Journal of Engineering Research and Reports

20(6): 75-87, 2021; Article no.JERR.67557
ISSN: 2582-2926

Hybrid Based Artificial Intelligence Short –Term Load Forecasting

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Authors' contributions

This work was carried out in collaboration among the authors. All authors read, reviewed and approved the final manuscript.

Article Information

DOI: 10.9734/JERR/2021/v20i617330
Editor(s):
(1) Dr. Guang Yih Sheu, Chang-Jung Christian University, Taiwan.
Reviewers:
(1) Siti Zulaiha Ahmad, Universiti Teknologi MARA (UiTM), Malaysia.
(2) Abdelhakim El hendouzi, Mohammed V University, Morocco.
Complete Peer review History: http://www.sdiarticle4.com/review-history/67557

Original Research Article

Received 01 March 2021
Accepted 05 May 2021
Published 10 May 2021

ABSTRACT

Electrical power load forecasting, which forms a key element in the power industry's electricity preparation, is used for providing required data for day-to-day system management activities and power utility unit participation. Since the statistical method is a linear model, and the load and meteorological parameters have a nonlinear relationship, the statistical method for load forecasting involves a great calculation time for parameter recognition. Using this tool for load forecasting often results in a major mistake in prediction. Due to the disadvantages of the statistical method of load forecasting Neuro-fuzzy model was used in this work. Three models: Adaptive Neuro-Fuzzy Inference System (ANFIS), Artificial Neural Network (ANN) and Multilinear Regression (MLR) were simulated in MATLAB environment and their output results were compared using root mean square error (RMSE) and mean absolute error (MAE). The ANFIS model outperforms the other models with least errors of RMSE and MAE of 2.2198 % and 1.7932 % respectively.

Keywords: Load forecasting; electrical load; electricity; neuro-fuzzy model; and artificial intelligence.

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1. INTRODUCTION

Electricity as a product compared to a material product has somewhat different characteristics. Electrical energy, for example, cannot be stored; it should be supplied as soon as it is needed. There are several strategic goals of every commercial electric power utility. One of these goals is to provide secure and reliable electricity to end-users (market requirements). Electrical Power Load Forecasting (EPLF) is therefore an important element use for planning in the electrical sector and the maintenance of electricity systems. Given the historical load and weather information, electrical power load forecasting is used to forecast future electrical load demand [1].

Electrical power load forecasting is divided into three main classifications; Long-term electric power load forecasting: is used to provide the management of electric utility companies with the forecast of potential demands require for growth, procurement of equipment, or recruiting of employees, and its duration is usually more than one year, Medium-term electric power load forecasting : usedduring the fuel supply preparation and unit maintenance and the period for this category of forecasting is generally from a week to a year and Short-term electric power load forecasting: Used to provide the appropriate information for day-to-day operations and unit interaction system management, the time frame for this type of forecast is usually from one hour to one week.

The prediction of electrical power load plays a significant role in assisting electrical utilities make important decisions on power load switching, voltage regulation, reconfiguration of network and construction of infrastructures.

It also assists the management of electric utility c ompanies in preparing expansion plans, scheduli ng fuel supplies and maintenance of units, and s cheduling loads.

Presently, the method of forecasting the electrical load can be divided into two groups. One is the classical statistical class prediction method, such as regression analysis, time series method and gray prediction method, and the other is the modern artificial intelligence class prediction method, such as expert systems and artificial neural networks [2].

Major interests and initiatives have recently been targeted at the implementation of artificial intelligence techniques for load forecasting. This involves the introduction of expert load forecasting systems and comparison of their output with conventional methods [3]. The use of fuzzy inference/logic and fuzzy-neural models is also included. Nevertheless, because of its capacity to learn and model nonlinear and complex relationships, the model that has earned a high share of efforts and focus is artificial neural networks (ANNs) [3].

The goal of short-term load forecasting is to forecastElectrical loads for one hour to one week. Because the daily load pattern is highly nonlinear and random, using statistical methods to achieve higher accuracy is extremely difficult. An advanced approach for accurate short-term load forecasting is the use of artificial intelligence (AI) techniques such as neural networks and adaptive neuro fuzzy inference systems [4].However, artificial neural networks cannot provide insight into the essence of the problem being solved and set rules for the selection of optimal topology for the network . In terms of physical parameters, the model obtained via the neural network is not understandable and it is difficult to deduce the result in terms of natural language [3].

The ANFIS structure is a meaningful assignment of node functions and allowing for a wide range of configurations. ANFIS is a hybrid of fuzzy logic and neural networks that combines the best of both methods.

1.1 Electrical Power Load Forecasting

Electrical Load Forecasting is an industry or utility company's future load assessment. The process of predicting with the help of prior data, what the future consumption will be is what is known as Electrical Load forecasting. It is an important facet of decision making. Electrical Load forecasting is the electrical load projection that a certain geographical area will need with the use of prior electrical load use in that geographical area [5].Electrical Load forecasting is used to estimate load data based on different factors at a particular moment in the future, such as operational characteristics, capacity expansion choices, natural circumstances, and social effects of the system when a certain amount of accuracy is required [6].Perfect load forecasting estimation will lead to significant economic savings in operating and maintenance costs [7]. To produce good quality power, power systems require effective monitoring functions that allows the power quality parameters to be immediately corrected. The short-term power load forecast is very important in the electric utility industry [8].

1.2 Factors affecting Electrical Load

Several factors affecting electrical load includes economic, time, weather and random disturbance. These factors are subsequently discussed.

1.2.1 Economic factor

According to [9], many economic variables can stimulate the change in the load pattern, such as the form of residential, agricultural, commercial and industrial customers, demographic factors, and population, per capital income, GDP growth, national economic growth and social activities. The long-term load forecasting primarily affects these economic factors.

1.2.2 Time factor

The key time variables that play a crucial role in affecting the pattern of the load are periodic effects, the regular cycle of the week, public and religious holidays. Weather summer or winter peaks are determined by the seasonal changes. Significant shifts in the load pattern arise progressively in response to the seasonal variance, such as the amount of daylight hours and changes in temperature. Seasonal events, on the other hand, introduce abrupt but substantial structural changes in the pattern of use of electricity. Changes to and from Day-light Time, changes in the rate structure (time-of-day or seasonal demand), the beginning of the school year, and substantial declines in holiday events. The weekly frequency of the load is a result of the service area population's work-rest pattern. There are clearly-defined load patterns for "distinctive" seasonal weeks. The presence of compulsory and religious holidays has the effect of reducing load values substantially to points far below "normal". In addition, shifts in the pattern of electricity use are observed in the days before or after holidays due to the propensity to create "long weekends" [10].

1.2.3 Weather factor

Meteorological factors are one of the causes for substantial disparities in load structures. This is because most utilities, such as those induced by space heating, air conditioning, and agricultural irrigation, have large weather-sensitive load components. The critical weather variable is the temperature in many systems in terms of its impact on the load. The difference of the temperature variable from the expected value for any given day can cause significant changes that involve significant changes in the unit commitment pattern. In addition, load profiles are often influenced by past temperatures. Humidity is a factor that can affect the device's load, especially in hot and humid regions. Owing to the change in temperature that they cause, thunderstorms also have a major impact on the load. Wind speed, precipitation, and cloud cover/light intensity are other variables that affect load behavior [10].

1.2.4 Random disturbances

The power system is made up of various types of users, such as residential, agricultural, and commercial. Good statistical rules show the total burden on domestic consumers. It is periodic, but on the other hand, however, industrial and agricultural loads are vastly inductive. Also, the start-up and shutdown of such a load type causes enormous spikes in the load curve. The random disruption is called spikes because it is very random in nature to start up and shut down these large loads and it is difficult to forecast the frequency of these spikes [11].

2. METHODS USED FOR ELECTRICAL LOAD FORECASTING

At present, it is possible to divide the forecast power load method into two groups. One is the classical forecast technique of the statistical class, such as regression analysis, method of time series, and technique of grey prediction. The other is the innovative artificial intelligence class prediction process, such as expert systems and artificial neural networks [2].

Artificial intelligence is an approach that, in an atmosphere of ambiguity and imprecision, resembles the extraordinary capacity of the human mind to think and understand. It is a technique to help computer-based intelligent systems emulate the ability of the human mind to use approximate rather than precise modes of reasoning. Artificial intelligence is a collection of disciplines, including fuzzy logic (F.L.), artificial neural networks (ANNs), fuzzy neural networks, evolutionary algorithms (E.A.s), such as genetic algorithms (G.A.s).

The artificial neural network is a concept used to generate a computational mathematical model and is identical to the structure and function of the brain. It consists of several simple processing units linked into a layered net-like structure,' cells' or 'nodes. 'The ANN cannot provide insight into the essence of the problem being solved and set rules for the selection of optimal topology for the network The need to hybridize the artificial neural network and Fuzzy logic arises due to some of the indecisions in the relationships between the input/output patterns eliminated by the fuzzy logic, thus there is increment in the functionality of the artificial neural network (ANN).

Artificial neural networks (ANNs), however, are the systems that have gained a high part of efforts and attention [3]. Recently, the application of artificial intelligence systems for load forecasting has centered on significant interests and efforts. This includes applying expert systems to forecast loads and evaluating their efficiency with traditional methods. The use of fuzzy and fuzzy-neural inference models is also needed.

According to [12], Artificial Neural Networks (ANNs) refer to a class of biological nervous system inspired models. The models consist of several computational components, typically referred to as neurons; each neuron has many inputs and one output [13], [14] [15]. It also contain nodes called synapses that link to the inputs, output, or other neurons. Most conventional ANN-based load forecasting techniques deal with 24-hour-ahead load forecasting or next day peak load forecasting.

The issue with this method is that load power changes drastically when rapid temperature changes occur on the expected day, resulting in a high forecast error. Conventional neural networks also, during the training process, use data from similar days. Training the neural networks using data from all similar days, however, is a multipart task and does not suit neural network learning [3]. In terms of physical parameters, the model obtained via the neural network is not understandable and it is difficult to deduce the result in terms of natural language.

2.1 Fuzzy Logic

According to [16], the usual Boolean logic that is used for digital circuit design is the basis of Fuzzy logic. In Boolean logic, in the form of "0" and "1" the input may be the true value. In the case of fuzzy logic, the input is linked to a quality-based comparison. For example, a voltage of a power supply may be "low" and "high". Fuzzy logic assists to logically derive the outputs from inputs. In this sense, the fuzzy simplifies mapping between inputs and outputs, such as curve fitting.

The merit of fuzzy logic is that mathematical models do not need to map between inputs and outputs, and there is also no need for accurate or even noise-free inputs. Properly designed fuzzy logic systems are stable on the basis of general principles for electrical load forecasting. There are several circumstances where detailed results are required. The"defuzzification" is carried to get the accurate results after the whole processing is completed using the fuzzy logic.

2.2 Adaptive Neuro-Fuzzy Inference System

According to [17], in 1993, The ANFIS technique was developed by Roger Jang to solve the shortcomings of ANNs and fuzzy systems. In short-term load forecasting (STLF), Neuro-Fuzzy methods have been commonly used. An integrated system consisting of Fuzzy Logic and Neural Network, the Adaptive Neuro-Fuzzy based Inference System (ANFIS), can answer and solve problems related to data non-linearity, randomness and uncertainty. According to [18], an adaptive network consist of a number of nodes, each node representing a process unit and the links defining the relationship between the nodes, linked by directional links. The ANFIS architecture for two input parameters, where nodes of the same layer have similar functions, is shown in Fig. 2. In ANFIS, some of the nodes are adaptive, while others are set. The Back propagation learning rule, which can be combined with other learning mechanisms to speed the integration of the learning process, is the key learning rule applied to the adaptive network [19]. Some node-relevant modifiable parameters depend on the performance of the adaptive nodes.

2.3 Methodology

2.3.1 Formulation of hybridized euro-fuzzy model

Adaptive Neuro-Fuzzy inference system (ANFIS) is a type of Neuro-fuzzy model. Both the Neural networks and fuzzy systems are stand-alone systems. ANFIS has the advantage of both neural networks and fuzzy logic. One of the advantages of the fuzzy system is that it describes fuzzy rules that more closely suit the definition of real-world processes. Its interpretability is an additional benefit of fuzzy systems; it is possible to describe the reason a specific value appeared at the output of a fuzzy system. Some of the key drawbacks of fuzzy systems are that expert expertise or guidelines are required to define fuzzy rules, and that the process of tuning the fuzzy system parameters frequently takes a very long period of time [20].

In the area of neural networks, a completely opposite condition can be encountered. Neural networks are known to be trained, but it is challenging to use previous information about the system under consideration and it is almost impossible to describe the actions of the neural network system in a specific situation. In terms of physical parameters, the model achieved by the neural network is not understandable and it is difficult to describe the outcome in terms of natural language. Several researchers have attempted to merge fuzzy systems with neural networks to make for the limitations of one system with the benefits of another system. A hybrid system named ANFIS has been proposed. Using a training algorithm, a fuzzy inference system is generated that allows the parameters of the fuzzy system to be tuned [18].

A Neuro-Fuzzy model is known as a combination of the Artificial Neural Network (ANN) and the Fuzzy Inference System in such a way that the Fuzzy Inference System parameter is determined by the learning algorithm of the Neural Network. The model is derived by using ANFIS to adjust the system of forecasting techniques, which is the method of formulating the mapping from a given input to an output using Fuzzy Logic.

Fuzzy systems are expert decision-making tools that need ANN support for inference generation. ANFIS is one of the best combinations of the concepts of neural-network and fuzzy-logic, offering smoothness because of the interpolation of Fuzzy Logic and adaptability owing to the backpropagation of ANN. ANFIS is capable of dealing with complicated and nonlinear problems. Even if the objectives are not given, they will easily achieve the optimum outcome. In short-term load forecasting, it offers quicker outcomes than ANN.

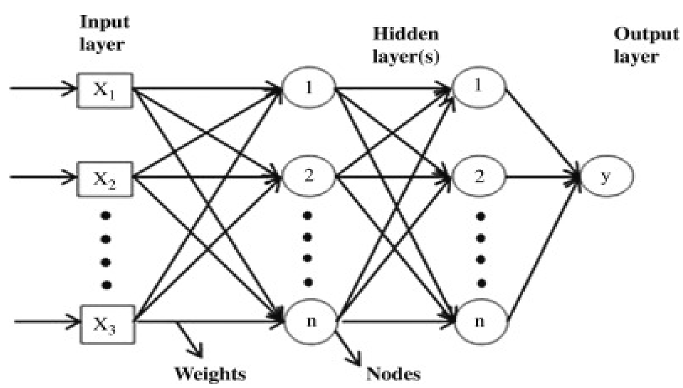

Fig. 1. Architecture of neural networks

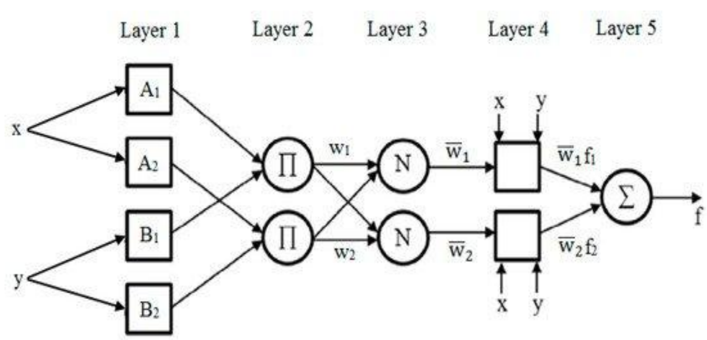

Fig. 2. Architecture Adaptive Neuro-Fuzzy inference systems

2.3.2 The ANFIS model

The operation of the model is shown using Figs. 3 and 4's flowchart and flow diagram, respectively. Firstly, all the parameters which are taken as input are initialized. Then it uses the dataset to train the ANFIS, then performs clustering on the basis of the dataset using KMC (K-Mean Clustering); after that, the Euclidian distance calculation takes place to forecast the values.After training the ANFIS with a data set, testing is conducted using a different dataset from that used for training and testing the outcome with the actual result and checking whether the accuracy of its forecast is achieved, then stopping the process otherwise beginning the same process again from initializing training, clustering, testing and then checking until the prediction is correct.

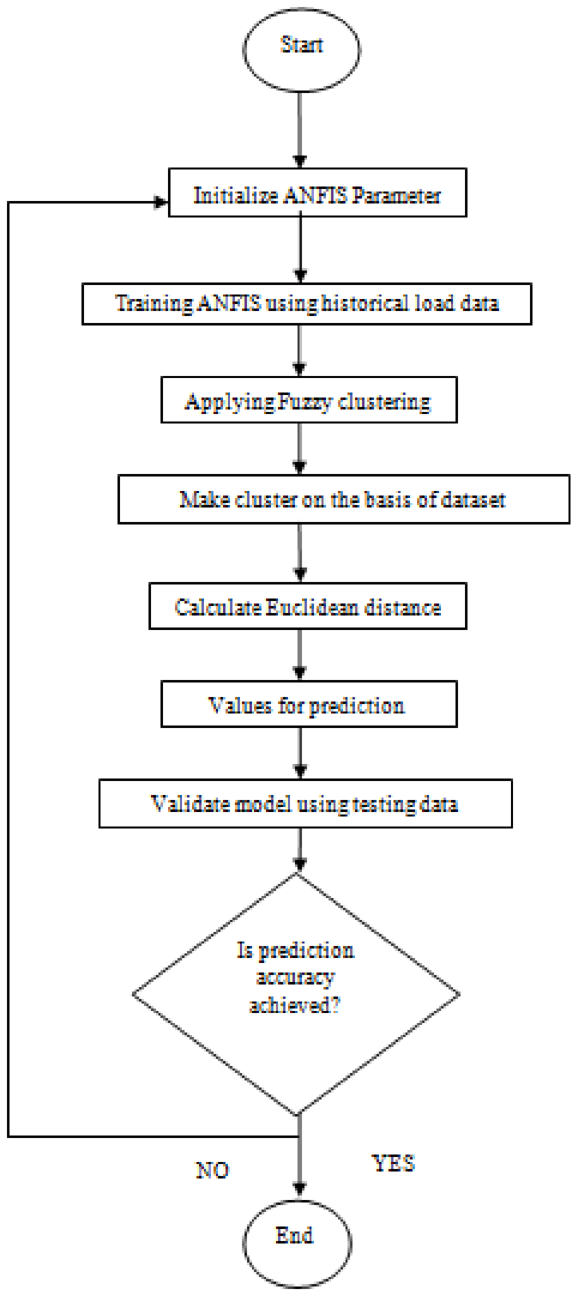

Fig. 3. Flow chart of the ANFIS model

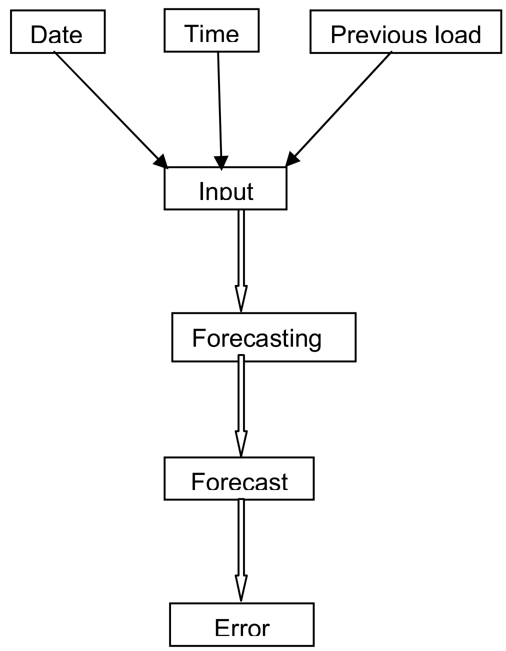

Fig. 4. The flow diagram of ANFIS model

2.3.3 Neuro-fuzzy model implementation

In the Fuzzy Logic Toolbox, the Fuzzy Logic Designer and Neuro-Fuzzy Designer systems are included. Neuro-Fuzzy Designer opens the Neuro-Fuzzy Designer app, which enables Adaptive Neuro-Fuzzy Inference Systems to load a data set and train (ANFIS). MATLAB's fuzzy logic toolbox makes it easy to construct fuzzy logic systems using the Graphical User Interface (GUI) and command line functionality features. Fuzzy Expert Systems and Adaptive Neuro-Fuzzy Inference Systems was developed using the tool (ANFIS). The ANFIS Editor display as shown in Fig. 5, is divided into four main sub displays:

i. Load data
ii. Generate FIS
iii. Train FIS
iv. Test FIS

2.4 Model Training

The objective of the ANFIS training algorithm is to minimize the approximation error. The historical data used in the Neuro-Fuzzy Model training are the hourly Electrical load data supplied to Oyo state in Nigeria, Ibadan City, to be precise, in August 2016 by Ibadan Electricity Distribution Company (IBEDC). Using these historical data, ANFIS used a hybrid optimization approach to change the generalized bell-shaped membership function parameter to decrease the error measure, which is the total of the squared difference between real and desired results.

2.5 Performance Evaluation

i. To test the neuro-fuzzy model, a portion of the historical load data collected was used; the data used for testing the model was not part of the data used for model training.
ii. The ANFIS model output was compared with the multilinear regression model output and the artificial neural network output.
iii. The output of the models were compared with the actual recorded load, and their performance was tested to assess forecasting performance using root mean square error (RMSE) and mean absolute error (MAE).

3. RESULT AND DISCUSSION

3.1 The Adaptive Neuro-Fuzzy Inference Model Implementation

The Adaptive Neuro-Fuzzy Inference model is the model utilized in this work. The systems for the Fuzzy Logic Designer and Neuro-Fuzzy

Designer are included in Matlab's Fuzzy Logic Toolbox. The Neuro-Fuzzy Designer apps allow the Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to load data set and train it, while the Fuzzy Logic designer allows the input variables and membership functions to be adjusted. The Adaptive Neuro-Fuzzy Inference model comprises of one output and three inputs, which are:

i. Hour of the day
ii. Day of the week
iii. Load of the previous hour.

3.2 Training of the Model

A 600 x 4 matrix data set was used to train the model. The model was trained using a hybrid optimization method for 150 and 170 epochs using different membership functions type; the results and the training model are shown in Table 1 and Fig. 6. The input layer has three inputs, and the load is the output parameter.

3.3 Performance Evaluation of the Trained Model with Testing Data

A collection of independent data not introduced during the training phase was used to evaluate the quality of the Neuro-fuzzy Model. A 20 x 4 matrix data set was used to evaluate the model. The test data set consists of 20 different data samples from different days only to test for the generalizing potential of the trained model, and these data samples have not been used for training purposes.

The testing process results are shown in Table 2 for the different membership functions type and each epoch.

Table 2 shows that for 170 epochs when a generalized bell-shaped membership function was used in training and testing the model, the Neuro-Fuzzy model gave optimum efficiency. The testing results are shown in Fig. 7. The plot of the actual load and predicted load by the Neuro-fuzzy model, artificial neural network and multilinear regression model are shown in Figs 8-10, respectively. It can be observed that the predicted data attained by employing the Neuro-fuzzy model closely follows the actual data.

3.4 Performance Evaluation of the Trained Model with Multilinear Regression Model

The output of the Neuro-fuzzy model, when compared with the output of the Artificial Neural Network (ANN) and Multilinear regression model, gives a better performance than the Multilinear regression model. When the three models were subjected to root- mean -square error (RMSE) and mean absolute error (MAE) test, it was observed that the Multilinear regression model has a RMSE of 4.4231%, Artificial Neural Network (ANN) has a RMSE of 2.7498% while Neuro-fuzzy model has the lowest RMSE of 2.2198%. Also, it was observed that the Multilinear regression model has a MAE of 3.7285%, Artificial Neural Network (ANN) has a MAE of 2.1887%, while Neuro-fuzzy model has the lowest MAE of 1.7932%. The results are shown in Table 3.

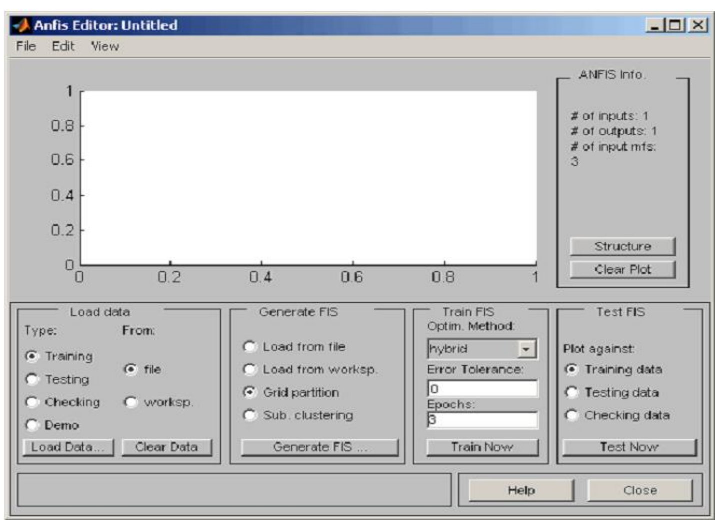

Fig. 5. Matlab Neuro-Fuzzy GUI

Table 1. Neuro-fuzzy model training result

Membership function type	Epoch	Training error
Generalized Bell	150	7.705
	170	7.6166
Triangular	150	8.2006
	170	7.6742
Trapezoidal	150	7.8931
	170	7.8931
Gaussian	150	7.7316
	170	7.7171

Table 2. Neuro fuzzy model testing result

Membership function type	Epoch	Training error	Average Testing Error
Generalized Bell	150	7.705	4.6673
	170	**7.6166**	**2.7352**
Triangular	150	8.2006	6.3603
	170	7.6742	7.1999
Trapezoidal	150	7.8931	5.6836
	170	7.8931	5.6836
Gaussian	150	7.7316	6.1133
	170	7.7171	7.3427

Table 3. Accuracy comparison of forecasting performance of Neuro fuzzy model and multi linear regression model

Performance metrics	ANFIS	ANN	MLR
RMSE	2.2198	2.7498	4.4231
MAE	1.7932	2.1887	3.7285

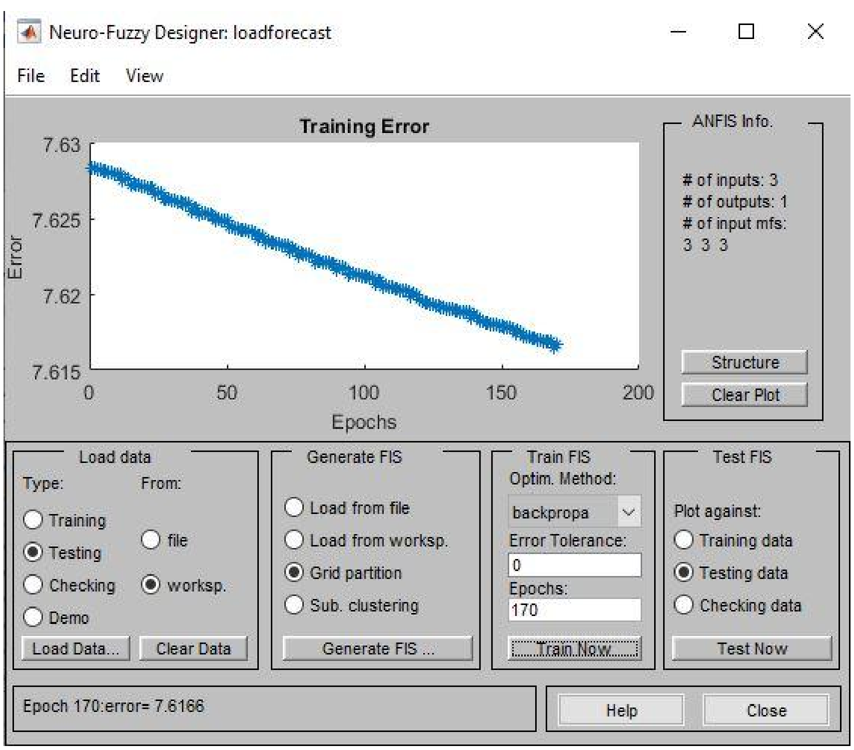

Fig. 6. Training data plot

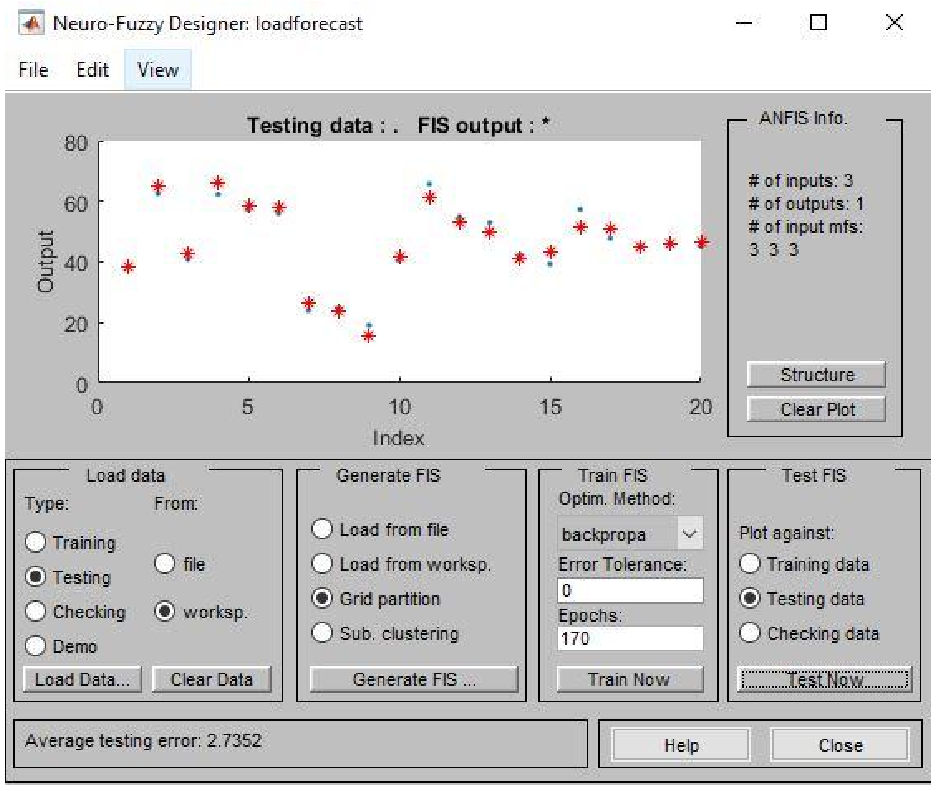

Fig. 7. Testing data plot

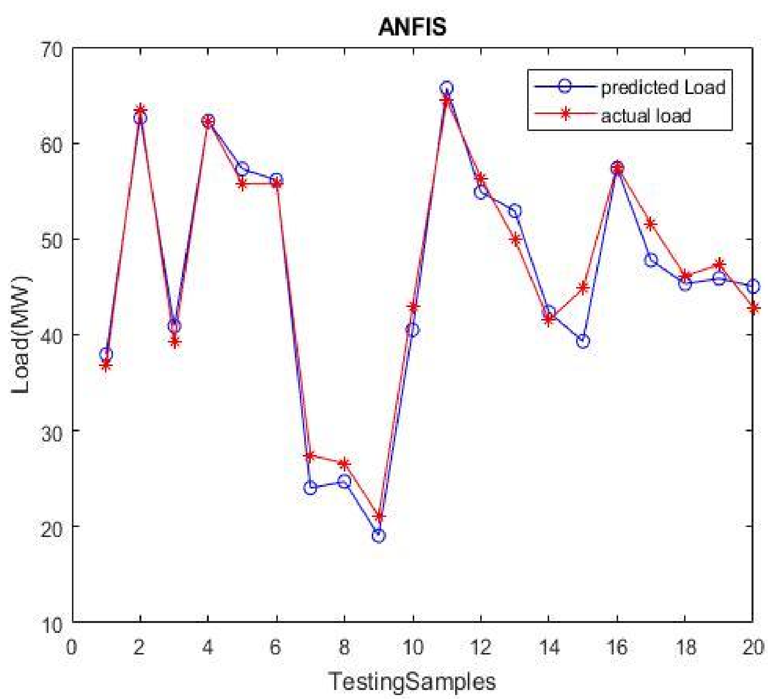

Fig. 8. Graph of Actual load and predicted load against time using Neuro fuzzy Model

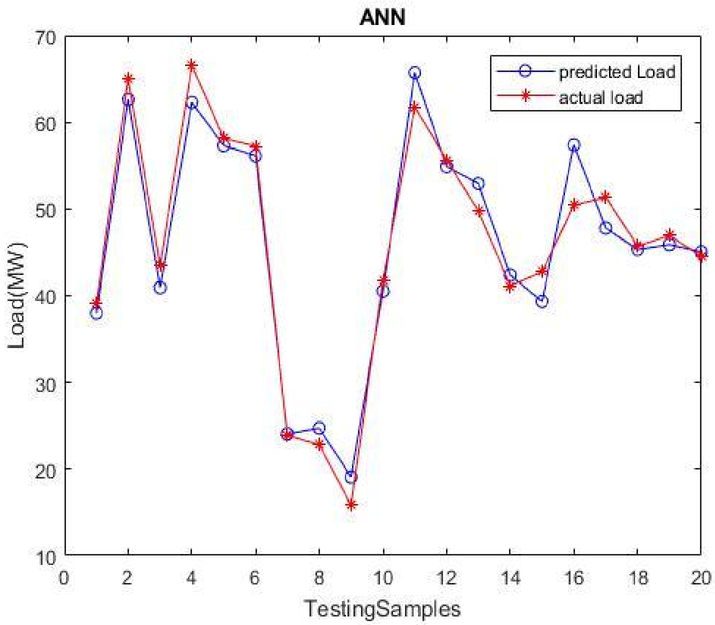

Fig. 9. Graph of Actual load and predicted load against time using ANN Model

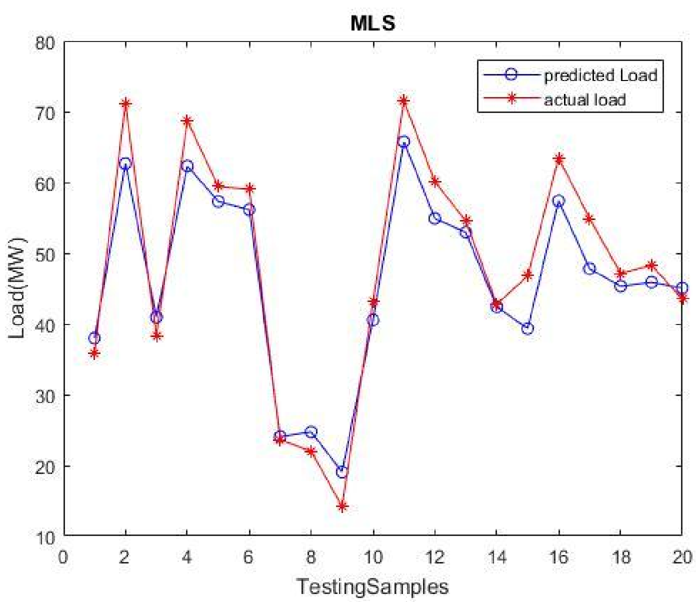

Fig. 10. Graph of actual load and predicted load against time using Multilinear regression model

4. CONCLUSION

This work focuses on using the Adaptive Neuro-Fuzzy Inference System (ANFIS) for electrical load forecasting. Compared to the Artificial Neural Network (ANN) and Multilinear Regression (MLR) model, the results obtained from the Neuro-Fuzzy Inference System (ANFIS) simulation show that the model gave the best output efficiency. The error produced by the Neuro-Fuzzy model is the lowest of three models compared.Due to the minimal error production in the ANFIS model, it can be deployed to forecast electrical load. The high accuracy of this model is important for the economical and effective planning of power plant operation and also for reducing the costs and losses of power generation. The results of this research when applied will aid in increasing the reliability of the power supply and delivery system, as well as in making important decisions for future development.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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Available:https://www.researchgate.net/publication/341426529

Peer-review history:
The peer review history for this paper can be accessed here:
http://www.sdiarticle4.com/review-history/67557