzy sets (as a membership function) and the consequent is a first order polynomial (a crisp function). We used the Gbell. membership function with product inference rule at the fuzzification level. A fuzzifier outputs the firing strengths for each rule. The vector from fire strengths is normalized and the vector obtained is defuzzified using the first order of the Sugeno Model.

ANFIS in the process uses a hybrid learning algorithm, a combination between Least-Squares Estimator (LSE) and Error Back Propagation (EBP) methods. In the structure of ANFIS, EBP is carried out in the first layer while LSE is carried out in the fourth layer. The parameter used in the first layer is the parameter from the fuzzy membership function that is non-linear towards system output. Learning process in the parameter uses EBP to renew the ratio of the parameter. Meanwhile, in the fourth layer, the parameter is a linear parameter towards system output that formulates the basis for fuzzy analysis. The purpose of the learning process is to renew the parameter. LSE is used in the layer. The process of ANFIS learning is described in Table 1.

Table 1: Two passes in the hybrid learning algorithm for ANFIS

	Forward pass	Backward pass
Premise parameters	fixed	Gradient descent
Consequence parameters	Least-square Estimator	fixed
Signal	Node output	Error signals

2.2 Methods of Comparison

In the study, the researchers proposed 3 (three) forecasting methods commonly used in electrical load forecasting: Time-series analysis, Sugeno Fuzzy Inference System, and Sugeno Fuzzy Inference Optimization using Strategic Evolution. The goal is to find out the level of accuracy and suitability of the method proposed by the researchers in powerful electrical load forecasting.

2.2.1 Time-series forecasting

Time-series analysis method uses historical data to make a prediction and the prediction assumes that the factors show formative relevance with one or more independent variables so that the relationship among dependent variables can be used to make a future forecasting ratio [4].

There are linear and multiple regression models with dependent variable (y) and several independent variables (x1, x2, ..., xn) of which the purposes are to describe a function that correlates y and all independent variables. A common form of Time-series Analysis is:

$$Y' = a + b_1X_1 + b_2X_2 + b_3X_3 + \cdots + b_nX_n \quad (1)$$

where:

Y’ : electrical load forecasting

$a + b_1$: regression coefficient

X_1 : average result of electrical load

X_n : results of the average price of electricity load

2.2.2 Fuzzy Inference System

Fuzzy modeling uses Boolean logic to logically assume outputs from fuzzy inputs. Hu [14] used fuzzy logic for rule classification. Khosravi and Nahavandi [3] explained the implementation of fuzzy logic for electrical load forecast. Asklany et al. [16] presented rainfall forecast using a rule-based fuzzy inference system. Mori [17] presented a Fuzzy Inference System (FIS) used for electrical load forecasting using the Tabu search method. The method assumed that weather and daily activities were affecting factors in electrical consumption, for example during holidays. The method worked effectively for forecasting with a time scale of one day up to one week. Khosravi and Nahavandi [3] used FIS type-2 for optimal type reduction. FIS analyzed the highly nonlinear relationship between weather as the parameter and the effect of weather towards electricity consumption. ANN was used to enhance learning of the highly nonlinear input-output mapping directly from the data training. There are various types of fuzzy inference systems; the Sugeno Fuzzy Inference System is the most frequently used forecasting method. The advantage of the Sugeno FIS method is that it can solve issues of data that are in the form of time-series with quite a high level of accuracy. However, the method also has some weaknesses in designing rules based on a regression function. Thus, when the data used are plentiful, the impact towards the rules becomes more complex. If the rule is built manually it will require considerable time and values for the coefficients in the rule are less accurate because there is still uncertainty for the determination and the resulting error level is still high. Figure 3 describes the general FIS flowchart.

Fig. 3: Fuzzy System

2.2.3 Optimized Sugeno FIS

The system deals with tolerance for inaccuracy and inconsistency of time. For forecasting, the system considers future load patterns as time-series signals and predicts future load using several techniques such as human skills, a biologically inspired computation model, optimization techniques, and numerical calculation. The second approach considers load patterns depending on previous load patterns and weather as well as other variables such as temperature, wind velocity, clouds, and humidity.

Fuzzy rules optimization is a crucial step in the development of a fuzzy model. A simple two-input fuzzy model will have more than ten thousand possible combinations of fuzzy rules. A fuzzy designer normally uses intuition and the trial-and-error method for the rules assignment. In order to obtain the optimum set of fuzzy rules, Sugeno FIS requires fixed and consistent procedures since they influence the accuracy of forecasting using this method. The level of accuracy in IF-THEN rules establishment should be combined with a heuristic algorithm, for example in Evolution Strategies (see Fig 4).

The suitable Evolution Strategies are used to find suitable coefficients based on the fact that some tests are needed to get expected results so that the Evolution Strategies can obtain solutions for optimum or nearly optimum issues so that everything, including the coefficient ratio can be optimized in basic rules that have been previously designed [18]. Evolution Strategies are able to provide a optimal or near-optimal solution to the problems so as to have optimized coefficient values in the base rules that were created earlier. Stochastic components are one of the most successful methods for global optimization problem; they accept refusal from local optima and affected premature stagnation. A well-known class of global optimization methods are successful evolutionary strategies within the real-valued solutions [18].

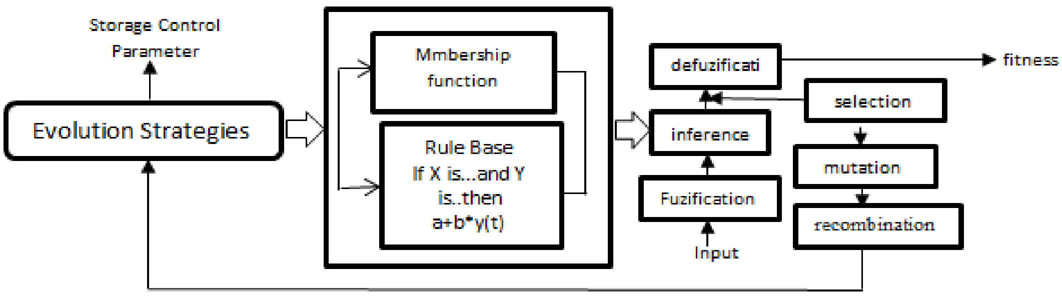

Fig.4: Block diagram of optimized Sugeno FIS using Evolution Strategies

3 Demand forecasting using ANFIS

ANFIS has been found to be extensively used to model nonlinear systems, predict chaotic time series, and identify nonlinear components on-line in a control system along with signal processing applications [19]. In ANFIS, the parameter related to the given membership function is not randomly selected and has an impact towards membership function adjustment for data input/output to calculate types of variance in data ratios. The learning method works in a similar fashion as a neural network [9].

3.1 ANFIS structure

To create the best architecture with the smallest errors, features that are different from parameters like the type of membership function, number of membership function, training method and so forth have been evaluated. The best obtained features of ANFIS after tuning process are detailed in Table 2.

Table 2: Tuned features of ANFIS

Parameter		value
Training	method	Gradient descent - Least-square Estimator
	epochs	100
Input layer	MF's	Gbell, Trapezium, Gaussian
	variables	Electricity load, temperature, and population
Output layer	MF type	Constant
	Defuzzification method	Weight Average
	variable	Annual electricity load

3.1.1 Forward pass

The forward pass of an ANFIS system consists of 5 (five) layers. On the first layer, fuzzification is carried out for data input from each period. The goal of the process is to map input data into a fuzzy set suitable with the selected classification. The architecture of ANFIS is described in Figure 1 using two inputs and one output.

In the process, the fuzzy membership function calculation is carried out towards input to transform the crisp set to a certain degree. The membership function used is Generalized Bell. Generalized Bell is a membership function with 2 (two) parameters, mean and standard deviation, which in the ANFIS method are called the premise parameters. On the second and third layers, the inference engine process is conducted and the fuzzy rule is decided for the following calculation process. This happens because the ANFIS system used is the result of the multiplication of the membership degree from the first layer. On the third layer, normalization of each node occurs and the normalized activation degree becomes the result. On the fourth layer, defuzzification process is carried out that transforms fuzzy result into crisp output. In the layer, LSE calculation is conducted to obtain the consequent parameter ratio. On the fifth layer, calculation process for the output from the fourth layer is carried out. In the ANFIS system, the fuzzy is located on the first, second, third, and fourth layers where the fuzzy system becomes the hidden note determiner located in the neural network system. The following is the explanation of each layer:

Layer 1:

The basic learning rule of ANFIS is gradient descent backpropagation, which calculates the error rates (defined as the derivative of the squared error for each output node) recursively from the output to the input nodes. Each node in this layer corresponds to a linguistic label and the output node is equal to the value of membership in this linguistic label. The parameters of a node can change the shape of the membership function used to characterize the linguistic label. For example, the function of the *i*-th node is given by

$$O_i^1 = \mu Ai\ (x) = \frac{1}{1+\left[\frac{x-ci}{ai}\right]^2} \tag{2}$$

where *x* is the input node *i*, *Ai* is a linguistic label like, *Small*, *Large*, *etc*. associated with this node, and {*ai*, *bi*, *ci*} is the set of parameters. The parameters in this layer are called *premise parameters*.

Layer 2:

Every neuron on the second layer becomes fixed neurons of which the output is the result. The AND operator is used. Each node represents α predicate (w) from the i^{th} rule. Therefore, the output of the second layer is the multiplication of the membership degree from the first layer. Each node in this layer calculates the firing power of each rule:

$$W_1 = \mu A_1 * \mu B_1$$
$$W_2 = \mu A_2 * \mu B_2 \tag{3}$$

Layer 3:

Every neuron on the third layer consists of a fixed node that becomes the result of the ratio from α predicate (w) from the i^{th} rule towards the total amount of α predicate. This result is known as the normalized firing strength.

$$\widehat{w}_i = \frac{w_i}{w_1+w_2} \tag{4}$$

where i = 1, 2.

Layer 4:

Each neuron in the fourth layer is adaptive to an output node.

$$w_1 y_1 = (w_1 x_1)p_1 + (w_1 x_2)q_1 + r_1 \tag{5}$$

$\hat{w}_i$ is the normalized firing strength on the third layer and p_i, q_i, r_i are the parameters of the neuron. The parameter of each layer is called consequent parameters. The following equations are used to determine the consequent parameter. To determine the coefficient of these parameters are:

$$p_1 = \bar{w}_i * x_1 \tag{6}$$

$$q_1 = \bar{w}_i * x_2 \tag{7}$$

$$r_1 = \bar{w}_i \tag{8}$$

Layer 5:

Neurons in this layer are a fixed node that is the sum of all inputs.

$$y' = \Sigma \bar{w}_i y_i = \bar{w}_1 y_1 + \bar{w}_2 y_2 \tag{9}$$

In order to conduct forecasting or prediction using ANFIS, the output from the fifth layer is divided by the data.

Load Forecasting of the i^{th} data equals to:

$$\sum \frac{\bar{w}_i y_i}{x_2} \tag{10}$$

After the inference stage of ANFIS model and forecasting, the following step is hybrid learning. During the forward phase, network input gradually moves forward until the fourth layer where c_{ij} parameters will be identified using the least squares method. Meanwhile, during the backward phase, signal error will slowly move backwards and the parameters will be improved using the gradient-descent method. The following is the calculation of forward learning using the Recursive Least Squares Estimator (LSE) method:

$$\Theta = A^{-1}Y \tag{11}$$

where matrix A is based on parameter coefficient that later is inversed. Y is target output (Y(t)).

3.1.2 Backward pass

The block diagram of Fig. 1 explained about the systematic backward flow of an ANFIS system. The Error Back Propagation (EBP) algorithm is conducted where the error calculation for ANFIS parameter update is carried out. The purpose of the process is to decide new adaptive a and c ratios.

4 Numerical example

We took the IESO Demand Ontario website as our empirical study; its operation data of electricity load is open to all researchers freely (http://www.ieso.ca/). We selected some electricity load data to be used for identifying and verifying for the model, from January 01, 2012 to December 31, 2012. As much as 5,089 data records were used in the model constructing. We took weather-related data consisting of humidity, wind direction, and temperature from the dataset of (https://archive.ics.uci.edu).

The ANFIS models used three inputs – past demand on the same day of the previous week, forecast temperature, and forecast population to provide an output of forecast demand for the day. For the input variable, three membership functions, namely, 'high', 'medium' and 'low', were used which later developed 27 rules to adjust the parameters of the network structure. The 'if-then' design rules for the fuzzy inference system depends on the number of membership functions used in each input variable using the system (e.g. our fuzzy inference system uses three input variables; electricity demand from the previous week (t-1), temperature of the previous week (t-2), and population from the previous week (t-3) in which each entry contains three membership functions; therefore the total number of possible combinations for the fuzzy-rules is 3 (e.g. 3*3*3=27)).

4.1 Membership Function testing

The Membership Function (MF) is a curve that shows the mapping of points of input data into membership values that have interval values 0 and 1. During the training and testing for each case, the model was tested with three inputs to predict the output load and three different types of MFs, Gaussian, triangular and Gbell. The results of each test are shown in Table 3.

Gaussian :

$$\mu_z(x_k, \gamma_k) = \exp\left(-\frac{1}{2} \cdot \frac{(x_k - center_k)^2}{{\gamma_k}^2}\right) \tag{12}$$

$$center_k = \frac{u_{k+}U_k}{2} \tag{13}$$

With $\gamma_{k \neq 0}\ for\ any\ k \in \{1,2, \ldots, n\}$

Triangular :

$$\text{triangle}\ (\text{x}; \text{a}, \text{b}, \text{c}) = \begin{cases} 0 \quad x \leq a & \\ \frac{x-a}{b-a} & a \leq x \leq b \\ \frac{c-x}{c-b} & b \leq x \leq c \\ 0 \quad c \leq a & \end{cases} \tag{14}$$

Generalized Bell :

$$bell(x, a, b, c) = \frac{1}{1 + \left|\frac{x-c}{a}\right|^{2b}} \tag{15}$$

Where:

x : input data

a : standard deviation

b : 1 (slopes) , always be positive

c : mean

For the purpose of evaluating out-of-sample forecasting capability, we examined forecast accuracy by calculating evaluation statistics, which are "the root mean square error (RMSE)".

Their definitions are:

$$RMSE=\sqrt{\sum_{i=1}^{n}\frac{(p_i-A_i)^2}{n}} \tag{16}$$

Table 3:Membership Function combination presented to ANFIS

MF's	RMSE	Time (hh:mm:ss)
Gaussian	0,0023996	04:44:12
Triangular	0,0026340	02:56:11
Gbell	0,0024448	03:33:00

where *Pi* and *Ai* are *i*th predicted and actual values, and *n* is the total number of predictions

4.2 Learning rate testing

Testing the learning rate was done to determine the optimal value of learning rate. The tests were performed on the learning rate of as much as 75% of the total data. The testing learning rate was in the range of 0.1 to 0.9. The greater the accuracy of the test on the learning rate, the higher the accuracy of the forecasting results. The results of these tests are shown in Table 4 and the results of each test in the form of a graph are shown in Fig 5.

Table 4: Learning rate

Range	Result Average
0.1	92,1216
0.2	91,9087
0.3	90,0092
0.4	91,0092
0.5	90,0928
0.6	90,7233
0.7	92,9280
0.8	91,0092
0.9	90,1216

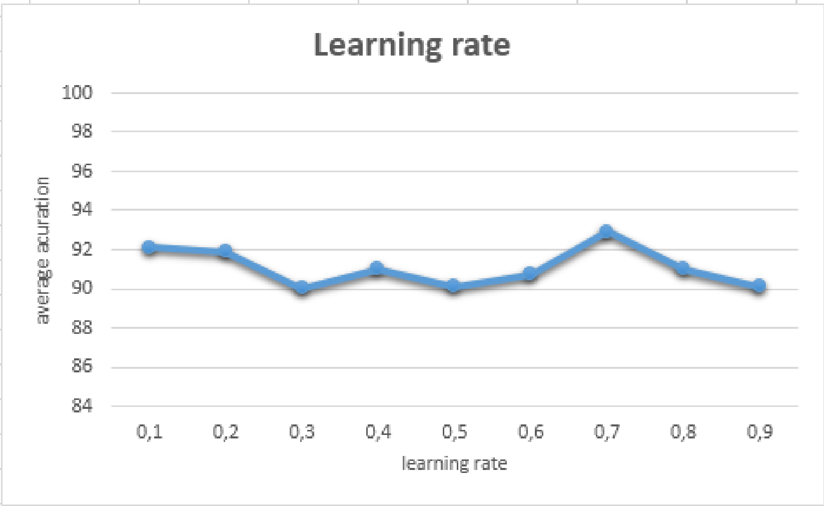

Fig.5: Learning rate ANFIS

5 Results

Looking at the results of the numerical example, we used the Gbell membership function for identifying the error value and the execution time with an RMSE of 0.0024448 and execution time of 3 hours and 33 minutes. The Gbell membership function is a function that is smooth and non-linear and has the parameters of {a, b, c}. The result of the calculation on the degree of membership of A, B, and C can be represented by the generalized bell curve in Fig 6-8.

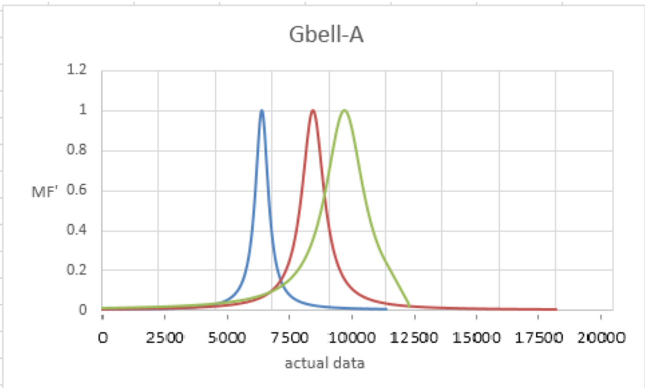

Fig.6: Generalized Bell membership function parameter A

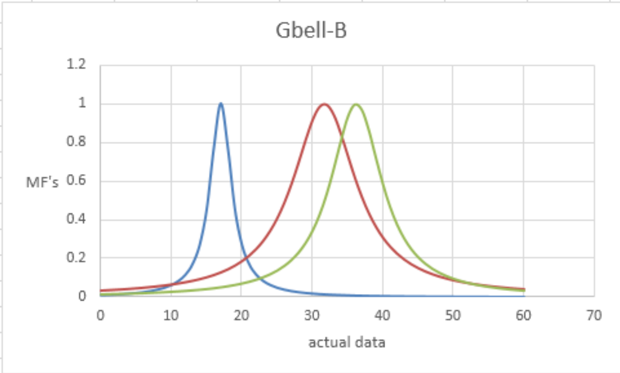

Fig.7: Generalized Bell membership function parameter B

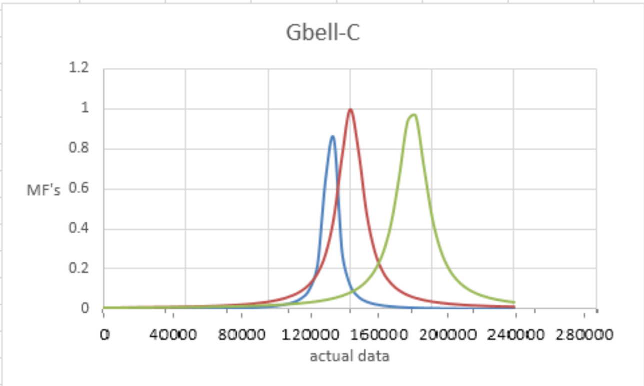

Fig.8: Generalized Bell membership function parameter C

After building MF with Generalized Bell, forecasting was conducted using actual data. The implementation of ANFIS used a learning rate of 0.7. Table 5 gives the result of short term load forecasting using ANFIS which uses 12 hour periode in a day. Table 7 provides RMSE results of forecasting for each method within one year.

Table 5: Forecasting results (05:00 to 16:00)

Time	Actual Load	Forecasting ANFIS	Error
05:00	13899	13899	-0.00013
06:00	13500	13500,01	-0.00692
07:00	13402	13402	0.00091
08:00	13398	13398	4.53E-05
09:00	13650	13650,01	-0.0089
10:00	14578	14577,99	0.007246
11:00	15966	15966	-0.00016
12:00	16796	16796	-0.00032
13:00	17434	17434	-0.0009
14:00	17997	17997	0.000116
15:00	18482	18481,99	0.011543
16:00	18613	18613	0.000515

Table 6 gives the results of electrical load forecasting. A comparison was performed among four methods of forecasting and actual data for a year.

Table 6: Result accumulation (one year)

Month (2012)	Actual Load (average)	ANFIS (average)	Time-series Analysis (average)	Sugeno FIS (average)	Optimized Sugeno FIS (average)
January	14039	14039,04992	14005,47	14016	14000
February	13592	13592,01748	13520,81	13569	13558,89
March	13316	13316,03589	13147,38	13293	13299,67
April	13287	13287,05082	13179,35	13264	13257,92
May	13639	13639,01925	13553,37	13616	13624,067
June	14700	14700,00784	14466,52	14677	14669,102
July	15999	15999,02727	15922,41	15976	15998,99
August	16833	16833,03805	16827,07	16810	16833,01
September	17305	17305,00195	17363,66	17282	17305
October	17838	17838,03681	17656,53	17815	17834,559
November	18127	18126,99558	17973,6	18104	18126,9
December	18134	18134,00012	18244,85	18016	18120,96

According to the forecasting results shown in Table 6, there are no a unique and more appropriate unbiased estimators that can be applied to see how far the model is able to forecast the values of electricity load, and thus error measure of accuracy are employed. For this reason, the models are evaluated by the square root of the mean square error (RMSE). Table 7 provides the RMSE results of each method forecasting within one year.

Table 7: Error of the result

Evaluation	RMSE
Timeseries Analysis	124,5497702
FIS Sugeno	40.56168142
Optimized FIS Sugeno	20.59360858
ANFIS	0.029817613

Table 7 shows that the proposed method gives a better result than the others because in ANFIS, neural networks recognize patterns and help adaptation to environments and the system possesses human-like expertise that adapts and learns to deal with the changes in the environment.

Fig. 9 gives the plots of actual and forecasted load profile for a year. As seen in Fig. 9, there was no considerable difference between test output and actual output in the ANFIS method. In other words, the test data and output data have the same trend. However, as seen in Fig. 9 in the Time-series analysis, the difference between test output and actual output is very high. In addition in Table 7, it is observed that the error for ANFIS is less than the other methods. It can be completely characterized that the ANFIS method has a considerable accuracy in electrical load forecasting. The most important reason is the ability of ANFIS to predict a natural system's behavior at a future time, which can be used for electrical load. In addition, ANFIS is less complicated than other procedures. Compared with fuzzy inference systems such as Sugeno, ANFIS has an automated identification algorithm with a simpler design. Moreover, compared with Optimized Fuzzy Sugeno, ANFIS has fewer parameters and faster adaptation.

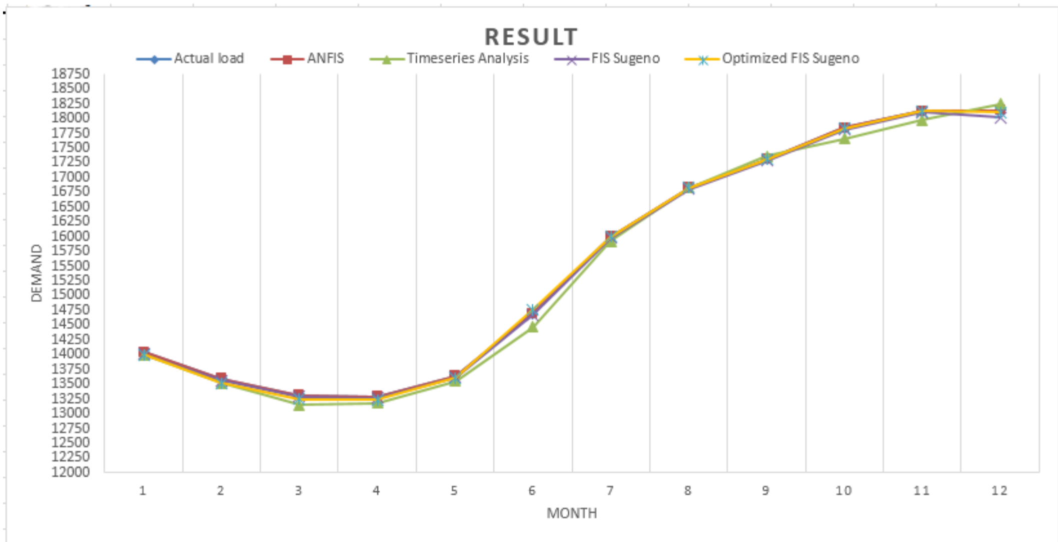

Fig. 9: Forecasting result

6 Conclusion

In our study, we used the algorithm based on the adaptive neuro-fuzzy inference system. This algorithm does not need the definition of the initial parameters for membership function by individuals' subjective sense. Those parameters are acquired by adaptive learning. The hybrid learning algorithm which is a combination of the least squares estimation method and backward propagation approach overcomes the shortcomings, such as heavy convergence, long training time, and the limitation of a local minimum point. The Ontario electricity market was taken as our empirical example. By the use of this data, we constructed an

ANFIS model. The results of the trials of the three MFs proved that the Generalized Bell is the most ideal among the MFs, considering that its computing time of execution reaches 0.0024448 in 03 hours and 33 minutes. The test results showed the learning rate of 0.7 with a value of 92.9280. RMSE testing was used to view the performance of the proposed method. The results of RMSE which was 0.0298 proved that ANFIS had a good forecasting precision with a fast running time, thus verifying that our proposed scheme is feasible. Further study is also to be carried out by considering other features that are specifically related to electrical load and for the delimitation membership function using meta-heuristic algorithms such as Genetic Algorithm [20], [21], Particle Swarm Optimization [22], and Variable Neighborhood Search [23] which have been proven to be successfully applied to a wide range of optimization problems.

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