Forecasting Electric Energy Consumption In A House Using Artificial Neural Network

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Abstract- *Electricity plays a significant role in human life. Human beings rely on electrical appliances in day-to-day activities. Electrical appliances includes electric stove, washing machine, refrigerator, air conditioner, fan, lights, electric bi-cycle, electric car, motors, buses, train, flights, etc. Electricity generation process relies on the amount of energy consumed by the occupants of a house. Electric energy can be generated by various renewable forms such as wind energy, solar energy, etc. In the scenario the prediction process is needed for generating required amount of energy for future. Artificial neural network provides different techniques to predict various time-series data like energy consumption, weather data, etc. The accuracy of different techniques for the prediction process can be varying based on its specifications. Predicting energy consumption can also contain some error rate. It differs from algorithms to algorithms. Accuracy and Performance metrics of prediction algorithms can conclude the best and worst algorithms to predict energy consumption. In this paper, three different algorithms such as Levenberg Marquardt, Bayesian regularization and scaled conjugate gradient are compared to predict energy data. In these algorithms, The Bayesian regularization algorithm provides the best results with minimum error rate which performs metrics such as root mean square error (rmse), normalized root mean square error (nrmse) and mean absolute percentage error (mape).*

Keywords- Prediction, neural networks, Bayesian regularization algorithm, performance metrics, error rates, Levenberg Marquardt, Bayesian Regularization, Scaled conjugate gradient.

I. INTRODUCTION

Prediction energy consumption is used to improve the energy utilization rate and also improves the efficiency of decision making. This process is used to generate only the needed amount of energy in a house for tomorrow which is relying on renewable energies. Energy consumption can be predicted using various techniques such as deep learning techniques [1], machine learning techniques and neural networks, etc. it includes various models such as backpropagation neural network model, support vector regression and multiple linear regression, etc. Neural network grey forecasting models [2] are also used for predicting energy data using various datasets. Chi-square test and visual inspection techniques [3] are used to check model adequacy. In this paper, Predicting energy is performed for a single house using artificial neural network techniques in the Matlab tool. Artificial neural network techniques have been a part of the supervised learning. It has three different techniques are used and compared for prediction. They are Levenberg Marquardt algorithm, Bayesian regularization algorithm and scaled conjugate gradient algorithm. These three different algorithms are compared using various metrics like MSE, RMSE, NRMSE, MAPE and R values.

In this paper, section 2 explains about the related works based on this paper, section 3 shows the information about dataset used for analysis process, section 4 explains about the methodology of the prediction process. Section 5 draws conclusion for the prediction process and its algorithms.

II. LITERATURE REVIEW

Chengdong Li et al [1] proposed the approach towards the prediction process which makes the process more accurate using extreme deep learning techniques which includes the combination of methods such as stacked auto encoders (SAEs) with the extreme learning machine (ELM). This combination proves better when compared to other machine learning methods such as backward propagation neural network (BPNN), support vector regression (SVR), the generalized radial basis function neural network (GRBFNN) and multiple linear regression (MLR). Yi-Chung Hu had proposed [2] the forecasting of energy consumption using neural-network based GM(1,1) model called NNGM(1,1) grey forecasting model which performs well. This proposed method performs prediction using two different data such as data from the Turkish Ministry of Energy and Natural Resources and the Asia–Pacific Economic Cooperation energy database. S S A K Javeed Nizami and Ahmed Z AI-Garni were developed [3] an artificial neural network model that relates the electric energy consumption in the Eastern Province of Saudi Arabia to the weather data (temperature and humidity), global solar radiation and population. Chi-square tests and visual inspection techniques are performed for model adequacy. This neural network model performs better prediction. F. T. Romero et al proposed [4] the prediction of energy data that correspond to the monthly maximum demand for electricity supplied by the Mexican Federal Commission of Electricity. The Backpropagation algorithm is used as a technique for prediction using an artificial neural network. Rafael Mena Yedra et al proposed [5] the energy consumption prediction for CIESOL research center using neural networks that perform different techniques for real data. D. Datta and S. A. Tassou and D. Marriott were proposed [6] the prediction of energy consumption using various independent input variables in a supermarket. It also compares the prediction performance of neural networks with more traditional multiple regression techniques. Adela Bâra and Simona Vasilica Oprea were developed [7] an artificial neural network that works for energy demand side management system that determines consumers' profiles and patterns, consumption forecasting and also small generation estimations.

III. EXPERIMENTAL SETUP AND DATASET

Data is collected for the first week of September from the year 2012 for a single house which includes minute wise energy consumption data measured by kilowatts. Energy data is gathered for seven days (3rd September — 9th September 2012). Total energy data collected for a week is 10,080(7days * 24hr * 60mins) and 1440 data (24hr * 60mins) for a single day in a week. The locality of the house is not made public to ensure privacy. The sums of the energy consumption of all appliances are taken for the prediction process. Weekdays (Monday to Friday) and weekends (Saturday and Sunday) data differ based on various factors like time, occupancy, etc.

Weekday's data are considered for the prediction process. The first four days of weekdays (Monday to Thursday) are taken as input. The rest of the weekdays (Friday) are taken as a target. In the entire data which are taken for the prediction process, 70 percent of target data (1010) is used for the training process. The network is adjusted according to its error during training. 15 percent of target data (216) are taken for the validation process. Validation is used to measure network generalization. The rest of the 15 percent of target data (216) are used for testing data. It provides an independent measure of network performance during and after training. Ten numbers of hidden neurons and two delays are created for constructing a neural network in the prediction process.

IV. METHODOLOGY

NEURAL NETWORK

The neural network is trained to perform a specific function by adjusting the value of weights between elements. By adjusting or training the neural network leads to find the appropriate output for the given input and target. Output and target are compared until output matches target while the neural network is in training. Figure 1.1 illustrates the process of a neural network.

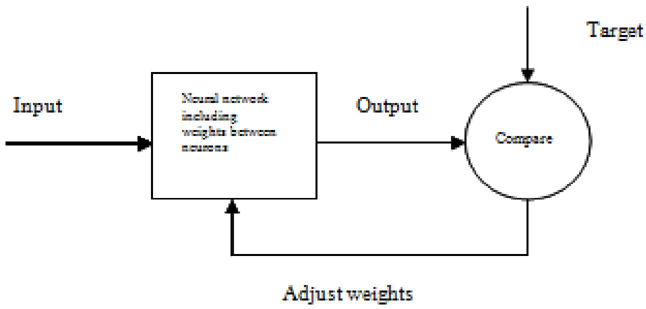

Figure 1.1 process of neural network

DYNAMIC TIME SERIES

Time series GUI is retrieved from master the GUI by using the command 'nnstart'.

Dynamic time series (ntstool) is the time series app in Matlab tool which is used to predict future time series values from past values.

Start GUI with the command 'nnstart' to open neural network. 'ntstool' command is used to open the time series app.

TIME SERIES PREDICTION AND MODELING

NARX Nonlinear autoregressive with exogenous input is one of the types of time series problem which is used to predict future values of time series (y(t)) from past values of time series and past values of second time series (x(t)). This NARX model provides better prediction when compared to other time series models. It predicts the future value of time series with past values which include both target and input values while other models like NAR (nonlinear autoregressive model) and NIO (nonlinear input-output model)predicts future value only with the target value.

Input and target values are loaded from workspace to time series tool. From 100 (1442) percent of data, 70 percent of data (1010) is used for the training process. 15 percent of data (216) are taken for the validation process to stop training before overfitting. The last 15 percent of data (216) are used for the testing process.

The NARX model is the feed-forward network which includes two layers such as the hidden layer and output layer. The hidden layer with sigmoid transfer function and an output layer with linear transfer functions are processed in this model. This network uses tapped delay lines to store previous values of x(t) and y(t). Output of y(t) is fed back to input of this network through delays is a function of y(t-1), y(t-2), ..., y(t-d).

Opened loop feedback provides efficient training. In this process true output available during training the network which is fed back as input instead of estimated output. It has advantages as it provides better accuracy and the resulting network has a purely feed-forward network.

NETWORK ARCHITECTURE

The network contains 10 hidden neurons and 2 delays. The training process continues until validation error failed to decrease for iterations (validation stops). It also provides a mean square value and response value.

Mean square error

Mean Squared Error is the average squared difference between outputs and targets. Least values are better than the highest values.

Regression

Regression values calculate the correlation between target and output. If R-value results with an average of 0 mean random relationship or 1 mean a close relationship.

GRAPHS

Time series prediction has various graphs that are plotted to show autocorrelation of errors, the correlation between inputs and error, data taken for training, validation and testing process, etc.

The autocorrelation of error explains the relation between errors. The input and error correlation graph shows the correlation exists between inputs and error. The response graph explains which data had taken for various processes like training, validation, and testing. Different colors are used to differentiate data taken for different processes.

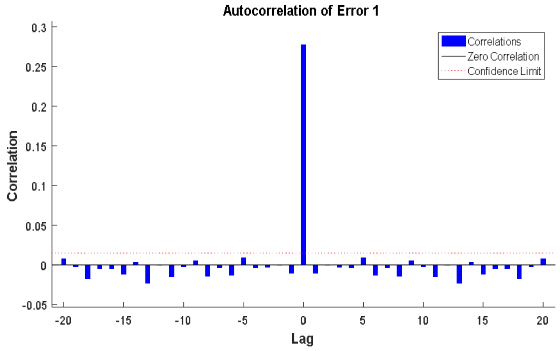

Figure 1.5.1 Autocorrelation of errors

Autocorrelation of error describes the correlation of predicted errors with time in the Figure 1.5.1. As shown in the Figure 1.5.1, it has only a single nonzero value that occurs at zero lag.

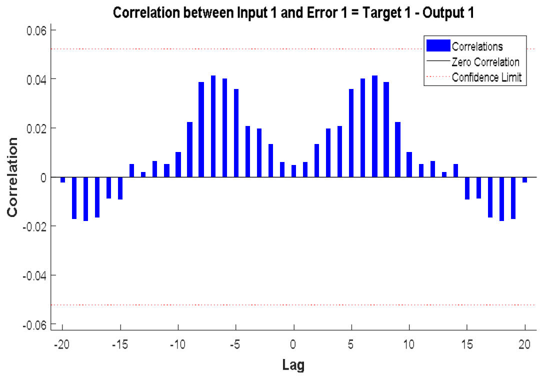

Figure 1.5.2 Input and error correlation.

Input and error correlation explains about the correlation between predicted errors and inputs in the Figure 1.5.2. As shown in the Figure 1.5.2, the correlation values are zero.

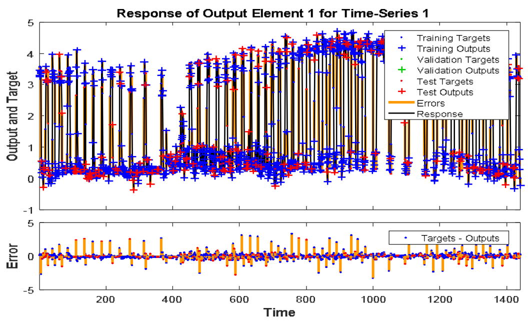

Figure 1.5.3 Time series response.

The time-series response graph describes the relation for inputs, targets, and errors versus time in the Figure 1.5.3. It also explains which data are selected for training, validation and testing Process.

ALGORITHMS

1.6.1 Levenberg Marquardt

Levenberg Marquardt (trainlm) is the algorithm that is widely used for optimization. It is an alternative of Gauss-Newton to find the minimum of function which is a sum of the squares of nonlinear functions. It is also known as the damped least-squares method. It provides a solution for nonlinear least square minimization. It needs more memory with less time. Training automatically stops when generalization failed to improve.

Syntax
net.trainFcn='trainlm'
[net,tr] = train(net,...)

1.6.2 Bayesian regularization

The Bayesian regularization algorithm (trainbr) needs more time. It provides better generalization when compared to other algorithms, even for difficult, large or small and noisy datasets. Training stops automatically based on adaptive weight minimization. It minimizes squared errors and weights that produce such a network which generalizes well.

Syntax
net.trainFcn='trainbr'
[net,tr] = train(net,...)

1.6.3 Scaled conjugate gradient

A Scaled conjugate gradient algorithm (trainscg) needs less memory. It is a training network that updates synaptic weights and bias according to scg method.

Syntax
net.trainFcn='trainscg'
[net,tr] = train(net,...)

PERFORMANCE METRICS

1.7.1 ACCURACY

Accuracy is defined to measure closeness to a specific value. It is the best way to check the quality of the techniques. Perfect prediction is impossible to predict the exact future values. It has some errors. The errors are calculated to know the best algorithm which gives the best results.

The average of three various metrics is performed to minimize the error. i.e., root mean square error, normalized root mean square error and mean absolute percentage of error. These metrics are used to reduce limitations in the process. The details of various metrics are given below.

1) RMSE (Root mean square error): RMSE is a standard deviation of residuals (prediction errors). It is used to measure accuracy and gives the values as non zero. It provides the square root of the average of squared errors. RMSE is calculated by the equation (1).

Formula

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

RMSE = sqrt(mean((V1-V2).^2) ----- eqn (1)

Where, V1= actual value,
V2 =predicted value.

2) NRMSE (Normalized root mean square error): This function is used to calculate the value as an absolute value between actual and predicted values using various types of normalized methods. It is calculated by equation (2).

Formula

$$NRMSE= \frac{RMSE}{\max_i \; y_i - \min_i \; y_i}$$

NRMSE = RMSE/(max(V2)-min(V2)) ----- eqn (2)
Where, V2= Predicted value.

3) MAPE (Mean absolute percentage error): It provides accuracy as a percentage. It is calculated as the average absolute percentage error for each time minus actual values further divided by the actual value. MAPE is calculated by equation (3).

Formula

$$MAPE= \sum_{t=1}^{n} \left|\frac{A_t - F_t}{A_t}\right|$$

MAPE= mean((abs(V2-V1))./V1) ----- eqn (3)

Where, V1= actual value,

V2 =predicted value.

COMPARISON OF ALGORITHMS

The three different algorithms such as the Levenberg Marquardt algorithm, the Bayesian regularization algorithm and the scaled conjugate algorithm are executed and compared for a better prediction process. Three different metrics such as RMSE, NRMSE and MAPE values are measured to perform a comparison between these algorithms. The error rates are calculated using the equations RMSE(1), NRMSE(2), MAPE(3).

Table 1.8.1 Comparison of performance metrics with three algorithms

Performance metrics	Levenberg Marquardt Algorithm	Bayesian regularization algorithm	Scaled conjugate gradient algorithm
RMSE	0.005299735	0.003207656	0.005721391
NRMSE	0.001192639	0.000629215	0.001243989
MAPE	0.003033117	0.001835789	0.003274437

The above Table 1.8.1 explains about the comparison of performance metrics such as RMSE, NRMSE, and MAPE for various algorithms. It shows that the Bayesian regularization algorithm gives a minimum error than other algorithms.

MSE and R values are also compared between three various algorithms.

Table 1.8.2 Comparison of MSE and R values between different algorithms

Metrics	Levenberg Marquardt	Bayesian regularization	Scaled conjugate gradient
MSE	1.096	1.0198	1.1118
REGRESSION	3.50378	3.5155	3.5003

Table 1.8.2, describes the comparison of mean square error and regression value for three different algorithms. For MSE values, the Bayesian regularization algorithm gives a minimum error rate than other algorithms. For Regression values, Bayesian regularization gives the closest relationship than others.

COMPARISON OF THREE VARIOUS ALGORITHMS FOR THREE PERFORMANCE METRICS

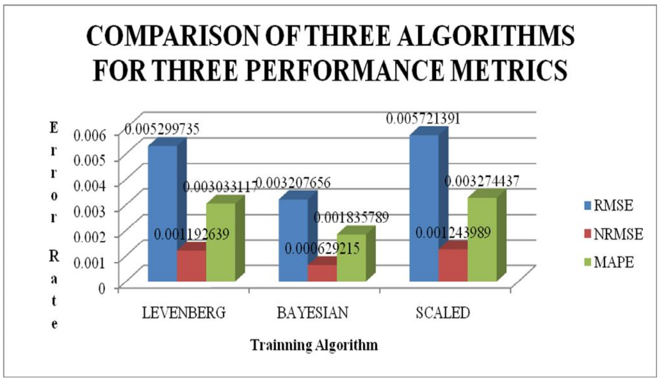

Figure 1.9.1, comparison of algorithms for performance metrics.

The above Figure 1.9.1 shows the comparison of three algorithms such as Levenberg Marquardt, Bayesian regularization and scaled conjugate gradient algorithm for various metrics such as RMSE, NRMSE and MAPE. As shown in the Figure 1.9.1 the Bayesian regularization algorithm provides better solution when compared to other algorithms. It gives minimum error rate for RMSE, NRMSE and MAPE.

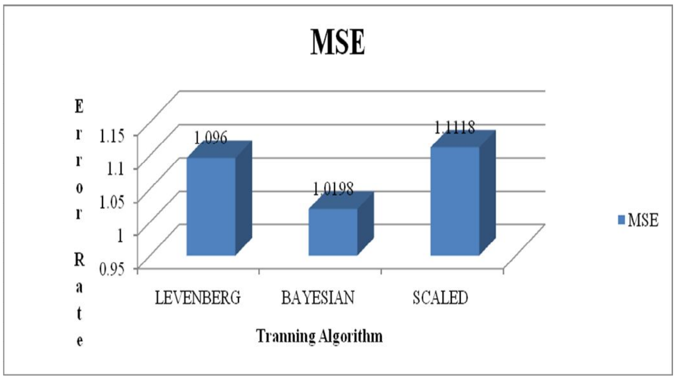

Figure 1.9.2, comparison of three various algorithms for mean square error.

The above Figure 1.9.2 explains the comparison of three different algorithms for the error rate mean square error. As shown in the Figure 1.9.2 the Bayesian regularization algorithm provides minimum amount of mean square error.

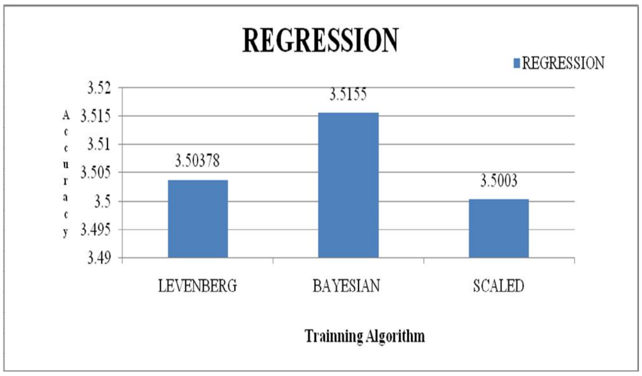

Figure 1.9.3, comparison of regression value.

In the Figure 1.9.3, Regression values of three different algorithms are compared. As shown in the Figure 1.9.3 Bayesian regularization algorithm provides better accuracy when compared to other algorithms.

COMPARISON OF ACTUAL VALUE AND PREDICTED

The three different algorithms had their own predicted values than the actual value. The actual values and predicted values are compared separately by various algorithms.

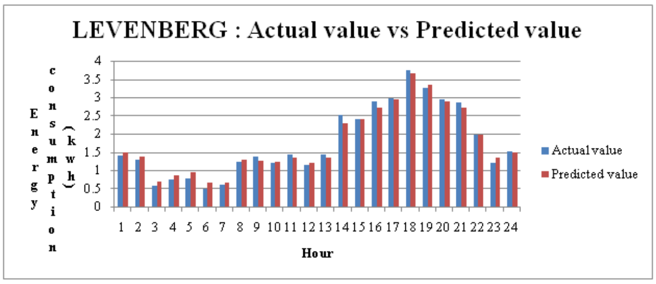

Figure 1.10.1, comparison of actual and predicted values of the Levenberg Marquardt algorithm.

The above Figure 1.10.1, explains the comparison of actual and predicted values which are predicted by using the Levenberg Marquardt algorithm. It shows the difference between actual and predicted values.

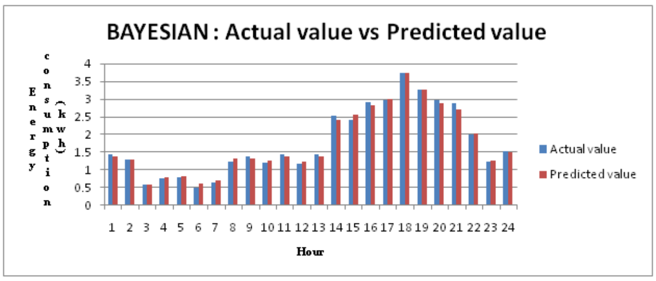

Figure 1.10.2, comparison of actual and predicted values of the Bayesian regularization algorithm.

Figure 1.10.2, describes the actual and predicted values of the Bayesian regularization algorithm are compared. It exhibits the results with very small differences.

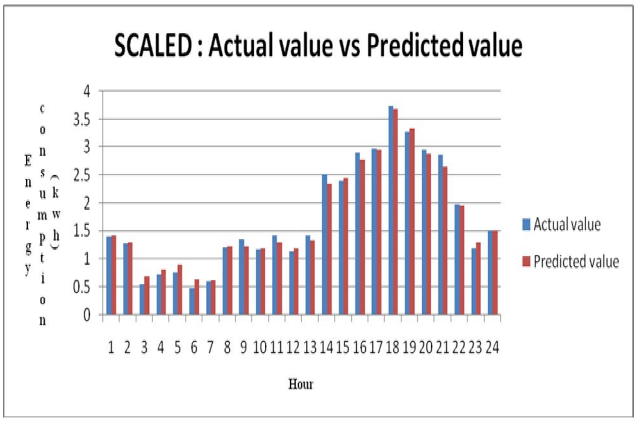

Figure 1.10.3, comparison of actual and predicted values of the scaled conjugate gradient algorithm.

The above Figure 1.10.3 shows the comparison of actual and predicted values of the algorithm scaled conjugate gradient.

From the above comparisons of actual and predicted values of three different algorithms, the Bayesian regularization algorithm shows a minimum of differences between actual and predicted values than other algorithms.

V. CONCLUSION

Predicting energy consumption helps to make decision about generating power for future. Predicting electrical energy in a house is very useful to generate only required energy. In this work, prediction is performed using three various algorithms. Three different algorithms are compared using three various metrics that shows the error rates of the prediction process. The result shows that, the Bayesian regularization algorithm provides a better solution when compared to other algorithms. It gives the predicted value with the minimum error rate even for difficult and noisy data.

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