Short Term Load Forecasting under extensive Power Outages using Domestic Energy Meter Load Profile; A case study

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Javaid Aslam [1], Muhammad Kamran [2, *], Arslan Arif [1,] Muhammad Wasif [1,] Jehanzeb Irshad [1] and Iftikhar Hussain [1]

1. University of Gujrat, Gujrat, Pakistan; Arslan.arif@uog.edu.pk, syed.wasif@uog.edu.pk, jehanzeb.irshad@uog.edu.pk, Iftikhar.hussain@uog.ed.pk
2. University of Engineering and Technology, Lahore, Pakistan; mkamran@uet.edu.pk

* Corresponding Author: mkamran@uet.edu.pk

ABSTRACT

Short-term load forecasting (STLF) is an obligatory and vibrant part of power system planning and dispatching. It is utilized for short and running targets in power system planning. Electricity consumption has nonlinear patterns due to its reliance on factors like time, weather, geography, culture, and some random and individual events. This research work emphasizes STLF through utilized load profile data from domestic energy meter and forecasts it by Multiple Linear Regression (MLR) and Cascaded Forward Back Propagation Neural Network (CFBP) techniques. First, simple regression statistical calculations were used for prediction, later the model was improved by using a neural network tool. The performance of both models compared with Mean Absolute Percent Error (MAPE). The MAPE error for MLR was observed as 47% and it was reduced to 8.9% for CFBP.

Keywords: Short Term Load Forecasting; Cascaded Forward Back Propagation Neural Network; Artificial Neural Network; Multiple Linear Regression; Machine Learning.

INTRODUCTION

The energy crisis in Pakistan urged the need to focus on running solutions along with planning the future to reduce the demand-supply energy gap (Gussan et al., 2016). This energy demand gap reaches its peak during summer due to a rise in temperature and air conditioning loads. The unit commitment for distribution companies is challenging during the summer. It is thus very effective if these months are planned in time. Short Term Load Forecasting becomes vital in this time.

Electrical load forecast is necessary due to the growing trends like population, urbanization, culture, economic trends, industrial growth, and uncertainties in weather. Previous data was gathered from a residential three-phase static energy meter installed under the Gujranwala Electric Power Company (GEPCo) division.

A good estimation is as best fit between prediction and target points. Estimation can result in both positive and negative variation from the required value. Regression through neural al network is most commonly used for short-term load forecasting (Hwang et al., 2016; Yildiz et al., 2017). Hidden layers are induced in regression models for better calculation like human brain mechanism.

Generally, energy forecasting methods can be broadly classified into three major classes .ie. Artificial Intelligence (AI) Method, Statistical Method, and Engineering Method (M.P. Abdullah 2014). Popular methods widely used in load forecasting is the Artificial Intelligence (AI) Method, which includes Support Vector Machine (SVM) and Artificial Neural Network (ANN). The other two techniques i.e Engineering Methods and Statistical Methods are yet connected, yet a few inadequacies distinguished in both strategies, midst the insufficiency in engineering method is its complexity to apply it for all intents and purposes, its absence of in-formation data (Pan et al, 2008). ANNs have been extremely great application in time-series prediction, because of their accuracy and simplicity. The erudition practice is usually relying upon slope strategy back propagation (BP) computation. Back spread estimation has noteworthy detriments: the learning strategy is repetitive and there is no meticulous statute for setting the number of covered neurons to evade over or under fitting, and in a perfect world, influencing the figuring out how to arrange concurrent. The comparison was made utilizing distinctive strategies (Anpalagan et al., 2015). STLF is more focused in terms of load forecasting, used ANN models as clustering to predict the busload for the next hour or a day (Panapakidis et al., 2016). The hybrid forecasted model gives improved accuracy than traditional models. This was tested on the bus model. PSF can be modeled with ANN. The model is in two levels first PSF is used for prediction than ANN is used to refine the results (Troncoso et al., 2013). STLF is nonlinear in nature. Regression with a combination of ANN is very suitable for load curves Spread parameter determines the performance of the GRNN. This problem can be dealt with using the fruit fly algorithm. SFOA is combined with GRNN with decreasing steps. This model is compared with other ANN on the basis of prediction error (Zeng et al., 2017) Neural networks have been very impressive for load forecasting in the present era many papers with different models have been published with practical application with high success rates (Guo et al., 2011; Shen et al., 2016; Guo et al., 2013; Chen et al., 2016 and Chu et al., 2011). ANN can completely adjust master information and change their parameters as needed to recreate the issue's attributions through preparing ideal models (Panapakidis et al., 2016).

MODELING AND ANALYSIS

The methodology of this work is well described in (Aslam et al., 2021) which is more elooratvie in Figure 1. The load profile collected from energy meter was in raw form.

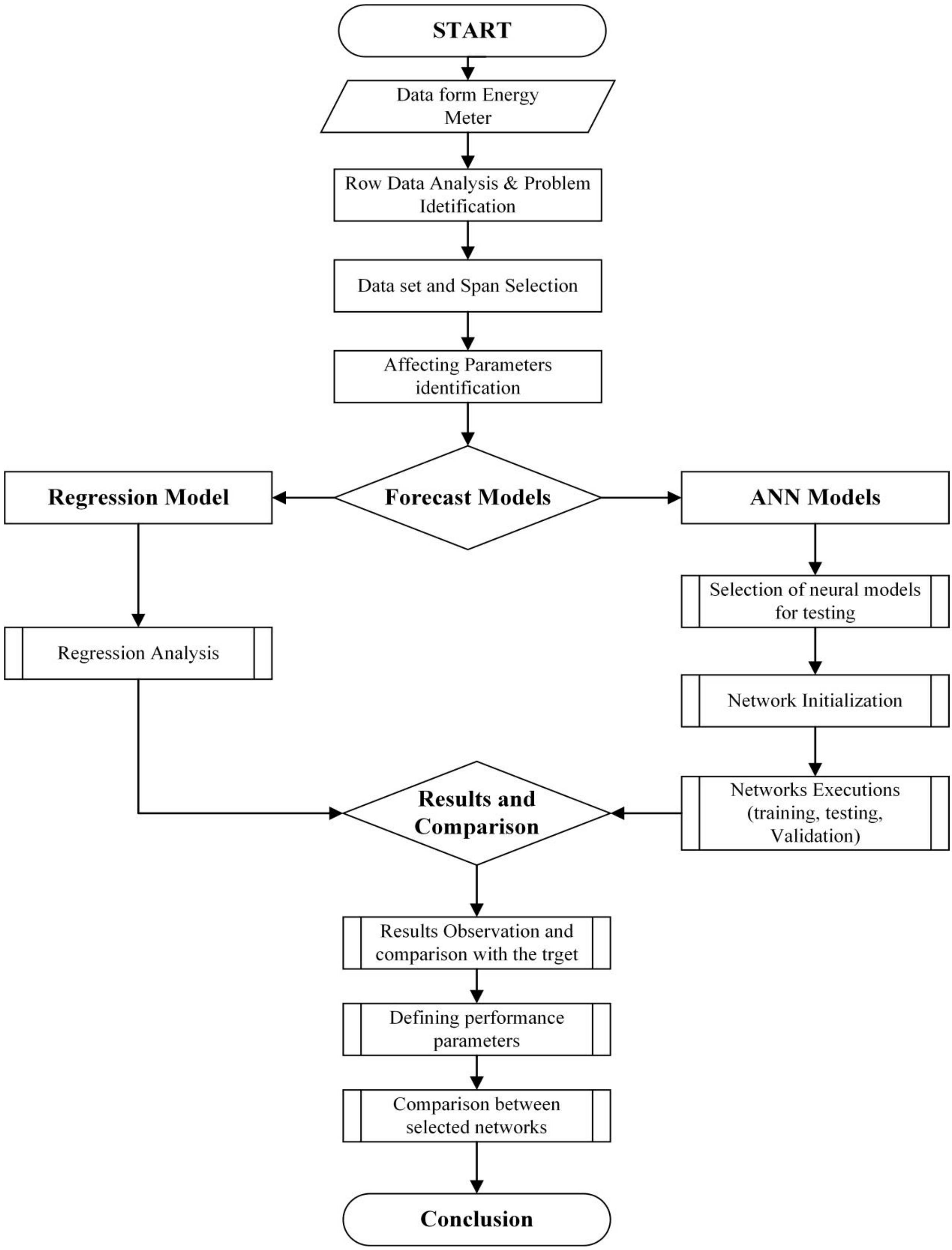

Figure 1. Methodology of the research work

Data obtained from the energy meter is represented in Figure 2.

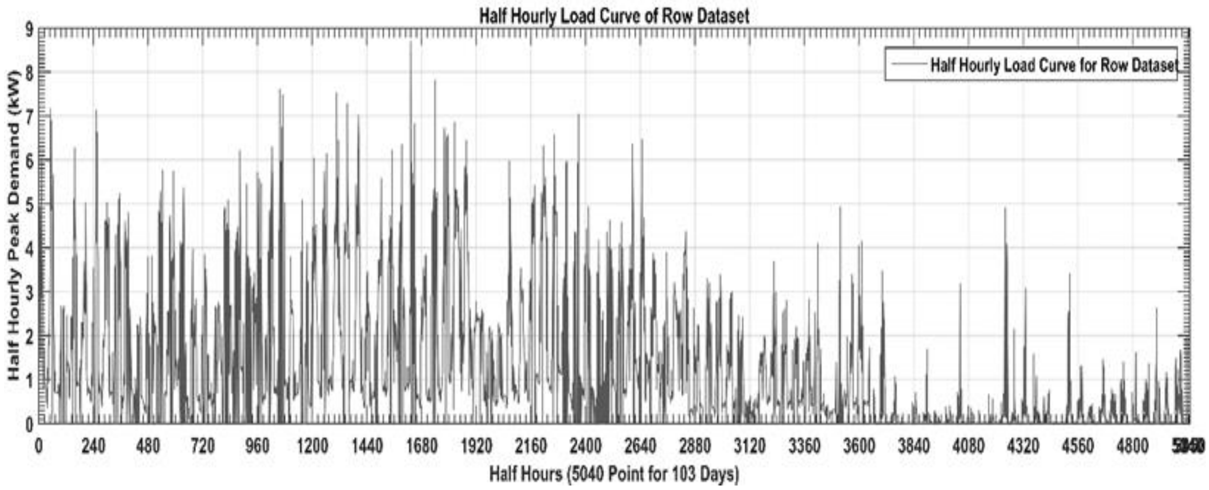

Figure 2. The half-hourly load curve of the unsorted data obtained from the meter. High non linearity ca be visualized

There were many power outages that can be noticed from profile as the gap of the continuity in the load profile timing as descripted in Figure 3.

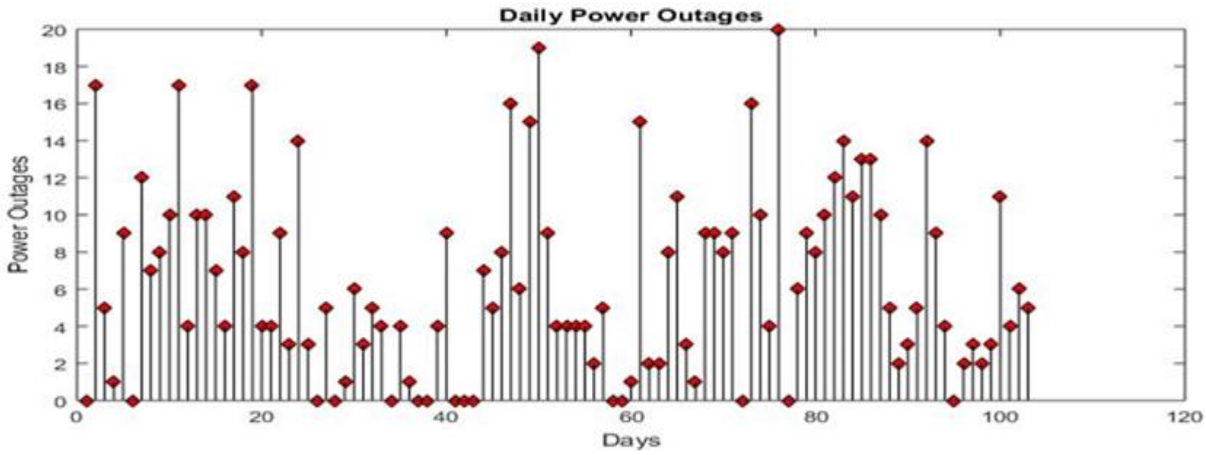

Figure 3. Daily power outages from unsorted data

Non-linear nature of electric load utilization can be observed in Month of year, Week of month, Day of week and hour of a day. Time of the day, week, month and year are impactable parameters for the dependency of load forecasting. Table 1 represents all the dependent parameters considered in this research work with alloted variables .

Table 1. List of dedpendent parametrs for forecasting model.

Factor considered	Variable
Hourly Temperature of the Day	X1
Pervious Day Half Hourly Demand	X2
Respective Power Outages in X2	X3
Half Hourly Load of last six days from target day	X4-X9
Repecttive Power Outages in X4-X9	X10-X1
Similar Temperature day Half hourly load profile in last three weeks	X16
Power outages in X16	X17
Average half horly load of last three weeks	X18
Average Power outages X18	X19
Similar day of week average half hourly load in selected duration	X20

Figure 4 depicts the weekly pattern of the profile load from which the target curve was set. Recuttancy in the load apttern can be observed from this fihure. Load curves are recurrent in pattern at any instance.

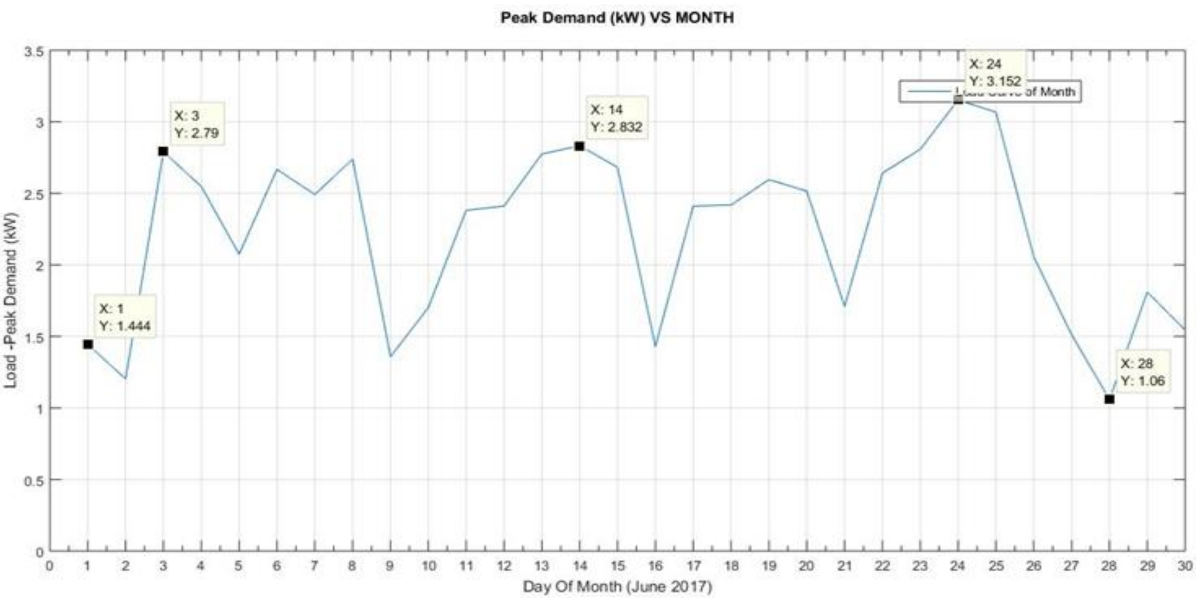

Figure 4. Load curve of the selected week from which target was selected.

From this data, 48 hours were randomly selected for the autonomy of the forecasting model. The load curve for this duration is shown in Figure 5. This was set as a target curve for the authenticity of the forecasting models.

The aim of the developed model was to fit this curve with maximum accuracy. At first, the Multiple Linear Regression (MLR) model was executed setting Mean Average Percent Error

(MAPE) as the measuring parameter for accuracy of developed models.

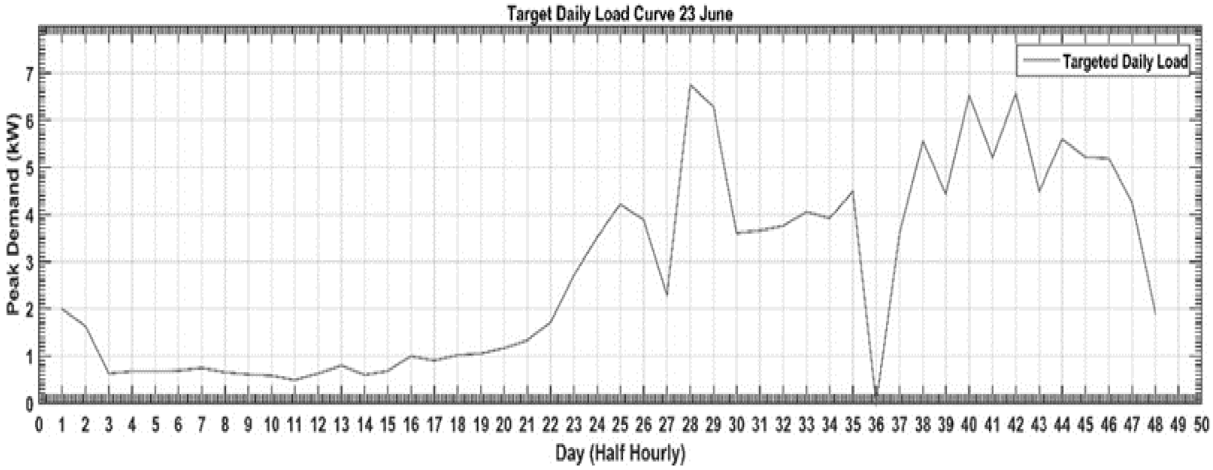

Figure 5. 48-Hours Target load curve for regression and ANN from sorted data

After analyzing and sorting the data collected from the energy meter, MLR model was executed and accuracy measured using Mean Square Error (MSE) as performance indicator of the output. Simple linear regression is not applicable here, so MLR with improved parameters (hidden layers) was the selected. Difference between SLR and MLR is represented in Figure 6.

(1)

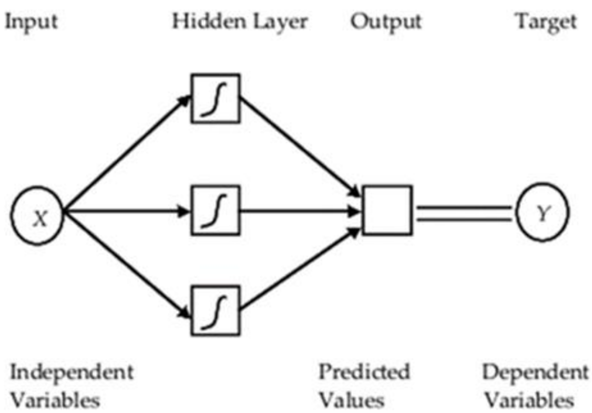

Figure 6(a). Simple linear regression for predicting a single variable (SLR)

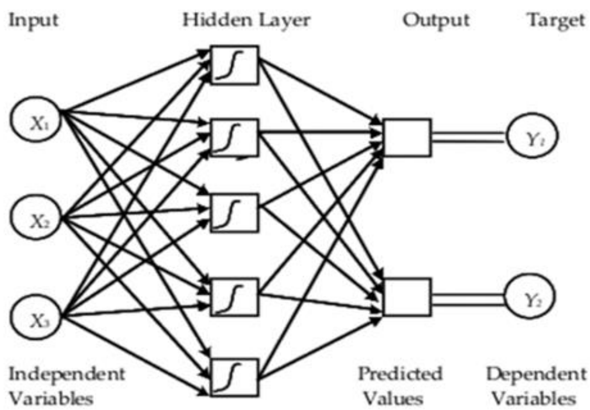

Figure 6(b). Estimating more than one variable through a greater number of hidden layers and complex variables (MLR)

MLR models was fed with all parameters represented in the Table 1, the model reduced the parameters with on variable X1, X16 & X18 as the most dependent parameters for this problem. The output of MLR model is described in Figure 7.

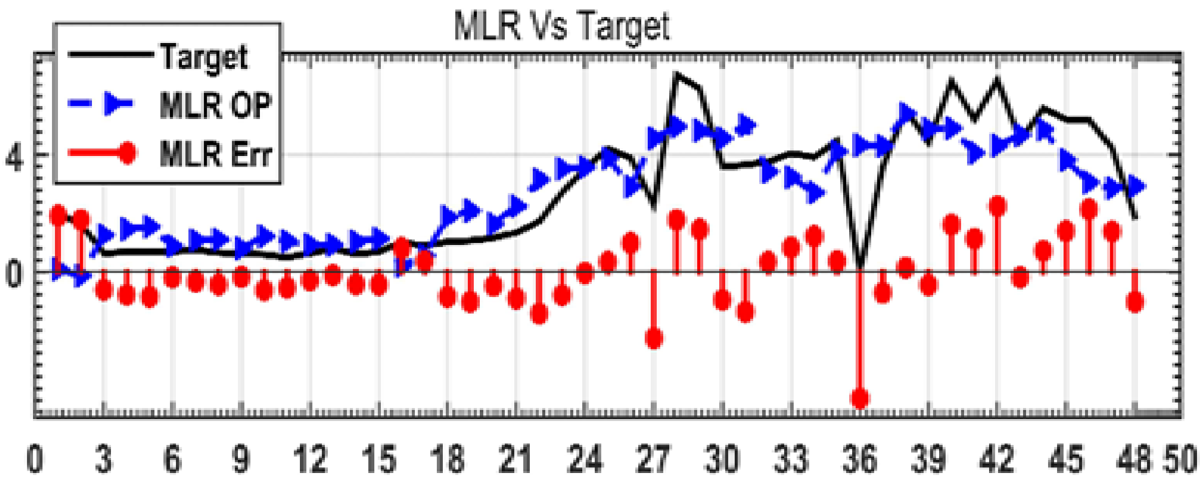

Figure 7. Output of MLR Model

Figure 7 spectacles the output of regression analysis. It shows the comparison of the original load curve the predicted fitting and error magnitude. Peak demand is measured in kW on the vertical axis and half-hourly time duration of one day on the horizontal axis. A noticeable difference can be observed in target and estimated values. Regression analysis seems to have a deficiency in fitting the higher sloped values. The error is minimized during constant intervals and expanded in positive and negative hikes. For improving the deaths in the regression model the intercept parameters should be found by differentiation and equating all to zero. This is the same as making the available data approximate to linear. The accuracy and robustness of estimation in regression models are increased with the number of observations. This analysis is not so much fruitful in a preset case study. The greater number of power outages induced high nonlinearity in the data which caused MLR to fail to provide greater accuracy.

ANN requires input and target data. The accuracy of the ANN output is very much effected by the type and depth of the data, it is not so much useful for fewer data. ANN accepts data in form of matrices. it took input as rows of a matrix and respective weights in the column. ANN train the input data and tries to fit the plot between target values. To improve the accuracy of the ANN, several types of data were fed to the input mentioned in Table 2.

Table 2. Data arrangement for ANN input.

Day/time	Peak Load(kW) of Hours of Days	Forecast
48 Days 48x1 matrix	Data from Meter 48x24 matrix weighted with X1-X20	48 Hours 48x1 matrix

The Neural Network created with succeeding parameters: Network Type was "Cascaded Forward Back Propagation Neural Network (CFBP)", Data division was set to "Random", Training function used "Levenberg-Marquardt Algorithm", Adaption function was "Grading Decent Learning with Momentum", Performance function was "Mean Square Error", Nos of layers were "2", Nos of neuron were layer1: 10, layer2: 1 and Transfer function were "TANSIG" at layer1 and "purelin" at layer2. The CFBP network can be generalized in Fig 8.

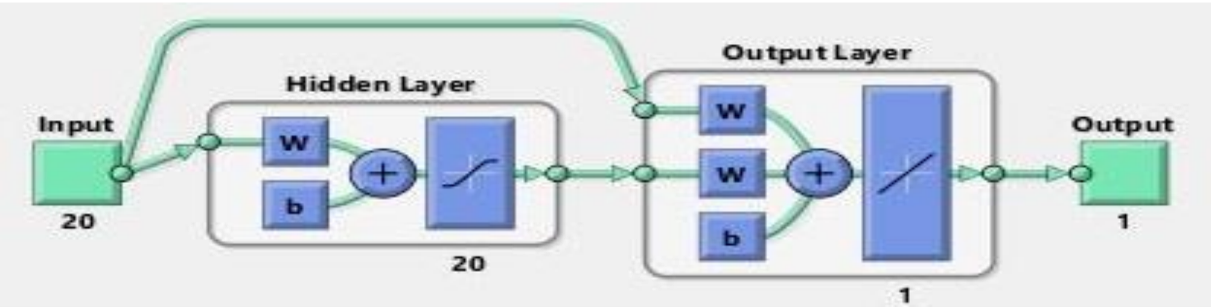

Figure 8. Cascaded Forward Back Propagation (CFBP) Network

This model executed for the same parameters and data that was used for MLR. The output of NN model is shown in Figure 9. The error was reduced to 8% which was up to 47% using MLR.

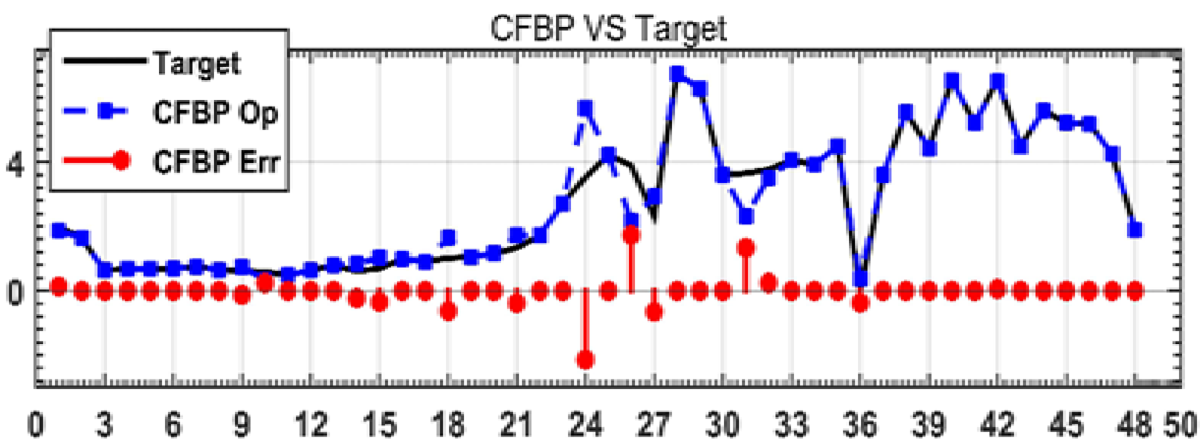

Figure 9. Cascaded Feedforward Back Propagation Neural Network Output

CONCLUSION

The limited scope of MLR over non-linear trends suggests using an alternate solution for energy forecasting. In the research work MLR has shown very less accuracy possibly due to the intense number of power outages (Pos). POs induced discontinuity in the recurrence pattern of the load curve, which caused deviation in the accuracy of MLR. Through the advancement of AI and its application in optimization, ANN tools are widely used for this purpose. This research work also proposed ANN best suitable for STLF. MAPE was used as performance comparison criteria for regression and proposed ANN. It was evident from the comparison results that CFBP excelled in contrast with MLR. The error was reduced to 8.9% by CFBP from 47% by MLR. Neural networks outperformed in forecasting with high nonlinearity and discontinuity. This work can be extended to more models and also if the data set is increased, it may be possible to extend the work to medium term load forecasting (MTLF) or long-term Load forecasting (LTLF).

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