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Convolution of Time Series Electrical Load Forecasting Using Recurrent Neural Network Techniques

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Abstract: Electricity energy is the major infrastructural prerequisite for developing nations. Modern energy services are dominant engines for the economic development of a country. However, countries must need to manage all the electrical energy resources in order to ensure continuity in energy supply. As the electrical energy can't be stored. So, the demand and supply should always need to be equal. Thus, electrical power system generation and consumption must be accurately forecasted and instantaneously controlled. Various statistical and probabilistic forecasting models are presented in literature till date, but all of these techniques are not precise in a satisfactory manner. In this research article, a recurrent neural network is used to forecast day-to-day power consumption. Two RNN techniques are used i.e. Nonlinear autoregression exogenous model (NARX) and Elman artificial neural network model (EANN). The performance of the proposed technique is assessed with the simulation on the load data collected from national grid of Rhode Island United States. The robustness of the proposed technique is judged by comparing it with the classical Artificial neural network (ANN) and Backpropagation neural network. The experimental results show that NARX is better in all the aspects. Finally, the robustness of the proposed technique is judged on the bases of their mean square error MSE and root mean square error RMSE.

Keywords: Electricity Load Forecasting. Artificial Neural Networks, Back Propagation Neural Networks, Elman Artificial Neural Networks, Nonlinear Auto Regression Exogenous.

1 Introduction

Electricity load forecasting is a vital research element of today's world power system. Technology has been achieving heights of novelty abruptly [1]. With these abrupt changes in technology, update for the power system management is necessary [2]. Using technology miracle, electrical utilities are classified into distinct categories with respect to their power consumption capacity [3]. Appliances which consume more power are termed as high voltage appliances. Similarly, there are medium and low power consuming appliances. In previous decades high voltage loads were limited to commercial and industrial regions but now a day's residential loads are so diverse, they have all the variety of loads [3]. Therefore, the planning for load consumption is necessary even on the residential side.

Electricity load forecasting is essential for energy planning of the government. Overestimated load means wastage of resources and finance [4]. On the other hand, underestimated load would lead to the energy crisis in a country, resulting in a massive economic failure [5]. To avoid both extremes it is wise to plan one's country energy requirement in advance [6].

Electricity forecasting models are established particularly for a country or a grid. The reason for a specific forecasting model for a grid or country is that every country has several factors affecting its load consumption. Even the patterns of load consumption vary from citizen to citizen and from state to state. So, the first and foremost step of load forecasting is identifying the factors which affect its load pattern. In [7] parameters like an hour of the day, the day of the week, dry bulb temperature, numbers of weekdays and weekends, humidity, previous day load, and temperature were used [1]. The second step is the choice of methodology for load forecasting model. Generally, the forecasting models are classified into two categories i.e. conventional techniques and modern computing techniques. The conventional methods include time series, regression, economic models while computing techniques include support vector machines (SVM), fuzzy logic and ANN methods [8], [9]. A brief literature survey is shown in the next section.

1.1 Literature Survey

A transformation technique which is further based on a regression algorithm has been adopted in [10]. The transformation function works with the aid of translation and reflection techniques. Daily peak load is forecasted. The author develops a forecasting technique which used nonlinear load-weather relationship and load-weather characteristics. The model has been evaluated based on absolute error and standard deviations.

Two statistical models were used on time series in [11]. Both models use two components for electricity load forecast. The one representing seasonality is a deterministic component. The other one is stochastic component representing noise. The seasonality reduction method used for Model A is differencing and on the other hand Model B utilized seasonality removal technique. Based on mean absolute percentage error (MAPE) it is observed that Model B outperform Model A.

Multiple linear regression (MLR) is investigated for short-term load forecast in [12]. The MLR has been implemented in Microsoft Excel software. The model is dependent on previous load values and temperature. It is stated that MLR performs well for short-term forecast only.

Based on support vector regression (SVR) machines, a collective strategy for immediate load forecasting is proposed in [13]. In the concerned study, researchers used two data sets. One is ISO New England and second is a North-American load. The authors proposed that the effectiveness of SVR is dependent on the structure of data sets.

A detailed survey on various forecasting models has done [14]. Support vector machine (SVM) is superior to other models. SVM is used for regression and data classification and implemented on time series data. Other forecasting models are a local model, Neural Network (NN) models. Also, a few other models are considered. These models have a different structure of data sets. The author suggested that SVM performed better than other models.

Large-scale linear programming support vector regression (LP SVR) has been studied in [1]. A comparison of LP SVR is done with other three non-linear regression models. A data set of New

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England power pool region is selected. Regression models are developed for eight different variables. Experiments show that MAPE is least for LP SVR.

A fuzzy logic based short-term load forecasting model is presented in [15]. Weather and previous years load are used as input. Fuzzy rule-based interference along with Kaplan filters are used. The technique produces spread and crisp values of forecasted load.

A simulated annealing (SA) and chaos search genetic algorithm (CGA), together with fuzzy neural networks are used in [16]. The proposed method offers better performance in term of error rate and forecasting accuracy.

The rest of paper is organized as follows, section 2 describe time series models. While section 3 deals with the proposed NN model. Section 4 will focus on results. Finally, the last section describes the conclusion and future recommendation.

2 Time Series Forecasting Models

A sequence of collected observations which is organized into data with respect to time is termed as time series. Time series can be categorized into two types: univariate and multivariate. Univariate is an important class of times series and is widely used in literature. The expression for univariate times series is $X=[x^1,x^2,x^3,\ldots,x^n]^T$, where x(t) is data observation at a time t.

The past and present data set is required for prediction in time series. Forecasting is a widely used phenomenon for time series data. Time series data required information like energy consumption detail, rainfall prediction, stock exchange, trading, economy and many more required forecasts for smooth and vivid working of concern departments.

2.1 Neural Networks

Neural networks (NN) is a computing system inspired by the human brain. The human brain works with biological neurons to perform its task. In the same manner, NN uses neurons to perform its various task. The neurons in NN receive a task-oriented signal and process the given signal to transmit the processed signal to next neurons.

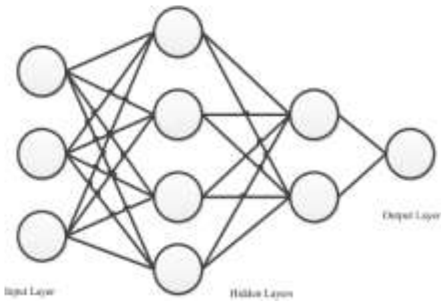

Figure. 1. A Structural Representation of Artificial Neural Networks.

NN generally composed of three main layers. First comes the input layer, all the input is processed by this layer. Then comes the hidden layer, this is the most important layer of NN. NN resembles the human brain, because of this hidden layer. In the hidden layer, that all the complex and long problems are solved. The last layer is the output layer, which gives the output of the given problem.

Fig. 1 shows a structural diagram of NN. In the input layers neuron accessed the input. Each of these neurons in the input layer along with some added preprocessed weight transmits input to each neuron in the hidden layer. The decision making of each input will be dependent on the weight added to it. The added weights have a preset threshold limit. The neurons in NN will fire if the weight exceeds its thresholds limit, else they will not fire. Many algorithms in NN allow neurons to adapt. Neurons adapt with respect to the weight associated with them.

In the hidden layer, every single neuron will get signals from inputs and again perceptron or weight will be added to each signal processed. As a result, the weighted signal will reach each output neuron. The neurons in the output layer processed these weighted signals and give an optimize output.

Compared to traditional computers, NN follows a different processing pattern. In computers, there are certain defined commands that are based on pre-defined algorithms to solve the problem. Whereas, in NN a parallel processing of neurons is going on. Instead of using a predefined command, learning of NN proceeds by example. So, the choice of example of the problem is crucial. NN itself decide how to solve a problem.

NN is in use for forecasting since 1943. When the system under consideration is nonlinear and have a noisy time series, neural networks perform well compared to conventional methods being used in literature. In this scenario, the nonlinearity of NN models and their better immunity to noise, are the reasons for the better performance of NN.

In this research work, various NN models are used for forecasting of a time series data. These include simple Artificial Neural networks (ANN), Back Propagation Neural networks (BPNN), Non-Linear Autoregressive with Exogenous Input (NARX) and Elman Artificial Neural Networks (EANN).

2.2 ANN

ANN is a simple feed-forward neural network model with time delay. ANN is the simplest neural network with no feedback provided. In comparison with other neural network techniques, ANN is less efficient, as there is no history of previous states available. Mathematically ANN can be expressed as follows,

$$y(t) = g(x(t-1), ..., x(t-m)) \tag{1}$$

Where y(t) is the output, x(t) is the input series and m is the delay. The m delay added to the input will enable output to look back at t-1 inputs.

2.3 BPNN

Rumelhart and McClelland [17], proposed a BPNN model. For time series forecast, BPNN is very popular feed forward NN model. The model has got a lot of praises due to its non-linear and non-parametric modeling. Also, it has parallel computing ability and robust flexibility. The BPNN model generally consists of an input layer, one hidden layer, and an output layer. BPNN gives desired results for time series data even with one hidden layer [18].

In BPNN, gradient descent and delta rule techniques are used. These techniques enable BPNN, to adjust weights to reduce error. The weights minimizing the error function will be considered a solution to the problem [19]. First, forward propagation is done in BPNN. Later error minimizing functions are implemented through back propagation to get better results.

$$I_j = \sum_{j=t-n}^{t-1} w_{ij} \times y_i + \beta_j (j = 1, ..., h) \tag{2}$$

$$y_j = f_h(I_j)(j = 1, ..., h) \tag{3}$$

$$I_0 = \sum_{j=1}^{h} w_{oj} \times y_j + \alpha_0 \tag{4}$$

$$y_t = f_o(I_o) \tag{5}$$

Where I represent input and y represents output. Eq. 2 and Eq. 3 shows input to output values for the hidden layer respectively. Eq.4 and Eq. 5 shows input to output values for the output layer [18].

3 Proposed Technique

3.1 RNN

Recurrent neural networks (RNN) have been in limelight for time series-based forecasting because they can tackle complex time-varying sequences. RNN resembles feedforward networks but compares to feedforward networks in RNN each layer has a recurrent connection with a tap delay associated with it. The feedback is connected to past decision, feeding their outputs instant to input. As a result, RNN has an infinite dynamic response to time series input data.

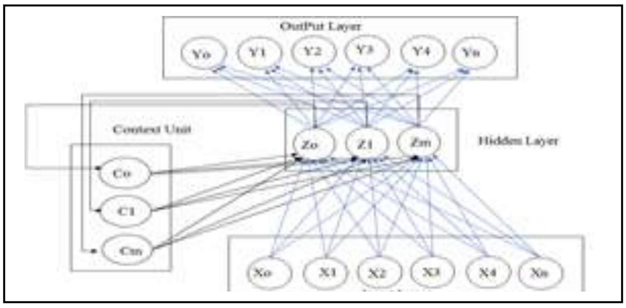

Figure. 3. Block diagram Representation of RNN

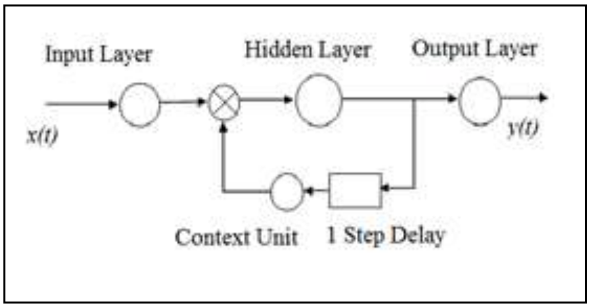

Figure. 2. Detail Neurons Based Structure of RNN.

RNN uses memory. This memory has a specific purpose in NN. The information in the network is in sequence and RNN uses this information to accomplish a task which feedforward network cannot perform [20]. A storage unit known as context unit is employed in first-order RNN. The common types of RNN are Nonlinear Autoregressive Extraneous Network (NARX) and Elman Neural Network (EANN).

3.1.1 NARX

In most of the times series data, there is a relation between the time series and external data. The external data can be any factor influencing the time series. In the scope of electric load forecasting, historic hourly load consumption is the main time series data. The external features which affect the time series data are year, months, weekdays, weather, temperature, humidity etc. Therefore, along with the time series, the knowledge of external factors which are influencing the time series is also important.

The nonlinear autoregressive with exogenous inputs has been proposed in [21]. NARX forecast a time series y(t) given f past values of series y(t) and another external series x(t). The equation describing NARX completely is mention below

$$y(t) = g(x(t-1), x(t-2), \dots, x(t-m), y(t-1), y(t-2), \dots, y(t-f) \quad (6)$$

Where, x(t) ϵ ℝ and y(t) ϵ ℝ, while m≥1 and f≥1, m≥f, are the input-memory and out-memory orders, respectively. The equation in vector form can be written as follows

$$y(t) = [g(y(t); x(t)] \quad (7)$$

Where, the vectors y(t) and x(t) denote the output and input regressors, respectively.

The nonlinear autoregressive model with external input is becoming popular for times series-based forecast. The external input is usually a feedback of output. Compare to ANN, the feedback in NARX improves its efficiency.

3.1.2 EANN

Elman discussed a new RNN based model known as Elman Neural Network (EANN). As compared to other models mentioned in this manuscript. EANN is a four-layered network as shown in Fig. 2. The input layer, hidden layer, a context unit (undertake layer) and an output layer.

Input layer, hidden layer, and an output layer of EANN are based on feedforward network as it can be seen in Fig. 2. Signal transmission is done by the input layer unit. While output layer unit behaves as a linear weighting tool. EANN main characteristics are its context unit. The context unit has delay storage and associates to the hidden layer [22].

The major function of the context unit is to store the computation history of state neurons in past time steps. With the history of the previous state, the context unit process present states of the neurons of the hidden layer. In EANN, the context layer creates a systematic history of hidden layer output.

$$y_i(t) = f\left(\sum_{k=1}^{K} v_{ik} y_k(t-1) + \sum_{j=1}^{J} w_{ij} x_j(t-1)\right) \quad (8)$$

Where, y_kt and x_jt represent the output of undertaking (context) unit and input neurons, respectively and represent their corresponding weights. The sigmoid transfer function is f(*).

For our concern study, preprocessing of time series data is essential. The dataset must be constructed as state space vector, for EANN to implement on data. For a time series, the phase space of output will be as under

$$y(t) = [(x(t), x(t-T), \dots, x(t(D-1)T] \quad (9)$$

Where, T is time delay,a D is dimension.

Taken theorem states that most of the attributes of the original time series can be generated from vector series. To work efficiently, values of D and T must be chosen wisely. It is proved, for the dimensions of the original attractor as d, then D=2d+1 will be used to regenerate the attractor.

In EANN, the regenerated vector will be used to train the network. In EANN one neuron in input and output layer will be used as one step ahead prediction. The EANN expands k steps in time, which is equivalent to dimension D.

4 Experimental Setup

4.1 Data Sets

For the proposed forecasting model is a time series based dataset. The dataset has been obtained from [12]. The dataset is derived from an estimated system of National Grid Distribution Companies for a residential group of Rhode Island in the northeastern United States. It consists of historical hourly load consumption for a period of January'2010 to present day. All the load is converted into MWh for the sake of ease.

For forecasting, all the data is divided into categories viz. (i) Training Data (ii) Testing Data. Training data comprise of maximum part of the data. This data is used for training the model for a problem. Later, testing data will be used to test the validity of our proposed model that already described in section 3. All the experiments are performed using MATLAB2014b on a personal computer with Intel Core 2.70 GHz CPU and 8GB main memory.

4.2 Data Preprocessing

Data processing contains mainly the parameters selection and the tuning of that selected parameters for the neural networks to check the performance and behavior of NN by performing the tuning test.

4.2.1 Parameter Setting Tuning Test

The performance of forecasting depends upon the NN model being used. NN model performance is dependent on the selection of NN's structure. For our concern study, one can experiment with as many structures as one wants. There is a lot of scope in Neural Network structures depending on: number of output layers, number of neurons and type of training function.

4.2.2 Network Parameters

The parameters which are changed for this research are presenting in Table 1.

4.3 Proposed Neural Networks Architecture

4.3.1 Hidden Layer Size

For this research, one hidden layer is utilizing for each network. In this case study, networks perform best with 30 neurons along with the neurons for the output layer are 10 and 10 delays are used in the hidden layer. The larger the number of delays the efficient the network will be. The

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number of delays is associated with past input values. It allows output to look backward in the input.

Table 1. Neural Networks Parameters

Hidden Layer Size	Network Type	Transfer Function	Performance Function	Training Algorithm
10	ANN	Logarithmic-sigmoidal	MAE	BFGS
30	BPNN	Tangential Sigmoidal	RMSE	Levenberg-Marquardt
50	NARX	Linear	…	Scaled Conjugate Gradient
…	EANN	…	…	…

4.3.2 Transfer Functions

Every neuron utilizes a transfer function, to provide output to its input. Below mentioned three transfer function are used for load forecast of given dataset:

1. The **logarithmic sigmoidal transfer function** comprehends an input value between positive infinity and negative infinity. It returns an output ranged between zero and a positive one.
2. The **tangential sigmoidal transfer function** comprehends an input value between positive infinity and negative infinity and produces an output, having a value between positive one and negative one.
3. The **linear transfer function** produces a linear delineate of input to output.

4.4 Neural Network Training

The training algorithm and performance function affects the performance of neural networks and the performance outcomes have discussed in the coming section.

4.4.1 Training Algorithms

Table 2 shows the training algorithm available in MATLAB. The choice of right algorithm is important. It depends on the complexity of the problem, datasets, training weights, biases and error goal.

All these algorithms are beneficial and work efficiently. The popular times series-based algorithms are the following:

The **Bayesian Regularization** is used to mitigate squared errors and weights. To get better generalization qualities, BR transforms linear combination. The BR algorithm works within the Levenberg-Marquardt algorithm. BR generally takes more time but ends at a workable solution for noisy and small problems. Bayesian regularization works well for most of the time series, but in this case study, the results were worst. That is why it has been omitted from this research.

Table 2 A Tabular Representation of Various Training Algorithms

Acronym	Algorithm	Description
LM	trainlm	Levenberg-Marquardt
BFG	trainbfg	BFGS Quasi-Newton
RP	trainrp	Resilient Backpropagation
SCG	trainscg	Scaled Conjugate Gradient
CGB	traincgb	Conjugate Gradient with Powell/Beale Restarts
BR	trainbr	Bayesian Regularization
OSS	trainoss	One Step Secant
CGF	traincgf	Fletcher-Powell Conjugate Gradient
CGP	traincgp	Polak-Ribiere Conjugate Gradient
GDX	traingdx	Variable Learning Rate Backpropagation

Levenberg-Marquardt algorithm approximates Newton's method by updating network weights and biases as given below:

$$x_{(k+1)} = x_k - [J^T J + \mu I]^{-1} J^T e \quad (10)$$

Where J is a Jacobian matrix, e is a network error's vector and μ is a scalar. J have first derivatives of network errors corresponding to weights and biases. μ is a measurement criterion for the algorithm, μ determines network approximation to Newton method. If μ is zero, then the above equation will be newton's method. If μ is large, the above equation becomes gradient descent with a smaller step size.

Scaled Conjugate Gradient algorithm is developed on conjugate directions as in other algorithms. The scaled conjugate gradient differs from other algorithms, as it does not do a line search for every epoch (iteration). The SCG compared to LM takes less memory. So, in low memory situation scaled conjugate algorithm is preferred. The training in scaled conjugate algorithm stops when improvement in generalization ends, which is indicated by an increase in mean square error.

4.4.2 Performance Functions

A supervised learning performance function is used in Neural Networks. The proper update of weights and biases are done in supervised learning. The Neural Network models are trained in supervised learning. The difference between target and projected output will be termed an error. For load forecasting, neural network's weights are adapted using one of the following two performance functions to reduce error:

1. Least mean of squared errors (MSE): minimizes the average of the squared network errors.
2. Root Mean squared errors (RMSE): represents the closeness between output and target.

5 Results and discussion

In this section the effectiveness of the proposed model and discussion of the result of each model has discussed in detail. A detailed comparison of the proposed model with the other well-known three models is also described.

ANN model is used for forecasting purpose in MATLAB environment. As discussed already, no history of previous states is present in ANN model and it is a simple feed-forward network with delay, so the performance of a simple ANN model compared to other models is not satisfactorily. Time series response for one month is shown in Fig. 4. Two months forecast is represented in Fig. 5. Three months forecast is shown in Fig. 6. The time series plot shows that output is not following target perfectly.

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BPNN model used to feed forward as well as back propagation. The back propagation enables this network to minimize the error. In our study, BPNN performs much better than ANN. This is mainly due to additional back propagation involved in the model. Fig. 7, Fig. 8 and Fig. 9 show time series response of BPNN for one month, two months and three months respectively.

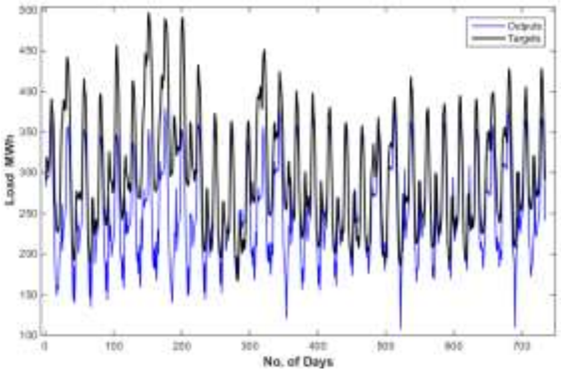


Figure. 4. 1-Month forecasting using ANN

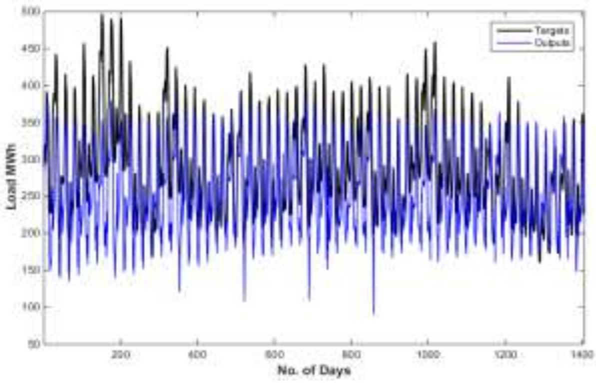
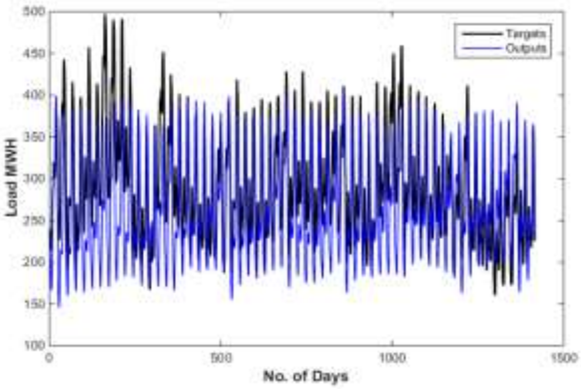
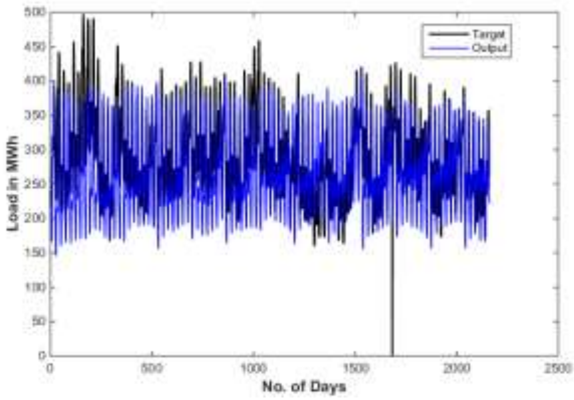


Figure. 5. 2-Months forecasting Using ANN





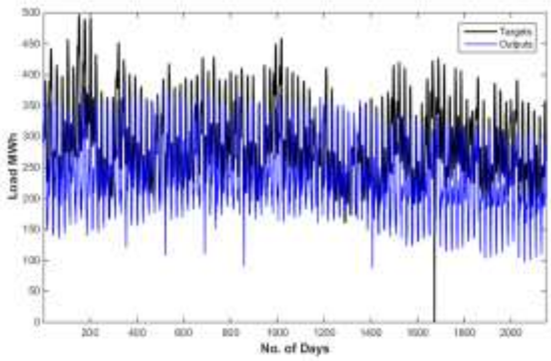


Figure. 6. 3-Months forecasting using ANN

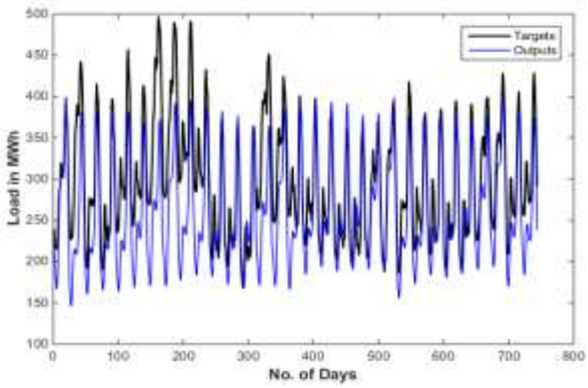


Figure. 7. 1-Month Forecasting Using BPNN

Figure. 8. 2-Month Forecasting Using BPNN

Figure. 9. 3-Month Forecasting Using BPNN

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In NARX due to feedback from the output, the history of the previously hidden state is available. Although NARX is a type of RNN and a feedback of output is available. It has been observed that in our scenario, BPNN perform much better than NARX. Fig. 10, Fig. 11 and Fig. 12 represents time series response for NARX. The mapping of targets and outputs is maximum using the NARX model.

EANN is a compact combination of feedforward and back propagation. The outstanding feature of EANN is its context unit. Fig. 13, Fig. 14 and Fig. 15 shows time response of EANN for one month, two months and three months respectively. It was observed that the performance of EANN is worst of all. EANN is unable to understand the problem accurately therefore, its performance is not satisfactory.

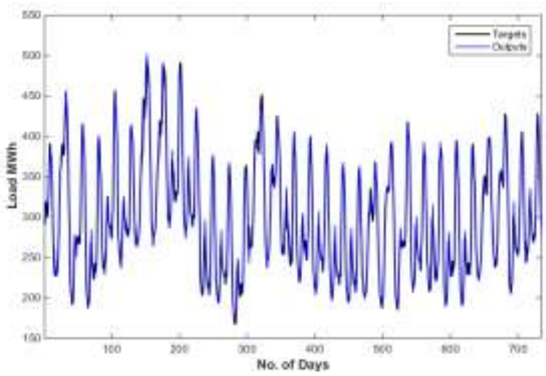

Figure. 10. 1-Month forecasting using NARX

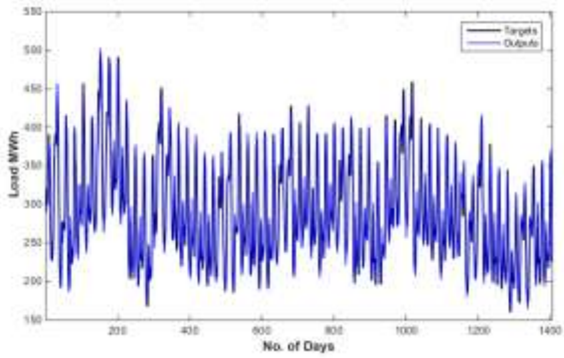

Figure. 11. 2-Months forecasting Using NARX

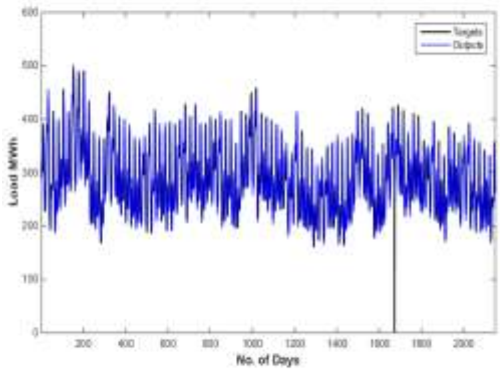

Figure. 12. 3-Months forecasting Using NARX

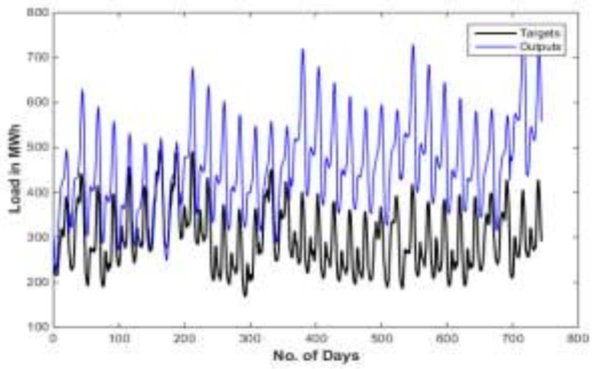

Figure. 13. 1- Month Forecasting using EANN

The error comparison of all the techniques is illustrated in Fig 16. It shows that the proposed NARX methodology indicate better results than all other techniques. However, table 3 demonstrate the Mean Square Error (MSE) and Root Mean Square Error (RMSE) of all neural network techniques. The mean square of NARX is 108.6 and the root mean square error is 10.42 which is more than ten time less than the error in ANN, BPNN and EANN. So, the results indicate that the NARX technique is better than all other techniques.

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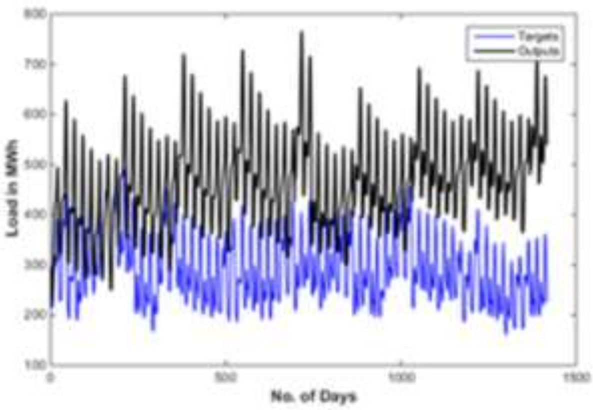

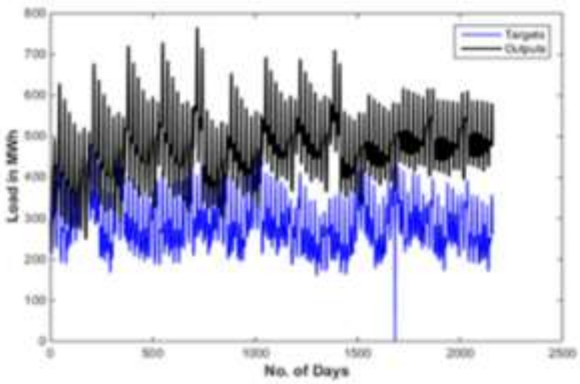

Figure. 14. 2-Month forecasting using EANN **Figure. 15.** 3-Month forecasting Using EANN

Table 3 MSE and RMSE Comparison of All Models

NN Model	ANN	BPNN	NARX	EANN
One Month MSE	3932.50	856.13	108.60	6.43e+03
Two Months MSE	3931.13	686.37	105.83	7.48e+03
Three Months MSE	3849.78	585.44	141.71	7.79e+07
One Month RMSE	62.70	29.25	10.42	80.21
Two Months RMSE	62.69	26.19	10.28	86.51
Three Months RMSE	62.04	24.19	11.90	88.31

6 Conclusions

In this research article, a time series load profile is obtained from national grids for Rhode Island United States. For the time series data, load forecasting is done by using the recurrent neural network with nonlinear autoregressive exogenous (NARX), and Elman artificial neural network EANN. Then for the comparison artificial neural network ANN, back propagation neural network BPNN are implemented. The training results of EANN are better than NARX, ANN, and BPNN. However, testing results show that NRAX outperforms all other mentioned models. Whereas, EANN perform

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worst of all. Furthermore, error for EANN is worst compared to others. However, the error of NARX is least. For future work, the NARX and EANN models can be combined to get better performance. The data can be trained using the EANN model and later can be tested using the NARX model.

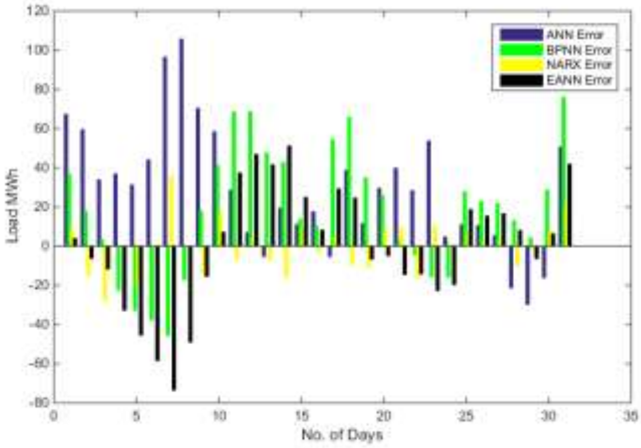

Figure. 16. Error Comparison of ANN, BPNN, NARX, and EANN

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