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# Load Forecasting using ANFIS

Mohammed Azhar, Dr. Imran Khan
Electrical Engineering, Azad Institute of Engineering and Technology
*mohmd.azhar@gmail.com, pe.imran@gmail.com*

**Abstract- In this paper, ANFIS is applied to the trouble of load forecasting in energy structures for an afternoon in advance. The ANFIS version learns both past and destiny family members from the load and the temperature. The proposed optimization model makes use of an evolutionary set of rules based on a local random managed search—simulated rebounding algorithm (SRA)—to choose the inputs to the ANFIS version. Using an optimization technique to decide linear and nonlinear relationships between the variables, a parsimonious set of input variables can be diagnosed improving the accuracy of the forecast. The input variables are updated while a new load pattern is passed off or while relative errors are unacceptable. With this replace is finished, a better tracking of the weight trend because of the process isn't strictly stationary. The ANFIS methodology is implemented to the Ecuadorian energy machine as an software example. Results and comparisons with different STLF methodologies (autoregressive incorporated transferring average, synthetic neural networks, and adaptive neuro-fuzzy inference machine) are proven, and conclusions are derived.**

## 1. INTRODUCTION

For hundred years there was a regulated electric power plants for the duration of the arena. In regulated demand in one location simplest one generating unit that produced, transmitted and sold electric energy and offerings. Regulated demand governed by vertically incorporated utilities. So there was monopoly (that means purchasers had no choice to choose their commodities supplier) of producing devices in regulated load demand. In early ninety's reforms of electricity demand commenced which included restructuring and unbundling of electric demand. Reforms had been primarily based on privatization of energy call for. Chile become the first u . S . A . Wherein restructuring of demand started, observed via a few Latin American countries and spread across the world. "Forecasting is a device used for predicting future demand based totally on beyond call for data." Forecasting is an essential making plans device that assists the choice-makers and planners to visualize and plan the destiny of the gadget in step with their necessity. In electric machine, time table and load forecasting are the 2 essential making plans equipment for generation, transmission and distribution systems. Forecasting is the procedure of creating statements about occasions whose actual consequences (usually) have no longer yet been found.

### 1.2 Importance of Forecasting:

Demand for products and services are usually uncertain.
Forecasting can be used for:

- Strategic planning (long range planning)
- Finance and accounting (budgets and cost controls)
- Marketing (future sales, new products)
- Production and operations

### 1.3 Types of Forecasting

1) Weather
2) Load
3) Price
i) Electricity Price
ii) Commodities

In this document our purpose is to forecast the electrical load call for as accurately as viable by way of designing a hybrid version and using numerous mistakes functions to test the accuracy of our result. Before deregulation come to existence a few decades back, the electrical electricity generation units were ruled by means of utilities that had full control over all activities within the location. However, after its first strive in Latin America, the unit has been in transition in most countries round the arena. In a deregulated demand, cease-use clients have the selection to pick out their power supplier.

## 2. RELATED WORK

Lei Wu, et al. (2010) [3] had proposed a hybrid time-collection and adaptive wavelet neural network (AWNN) model for the day-beforehand strength market clearing load forecast. The autoregressive moving common with exogenous variables (ARMAX) version is used to catch the linear courting between load go back series and explanatory variable load series, the generalized autoregressive conditional heteroscedastic (GARCH) model is used to unveil the heteroscedastic character of residuals, and AWNN is used to present the nonlinear, nonstationary effect of load collection on power loads. The Monte Carlo approach is followed to generate more calmly disbursed random numbers used for time series and AWNN models to accelerate the convergence. Several criteria together with common mean absolute percent blunders (AMAPE) and the variance of forecast errors are used to evaluate the version and measure the forecasting accuracy. Illustrative load forecasting examples of the PJM market had supplied to show the performance of the proposed method. The proposed hybrid time-collection and AWNN version composed of linear and nonlinear relationships of masses and explanatory variables, improves the performance of forecast effects. The utilization of one-length continuously compounded go back collection and AWNN has an advantage of modeling nonstationary power masses, specifically load spikes.

J.P.S. Catalao, et al. (2011) [4] supplied a hybrid shrewd approach for brief-time period power loads forecasting in a aggressive market. The proposed technique is based on the wavelet transform and a hybrid of neural networks and fuzzy common sense. The MAPE has an average cost of 6.53%, whilst the common computation time is much less than five s. Hence, the proposed method gives the high-quality trade-off among forecasting accuracy and computation time, thinking of the effects of previous guides. The results had been confirmed by using the use of the data of mainland Spain power marketplace.

Anbazhagan, et al. (2013) [5] had proposed a recurrent neural community model for the day ahead deregulated electricity marketplace load forecasting that would be realized using the Elman community. The proposed Elman network approach has been compared with autoregressive integrated moving average (ARIMA), combined model, neural community, wavelet ARIMA, weighted nearest associates, fuzzy neural community, hybrid sensible gadget, adaptive wavelet neural network, neural networks with wavelet rework, wavelet rework and a hybrid of neural networks and fuzzy logic, wavelet-ARIMA radial foundation characteristic neural networks, cascaded neuro-evolutionary set of rules, and wavelet rework, particle swarm optimization, and adaptive-network primarily based fuzzy inference system procedures to forecast the power market of mainland Spain. Finally, the accuracy of the weight forecasting had additionally implemented to the power marketplace of New York in 2010, which indicates the effectiveness of the proposed approach. Prediction results of real-global strength marketplace of mainland Spain and New York for the four weeks of the year 2002 and 2010 had been stated, yielding a median weekly MAPE near 6.Fifty six% and 3.82%, while the average computation time is much less than 650 ms and has better capability to enhance the trouble of predicting load spikes. The simulation consequences from the comparisons truely confirmed that the proposed technique is good in forecasting accuracy than different forecast strategies except for the hybrid models inclusive of WNF, wavelet-ARIMA-RBFN, CNEA, and WPA; and the average computation time became less compared to above hybrid models.

Sergey Voronin, et al. (2013) [6] had proposed a hybrid method for the prediction of ordinary variety power marketplace masses which additionally has the ability to predict the incidence of strength market load spikes. The proposed mixed time series and ANN fashions, composed of linear and nonlinear relationships of loads and exogenous variables, improved the overall performance of normal range load forecast effects. An ARMA based model is used to trap the linear relationship between the ordinary variety load series and the explanatory variable, a GARCH version is used to unveil the heteroscedastic man or woman of residuals and a neural community is implemented to present the nonlinear effect of the explanatory variable on energy loads and enhance predictions based totally on time collection techniques.

Marin Cerjan, et al. (2013) [7] provided a paper which offers a top level view of terrific load forecasting strategies which have been published in studies papers. This paper supplied an outline of contemporary trends in the field of strength load forecasting as well as an outlook for in addition load forecasting strategies improvement. This paper also included statistical overview of carried out techniques embracing time frame, geographical heritage, statistical errors and other precise facts. Finally, consequences were mentioned with recognize to qualitative and quantitative statistical evaluation, with emphasis on the load forecasting accuracy.

## 3. METHODOLOGY

A fuzzy inference gadget can use human know-how via preserving its critical additives in rule base and database, and perform fuzzy reasoning to infer the overall output value. The derivation of fuzzy if then policies and constant membership features rely deeply at the a priori knowledge approximately the gadget under challenge. However, there are nevertheless basic but critical problems concerning the guidance and manipulation of knowledge. Firstly, no systematic manner exists to transform enjoy or expertise of human experts to the expertise base of a fuzzy inference machine and secondly, there may be nonetheless a want of adaptability or mastering algorithms to track the club features so that you can minimise the discrepancy between fashions (calculated) output and preferred output [8][9]. These problems substantially restrict the utility domains of FIS. On the alternative hand, Neural Network modelling does now not rely on human information. Instead, it employs a mastering process and a given schooling records set to solve a fixed of parameters ( i.E. Weights) such that the required functional behaviour is achieved. No powerful strategies have been proposed to determine the initial weight values and network's configuration ( e.G. Variety of hidden layers and hidden nodes ).

Thus the drawbacks pertaining to those techniques seems complimentary. Therfore it appears herbal to remember constructing an incorporated machine combining the ideas of fuzzy common sense modelling and neural network modelling. In other words, the included approach, or neuro-fuzzy modelling, ought to comprise the three most critical functions,

Meaning and concise representation of established knowledge.

Efficient getting to know functionality to perceive parameters.

Clear mapping between parameters and dependent information.

**Approach for forecasting model development:**
Here it has been described that how the ANN and fuzzy logic approach are developed and used for load forecasting model development. Using the ANFIS and fuzzy logic toolbox.

1. Acces the data in excel format from data link http://rpubs.com.
2. Arrange the data in consecutive month wise sequence or day wise sequence.
3. Import data to the matlab.
4. Randomly shuffle the data.
5. Distribute 70% percent part as training dataset,15percent as validation and remaing as testing data set.
6. Apply ANN training algorithm to generate fuzzy logic equation by using training data.
7. Find mean square error in validation data.
8. Update the fuzzy logic equation parameters by random way as done in hit and trial method as per value of validation error.
9. Iteratively updates the equation parameters until lower mean square error not obtained.
10. Continue the parameter update and error based cheking until further decrease in MSE is not stopped.
11. Find the testing error and if testing error is found to be very small then apply foresating using the developed model.

## 4. RESULT AND DISCUSSION

An algorithm using ANFIS based model development using ANN based approach for developing Fuzzy logic system is applied on MATLAB based programming using ANFIS and fuzzy logic toolbox. Results are validated on showing the performance plot in terms of Mean square error as shown in figure 1. It can be seen that the MSE is found to be 19.9096 MW on validating the developed load forecasting fuzzy model.

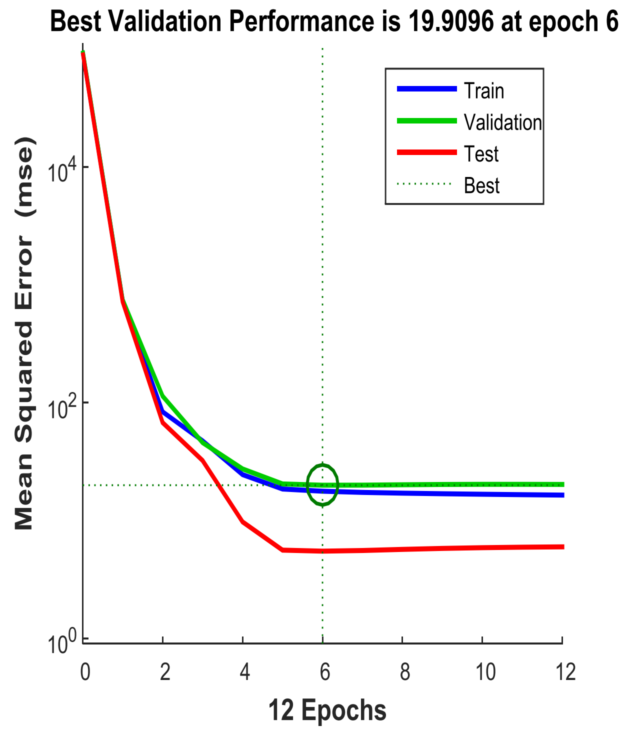


**Fig. 1. Training, validation and testing performance in terms of error in ANFIS**

After getting the performance in terms of MSE the regression value for training , testing , validation and all data is demonstrated. Training data is 70% of all data used by ANN to find the Fuzzy Logic Equation by hit and trial iteratively. Validation is run alongwith traing to update the equation parameters. While testing is applied on all the developed models during traing.Both validation and testing data are 15% of all data. The regression value represent the fitness of forecasted value with actual value. Larager regression value (near about 1) means forcasted and actual value are well proportionate and very close to each other. These vlue are shown in figure 4.2.All regression values are very close to one.

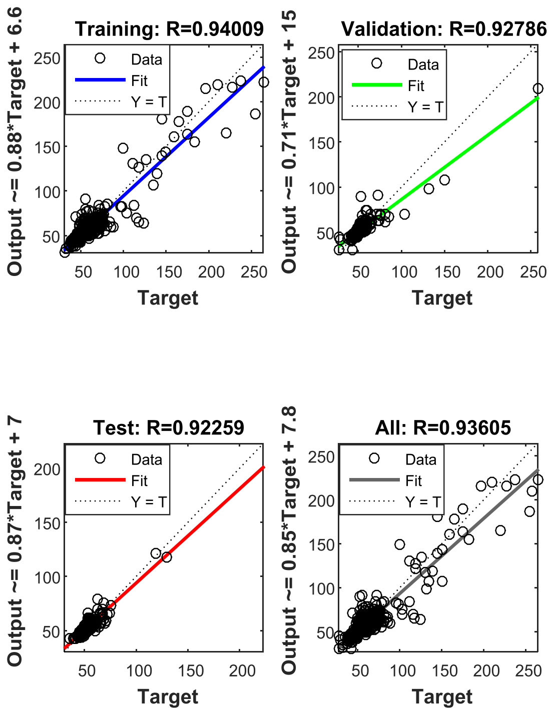


Fig. 2: Regression plot

Finally plots are generated in between actual and forecasted values after perormin prediction it can be seen in the figure 3 that the forecasting on the week ahead forecast data for NSW electricity is varying in proportion with actual load data for spring season. The approximated.

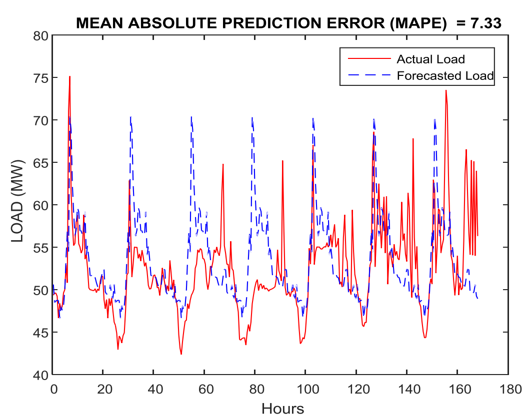


**Fig. 3. Actual and forecast week-ahead NSW electricity load in spring season.**

Similarly plots are generated in between actual and forecasted values after perormin prediction it can be seen in the figure 4 that the forecasting on the week ahead forecast data for NSW electricity is varying in proportion with actual load data for summer season. The aporoximated error value is also plotted and the MAPE value is found to be 4.77 MW.

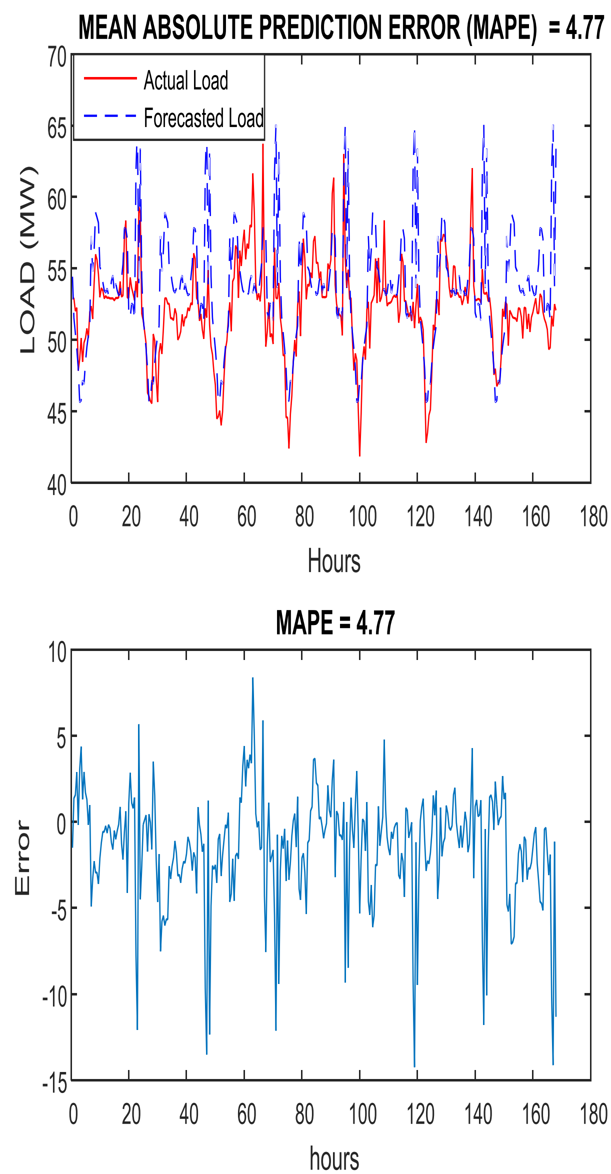


**Fig. 4. Actual and forecast week-ahead NSW electricity load in summer season.**

Similarly plots are generated in between actual and forecasted values after perormin prediction it can be seen in the figure 5 that the forecasting on the week ahead forecast data for NSW electricity is varying in proportion with actual load data for autumn season. The approximated error value is also plotted and the MAPE value is found to be 11.65 MW and 565 MW for winter season (Figure 4.6).

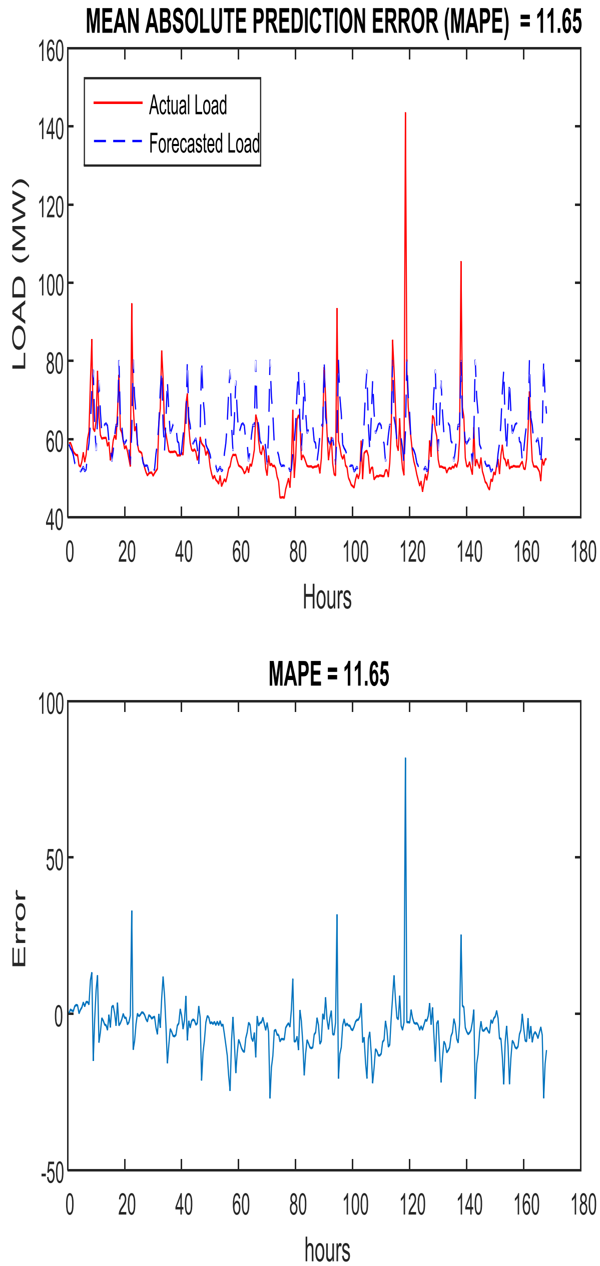


**Fig. 5: Actual and forecast week-ahead NSW electricity load in autumn season.**

All the results are also compared with existing models like regression based forecasting that is ARIMA and ANN based load forecasting for day head and week ahead load forecasting. All the results are tabulated in table 1, 2 and3.

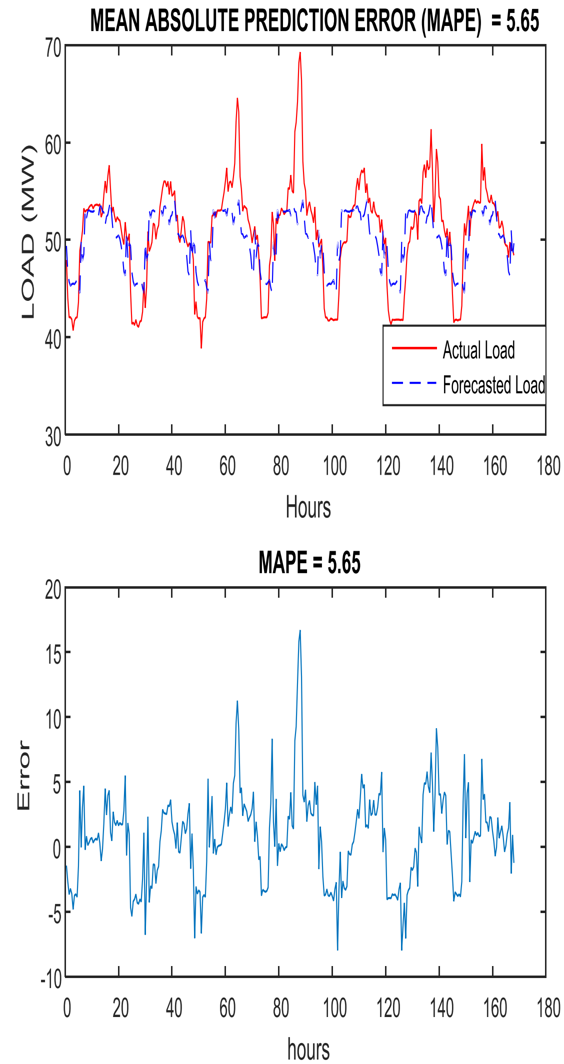


Fig. 6 Actual and forecast week-ahead electricity load in winter season.

**TABLE 1: Comparison of MAPE results between various models for a day ahead**

| Seasonal /Period | ARIMA | ANN | ANFIS |
|---|---|---|---|
| Summer | 13.39 | 10.70 | 8.69 |
| Autumn | 9.27 | 6.78 | 8.37 |
| Winter | 6.32 | 4.78 | 6.20 |
| Spring | 6.36 | 5.69 | 6.61 |

**TABLE 2: Comparison of MAPE results between various models for a week ahead**

| Seasonal /Period | ARIMA | ANN | ANFIS |
|---|---|---|---|
| Summer | 16.06 | 10.70 | 4.7 |
| Autumn | 13.78 | 12.27 | 11..65 |
| Winter | 14.30 | 9.78 | 5.65 |
| Spring | 10.46 | 8.78 | 7.36 |

**TABLE 3: Forecasting results for a week with ANFIS Model**

| Seasonal /Period | RMSE | MAE | MAPE(%) |
|---|---|---|---|
| Autumn 21-27/05/10 | 4.70 | 2.62 | 4.7 |
| Winter 20-26/08/10 | 10.70 | 3.98 | 11..65 |
| Spring 22-28/10/10 | 2.38 | 1.90 | 5.65 |
| Summer 22-28/01/11 | 6.50 | 4.92 | 7.36 |

## 5. CONCLUSION

An accurate forecasting power load is a critical trouble of problem for all market contributors, either for growing bidding strategies, or for making investment decisions. In this thesis, a Neuro Fuzzy version turned into proposed for load forecasting. The overall performance of the proposed model is established using New South Wales (NSW) electricity load statistics. Adaptive Neuro Fuzzy Inference System technology is a promising approach for strength load forecasting because of its effective ability in nonlinear simulation. In this thesis report, a multilayer perceptron Adaptive Neuro Fuzzy Inference System version is constructed for dayahead power load forecasting in deregulated electric electricity marketplace. By the outcomes observed in this paintings it could be concluded that the proposed models have generated reasonably properly forecast effects. The training of the Adaptive Neuro Fuzzy Inference System with special training algorithms and blunders capabilities gives the great outcomes. The load charge records is highly risky and non-desk bound in nature which needs to be tuned up for higher forecasting effects. I even have implemented the ANFIS model and Fuzzy-ANN model for power load forecasting with specific education algorithm. The errors may be minimized the use of hybrid models that's the aggregate of Fuzzy with ANN.

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