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Short term electrical load forecasting for an urban 11 KV feeder using machine learning techniques

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Abstract. Accurate electricity load estimation is an essential issue for the operation of the power system, and it is one of the essential works of future power planning for large cities. Every power prediction model has its benefits and drawbacks and has its particular application range. Researchers categorized the load energy forecasting as Short-Term Load Forecasting (STLF), Medium-Term Load Forecasting (MTLF), and Long-Term Load Forecasting (LTLF), which entirely depends on the time in which estimation is scheduled. As electricity load forecasting can be seen as a machine learning problem, several automated methodologies and models are included in the literature review. In this work, we aim to explore and implement state-of-the-art machine learning techniques like Polynomial Regression, Support Vector Regression (SVR), and Artificial Neural Networks (ANN) to predict the short-term and medium-term load consumption for the historical data accurately. For this study, hourly load data of an Urban 11 KV Feeder was collected from the 220 KV grid station. Weather parameters like temperature, pressure, and humidity data for the particular region were taken from Lahore Meteorological Department. Data were divided into several datasets (daily, weekly, and monthly) to achieve short-term and medium-term electrical load prediction using the techniques mentioned earlier. Input parameters used in this study were temperature (both dry and wet), humidity, and pressure, while predicted hourly load demand was used as output. The final results tables show that the performance of the SVR predictor is much better than other techniques both in the short term and medium load forecasting.

Key words: *artificial neural networks, feed forward neural networks, polynomial regression, short term load forecasting, support vector regression, radial basis function*

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1. Introduction

The recognition of future power utilization patterns is a critical part of arranging, operating, and investigating Electrical Power systems. Load forecasting is very useful for the estimation of energy management systems. Load forecasting alludes to projected load necessity by utilizing a systematic procedure of characterizing load adequately to make important power system decisions. Full forecast attained by merging forecasts for different customers like residential, commercial, and industrial. Load Forecasting errors are critical because power system effectiveness and quality control concerning operations are very sensitive. So, evaluating future power utilization accurately is required for the circulation of energy and production management. Keeping in view the ultimate objective for enhancing the efficiency and dependability of the distribution sector, the distribution management system applications were developed for monitoring and controlling the electricity distribution system. The need for comparison between power generation and power utilization has become essential for forecasting electrical load demand.

Electrical load estimation has dependably been a vital issue in the power industry. Load estimation is typically made by developing models on comparable data, for example, atmosphere and previous load demand information. Load estimation is depicted as the phenomenon utilized by the power service organization to make essential decisions on buying and producing electrical power, infrastructural betterment, and load switching. Numerous researchers have focused on the time series analysis, which is broadly used in different fields, such as industrial automation, hydrological, stock market, and military science. Load forecasting and accuracy for any power utility system are dependent on the generation, transmission, and distribution capacities. Electricity load estimation using effective methods is required to improve efficiency for the supply of electrical energy by which necessary operating costs for supplier companies can be reduced.

Load estimation techniques can be classified into three categories: Short term load estimation– as hourly, daily, or weekly forecasting; Mid-term load estimation– Extends from one month to one year; and Long-term load estimation– ranging from one year up to ten years. It is pretty noticeable that the effective load estimation technique remarkably affects the financial operation of any power utility system as most of the decisions can be made based on forecasted values. Due to complex and non-stationary relationships among several parameters, the electricity load is characterized by climatic conditions and previous load patterns [1]. For electricity load forecasting, various automated techniques have been proposed wherein different sets of features have been used. Due to the explosion of population and fast economic growth in major cities, where power demand is continuously increasing than the power supply, the load forecasting over a monthly time scale plays a vital role.

Several practical techniques have been proposed for electric load estimation by considering the non-stationary factors that affect the electric power load and their relationships [2]. Noticeably, the power load is necessarily influenced due to variations in weather conditions, and hence, the previous research work, especially on short-term load forecasting, has tried to overcome and cater to this sensitivity [3]. Predicting the electricity load demand in advance allows a power system to operate accurately by managing and implementing effective planning, risk assessment, marketing, and billing practices. The network's reliability is also improved by reducing the chances of occurrence of equipment failures by increasing security [4]. The forecasting accuracy is of very much importance as over- prediction will engage more power generators, thus wasting electricity.

In contrast, under-prediction will disrupt electricity supply disruptions, resulting in higher electricity buying [5]. Artificial Neural Networks (ANNs) techniques have earned a great deal of attention since the mid- 1980s, and they were proposed as powerful mathematical and computational tools for solving electrical load estimation problems. ANNs can achieve better accuracy and performance while dealing with complex and nonlinear relationships among their input parameters.

2. Materials and methods

Several Artificial Neural Networks (ANN) based techniques have been developed by the researchers for electricity load forecasting [6]. Nasr et al. developed ANN to predict electrical energy consumption [7]. Historic energy data of three years were utilized for training the model, while two years of data were used to test and validate the model. MAPE values for both of the developed models were achieved to be 5.03 and 4.43, respectively. Peak load forecast and multilayer perceptron-based energy-based models were suggested in [8]. They used monthly historical data of 6 years and analyzed to forecast data with the help of ANN and multiple linear regression techniques. They suggested that the regression method has a higher error rate concerning ANN.

2.1. Related work

2.1.1. Load forecasting using artificial neural networks

ANN implementation with the back-propagation feed-forward technique presented in [9]. Its resultant accuracy (MAPE) of 2.29%, which forecast based on annual energy feeding, monthly energy consumption, and monthly peak load. Adaptive neural networks used in [5] to reduce the problem of forecast hourly load stresses and used Particle Swarm Optimization (PSO) training algorithm in which result shows that MAPE obtained using the PSO method was better (1.98%) as compared to the old-style Back Propagation (BP) algorithm (3.51%). Hamzacebi [7] designed neural network-based prediction models for the utilization of electricity demand for Turkey. They estimated the electricity utilization for four different regions of turkey like industrial, residential, transportation, and agriculture. Over 35 years of data were utilized for developing, validating, and testing the model. The prediction of four developed models for different regions resulted in MAPE errors of 2.25%, 3.26%, 23.59%, and 2.56%, respectively. The Feed-Forward Neural Network (FFNN) based long-term electricity estimation was studied and presented by Ekonomou [6]. The network architecture was selected with two hidden layers with 20 neurons in the first hidden layer while 17 neurons in the second layer, one input layer with 4 neurons, and one output layer with a single neuron. The previous historical data over 13 years was utilized for testing purposes, whereas the four years of data were used to test the model. The ANN forecasted results were much similar to that of test samples.

In [10], Brendal and Twanabasu forecasted load for the smart grid-oriented building. They used three different methods ARIMA, ANN, and SVM used for analyzing the forecasts. Ostfold University College of Halden, Norway, used the hourly electricity load data for three years. They individually treated the holiday periods. Results indicated that the estimation accuracy by ARIMA (MAPE of 5.67%) was adopted compared to the ANN and SVM techniques, which resulted in the MAPE of 5.31% and 7.68% accordingly. In [11], Sharif and Yasmeen proposed ARIMA models for forecasting electricity utilization in Pakistan. Monthly historical data over twenty years from 1990 till 2011 was used for prediction. Results expressed that the ARIMA model (3, 1, 2) with the MAPE value of 5.99% is more suitable than other models in electricity forecasting.

2.1.2. Load forecasting using support vector regression

Regression is one of the famous and most frequently used statistical approaches and is easier to use and implement. The regression techniques are commonly employed to represent the relationship between load utilization and other factors like weather variables, customer classes, and day types. This method considers that load can be categorized into a standard load pattern, and that pattern is linearly dependent on a few factors which influence the load. The method's efficiency depends on a suitable representation of the future conditions using historical data, but the measure for detecting any inaccurate forecasts could be constructed quickly. Ogcu et al. [12] implemented SVM and ANN to predict the electricity utilization of Turkey. Two years of monthly electrical energy utilization data were used to design the model. They developed models based on the utilization of two years of monthly electricity consumption data. The MAPE for testing datasets, both ANN and SVM, were 3.9% and 3.3%, respectively.

An SVM-based generic methodology for short-term load forecasting was presented in [13] by Ceperic et al. They explored implementing a technique based on particle swarm global optimization and analyzed the algorithms for the Feature selection of an automatic model input to achieve the optimization of SVR. Two different datasets were used in order to train and test the model separately. The modeling results demonstrated an increase in accuracy from 2.5% to 34.2% for one dataset while 20% to 23.4% for another dataset. The training time for the presented model was approximately 40 minutes, using work station based on Linux having two Intel Xeon X5675 Processors. Kaytez et al. [14] compared regression analysis, LS-SVM, and ANN to forecast electricity energy utilization in Turkey. The recorded dataset from 1970 to 2009 was used with aggregate electricity generation, total subscribership, installed capacity, and population as four input parameters. The LS-SVM outperformed the other two techniques with the testing results of MAPE 1.004% compared to 3.34% for multi-linear regression and 1.19% for ANN. Liu et al. [15] studied the prediction of the time series method using SVM for forecasting the building energy consumptions. Hourly electricity utilization data of one month was analyzed, and samples of the first three weeks were considered as training data while the model was separately tested and validated on two different buildings using test data of the last week. The model resulted in the MSE of 0.091 and 0.0186 for those two buildings correspondingly.

2.1.3. Load forecasting using polynomial regression

2.1.3.1. Linear regression

In the linear regression model, the x is an independent variable of time while the dependent variable y, which represents power load, depends on x. Assume that the relationship between x and y is denoted as given below

$$y = a + bx + \varepsilon \tag{1}$$

Where ε indicates a random error, also called random disturbance, which is subjected to the average distribution N (0, σ^2). a, b and σ are all unknown variables, and these are independent of x.

2.1.3.2. Multiple regression

Multiple regression analysis is the modeling approach for investigating the relationship between one or more than one independent variable x_1, x_2, …x_k, and a continuous dependent variable y. The objective of the regression analysis is to find a function that expresses, as near as possible, the relationship among those variables to predict the dependent variable within the range of independent variables. In multiple linear regression techniques, the electrical load is expressed in terms of the independent variable like weather and other variables which affect the electric load [16]. The load model using the multiple regression method can be defined as

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots \beta_k x_k + \varepsilon \tag{2}$$

Where y is the electrical load to be predicted, x_i are the influencing factors, ε is the error term, and β_i are regression parameters related to x_i, and. The ε (error term) has constant variance and a mean value of zero. As β_i are unknown parameters, they can be evaluated from the observations of dependent variable y and independent variables x_i. Let bi (i = 0,1,2,...k) be the forecasts in terms of (i = 0,1,2,...k) β_i. Thus, the forecasted values of y are written as:

$$y = b_0 + b_1x_1 + b_2x_2 + \cdots bx_k \tag{3}$$

2.2. Data description

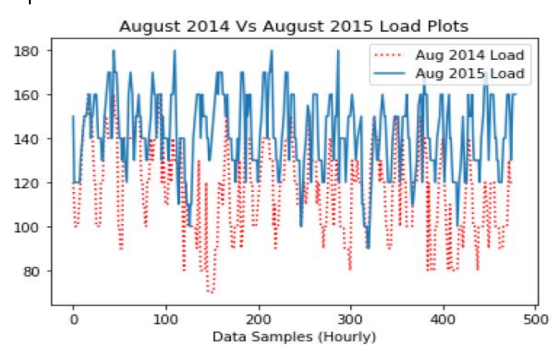
Data were obtained from an 11 KV feeder of 220 KV substations situated in the D.G Khan City of Punjab province for this work. Hourly weather data for a particular city (D.G Khan) were obtained from the Meteorological Department Lahore. Weather parameters included in this study are dry temperature, wet temperature, humidity, and pressure. For this study, the data is hourly electricity consumption data recorded over 4 years depending on the summer and winter seasons.

2.2.1. Data preprocessing

Due to the manual reading of load data from the 11 KV feeder, there were missing values due to the load shedding of electricity in that particular region. For accurate estimation of load demand, data must be preprocessed before training the model. Preprocessing data can be achieved by any of the most valuable techniques like normalization, feature extraction, interpolation (handling missing data), and nonlinear transformation. Normalization of data is essential to help the model extract relevant information during the training process. Model performance can be sensitive to insufficient data. The interpolation technique was applied to our data to handle missing values and remove outliers to improve prediction accuracy.

2.2.2. Parameters selection

Initially, weather variables data we collected from the Meteorological Department contained six parameters dry temperature, wet temperature, humidity, pressure, visibility, and wind speed. Correlation between the target variable and each weather parameter was performed separately to identify variations, i-e which variable follows the behavior of load. It was observed that the parameters dry temperature, wet temperature, and humidity were closely related to the load data as compared to the remaining three parameters.



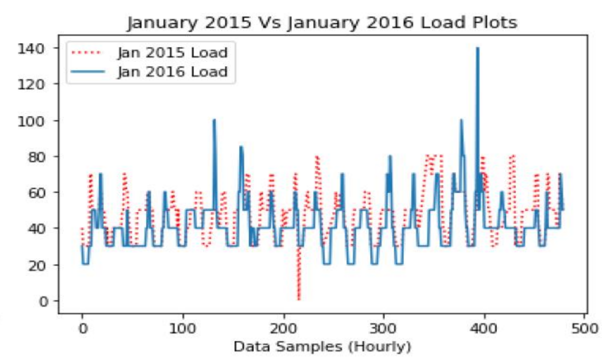


Figure 1. Monthly Electricity Load Consumptions (Summer Season) and **Figure 2.** Monthly Electricity Load Consumptions (Winter Season)

2.2.3. Data plotting

Dataset was divided into different time horizons so that different types of forecasting can be achieved. Monthly load consumptions for both summer and winter seasons are shown in Figure 1 and Figure 2, respectively. For the summer season (August 2014 and 2015), the maximum peak load value is 180 Amperes, and the minimum value is about 65 Amperes. Similarly, the maximum peak load occurs at 140 Amperes, and the minimum load values are at 10 Amperes for the winter (both January 2015 and January 2016) season. The behavior of hourly load demand and humidity for the third week of August 2014 is depicted in Figure 3, while Figure 4 shows the load demand vs. dry temperature. It can be seen from the above figures that humidity closely follows the electricity load pattern as compared to the dry temperature.

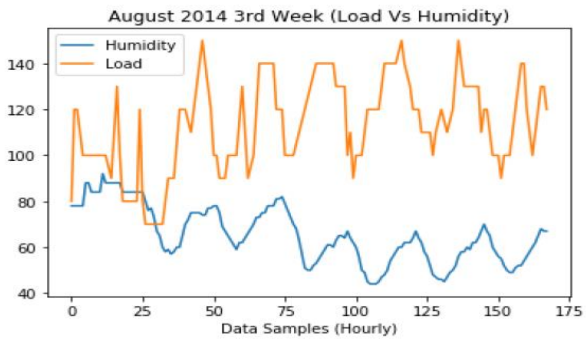


Figure 3. Hourly Electricity Load and Humidity Curve

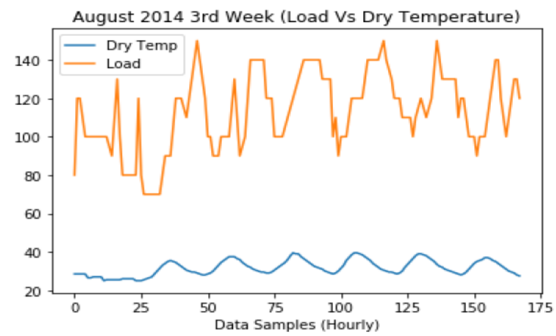


Figure 4. Hourly Electricity Load and Temperature Curve

2.3. Methodology

2.3.1. Artificial neural network

Artificial neural network systems are computational tools initially encouraged by the way the human brain processes data. An artificial neuron is a basic unit that accepts numerical information through various input nodes, internally processes the information, and puts out feedback. The processing is generally accomplished in two phases: firstly, the input values are combined linearly, and then the result of linearly combined input values is utilized as an argument of the nonlinear activation function. We should be most concerned about the network type in this study: Multi-Layer Perceptron (MLP) network, where neurons are grouped to form the layers. In each layer, neurons might share the same inputs, but they are not directly connected. In feed-forward network architecture, the outputs from one layer are used as inputs for the next layer. The layers between the input layer and the output layer are known as the hidden layers.

2.3.2. Selection of network type and network architecture

A fully connected network (Dense Neural Network) architecture with a different number of hidden layers and different layers, sizes were tried and observed. The best results were achieved with two hidden layers having four input parameters. The size of the first and second hidden layers was selected to be 16 and 32, respectively. As our load data, and input parameters, have only positive values, the ReLU (Rectified Linear Unit) activation function was used to avoid any pessimistic predictions. It ranges from 0 to infinity i-e ReLU is half rectified activation function because function value is equal to zero if z is less than zero and function has a positive value when z is greater than or equal to zero as shown in Figure 5. Currently, ReLU is one of the most broadly used activation functions as most of the convolutional neural networks, and deep networks use this activation function.

2.3.3. ANN optimization algorithm

Adam's optimization algorithm was used to iteratively update the network's weights based on the training data. Adam is one of the popular algorithms in the deep learning field as it achieves good results quickly.

2.3.4. Adam configuration parameters

Alpha: It is also called a step size or learning rate. Smaller values result in slower initial learning, and larger values result in faster learning before the weight is updated. The default value for alpha is 0.001.

Beta 1: The exponential decay rate of the first moment estimates (default 0.9).

Beta 2: The exponential decay rate of the second-moment estimates (default 0.999).

Epsilon: It is a minimal value to prevent the division by zero. The default value of epsilon is 10E-8.

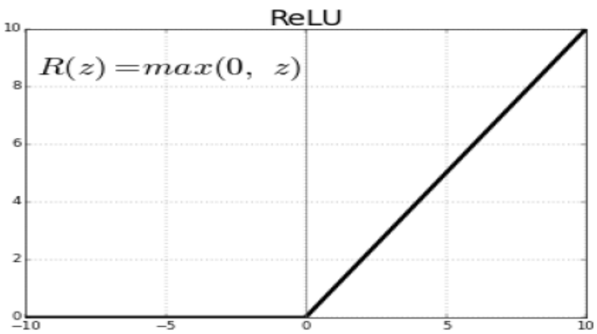


Figure 5. ReLU Activation Function Behavior [16]

Different values of each parameter were tried, and the following parameter values were selected, which resulted in better accuracy and minimum errors.
Alpha = 0.01, Beta1 = 0.5, Beta2 = 0.999, Epsilon = 10E-8.

Sometimes the model stopped improving at a particular value of learning rate, so the training model must improve learning by reducing the learning rate to improve the model's efficiency. Keras class "ReduceL Ron Plateau (monitor, factor, patience, min_lr)" was used to reduce the learning rate of the network when a particular metric has stopped improving. It has the following configuration parameters.
Monitor**:** Quantity being monitored.
Factor: Factor by which learning rate needs to be reduced i-e new_lr = lr * factor
Patience: Number of epochs after which the learning rate will be decreased
Verbose**:** int. 0: quiet, 1: update messages. min_lr**:** Lower bound on the learning rate.
After tuning different parameters, the following parameter values were opted for better results and minimized errors.
Factor = 0.01, Patience = 3, Batch size = 512, Epochs = 50

2.3.5. Support vector regression

Support vector regression (SVR) has demonstrated exceptional generalization capabilities for the forecasting of energy demand load. The main idea of the SVR method is to identify the model function that represents the relation between input parameters and the target. The whole training dataset is represented as (x_1, y_1), (x_2, y_2), and (x_i, y_i), where vector xi is the i^{th} sample of input parameters, y_i is the associated target values, and i is the sample number. The dimensionality of input vector x_i will be n if training data contains n number of features [17]. The popular choices of kernel functions are linear, polynomial, and sigmoid and Radial Basis Function (RBF), representing different mappings from lower to higher feature space [8].

2.3.6. Algorithm of feature selection

The main objective of feature selection is to identify and choose the most appropriate features to develop a good predictor for a concerned learning algorithm. Dimensionality can be decreased by discarding unnecessary and insignificant parameters. Wisely performing the selection procedure can result in many benefits. In order to avoid the curse of dimensionality, first, we should simplify calculations, and the second step is that the accuracy of the established models should be improved if possible. The third step is the enhanced illustrate ability of designed models, and the last step is the usefulness of achieving proper feature samples, specifically for the practical problems of time series predictions [17].

2.3.7. Selection of kernel function

The SVR method from the sci-kit learn library was used for predicting the load data using support vector regression. This method uses different kernels like Linear, RBF (Radial Basis Function), and Polynomial to fit the training data. Due to the nonlinearity of our data, the RBF kernel was selected as it best fitted the data with C = 1000, which is the penalty parameter of the error term, and gamma = 1, which is the free parameter of the Gaussian Radial Basis Function.

2.3.8. Polynomial regression

Regression analysis is a modeling method to analyze and observe the relationship between a dependent variable y and one or more independent variables x_1, x_2, … x_k. The objective of the regression technique is to determine a function that identifies the closest possible relationship between these variables such that the values of independent variables can be used to forecast the values of dependent variables. The simple equation for the linear model is given below:

$$y = \beta_0 + \beta_1 x + \varepsilon \quad (4)$$

Due to the nonlinearity of our data, the linear regression model did not fit well on training data, so we predicted the values of y as 3rd, 5th, and 7th-degree polynomials individually on different datasets in order to get better prediction results. The best results were achieved by using 7th-degree polynomial both in Short Term Load Forecasting (Daily and Weekly) and in Medium-Term Load Forecasting (Monthly). The general nth order polynomial equation is as follows:

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \cdots + \beta_n x^n + \varepsilon \quad (5)$$

Where ε is random error and $\beta_0, \beta_1, \ldots\ \beta_n$ are unknown parameters.

2.4. Forecasting evaluation parameters

The performance criteria used in this study are listed below:

2.4.1. Mean absolute percentage error (MAPE)

MAPE determines the percentage size of the error term.

$$M = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{A_t - F_t}{A_t}\right) \quad (6)$$

Where A_t is the actual value and F_t is the forecasted value.

2.4.2. Mean squared error (MSE)

It is defined as an average of squared predicted error values. Squaring the predicted values enables them to be non-negative.

$$MSE\ (y_k - \hat{y}_k) = \frac{1}{|X_k|}\sum_{x \in X_k} (y_x - \hat{y}_x)^2 \quad (7)$$

Where $y_x \in y_k$ is the ANN output when input $x \in X_k$ is processed, and $\hat{y}_x \in \hat{y}_k$ is the actual value that the network must learn to reproduce. The MSE penalizes larger errors more heavily.

2.4.3. Root mean squared error (RMSE)

The RMSE is a quadratic scoring rule which measures the average magnitude of the error. In RMSE, the difference between forecasted and corresponding actual values are squared, and then their mean is calculated. Finally, the square root of their average is taken. The RMSE gives a relatively high weight to more significant errors because the errors are squared before computing the mean. This implies that the RMSE is most suitable when more significant errors are particularly undesirable.

2.4.4. Mean absolute error (MAE)

MAE is a quantity used for determining how close forecasts are to the actual outcomes. The mean absolute error is given by

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|f_i - y_i| = \frac{1}{n}\sum_{i=1}^{n}|e_i| \quad (8)$$

Where f_i is the predicted value and y_i the actual value, MAE tells us how big of an error we can expect from the forecast; on average i-e, MAE penalizes all errors uniformly.

2.4.5. R-squared

R-squared is a statistical measure to identify the closeness of data to the fitted regression line i-e the higher the R-squared value, the better the model fits the data.

$$ei = yi - \hat{y}i \quad (9)$$

$$SSR = \sum_{i=1}^{N} e_i^{\,2}$$

$$SST = \sum_{i=1}^{N} (yi - \hat{y}i)^2$$

$$R^2 = 1 - \frac{SSR}{SST} \quad (10)$$

Results and discussion

In this section, four different scenarios (daily, weekly, monthly, and season vise) will be illustrated for each model we have developed. The initial hourly data of electricity consumption for different time horizons were taken and split into the training and test data with a ratio of 80% and 20%, respectively. Four input features dry temperature, wet temperature, humidity, and pressure; the model was trained separately with each input parameter using load as a target feature. The best prediction results in both seasons (for all four scenarios) were selected based on the minimum error performance parameters and R-squared value, indicating how close the data are to the fitted regression line.

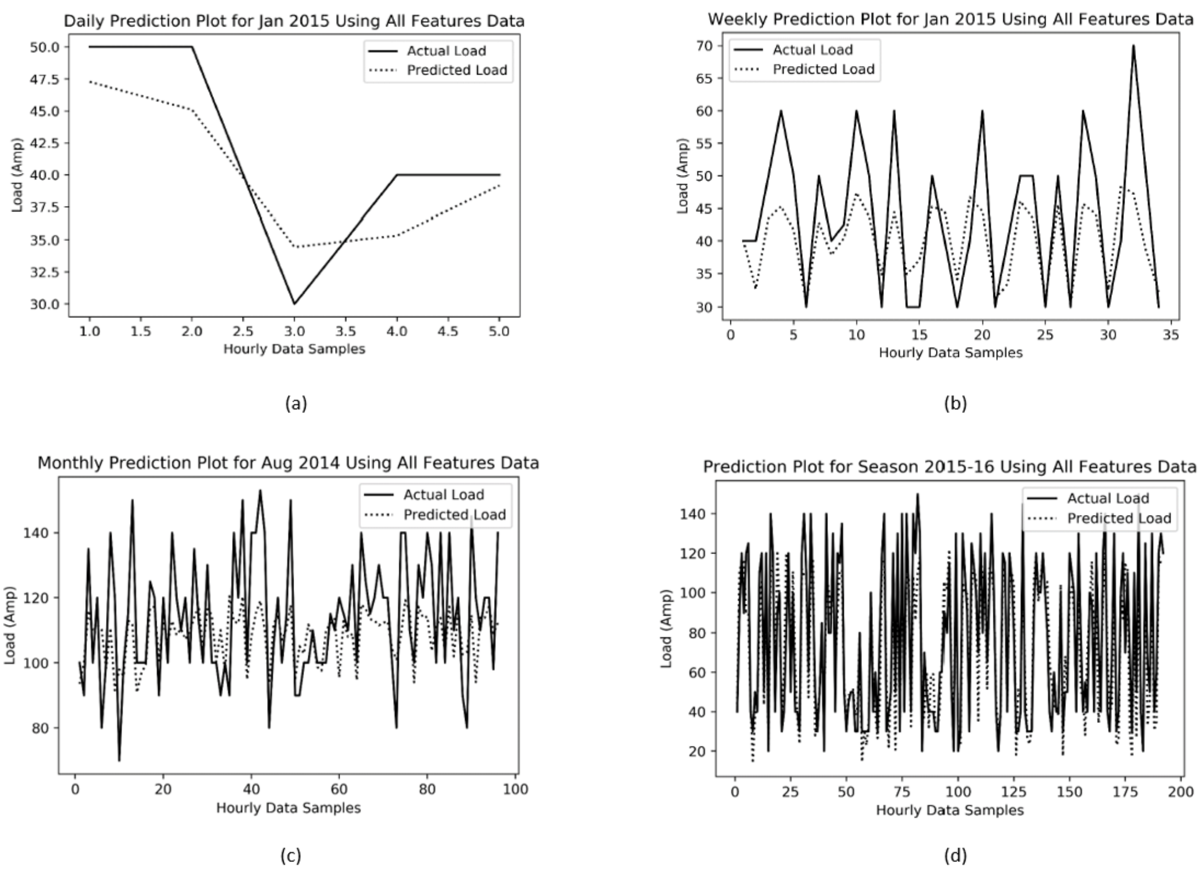


Figure 6. **(a)** ANN Predictions for January 15, 2015. **(b)** ANN Predictions for Week in January 2015. **(c)** ANN Predictions for Month of August 2014. **(d)** ANN Predictions for Season 2015-2016

Table 1. ANN prediction results

Parameters	R-squared	MAPE	MAE	RMSE	MSE
Daily	0.73681	8.76114	3.5136	3.83906	14.7384
Weekly	0.4483	13.98	6.6949	8.4398	71.23079
Monthly	0.212348	11.286	13.1289	16.7310	279.92787
Season-Vise	0.78103	23.5610	14.906	18.50553	342.4548

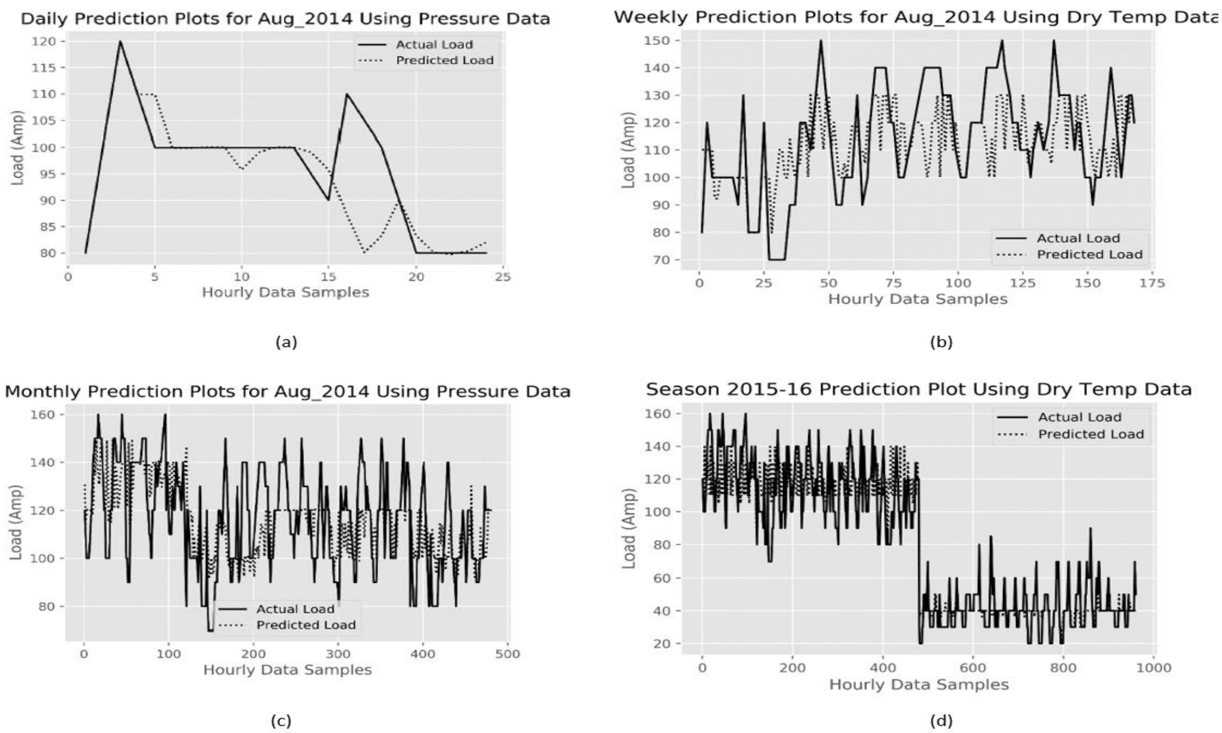


Figure 7. (a) SVR Predictions for August 15, 2015. **(b)** SVR Predictions for Week in August 2014. **(c)** SVR Predictions for Month of August 2014. **(d)** SVR Predictions for Season 2015-2016

Table 2. SVR prediction results

Parameters	R-squared	MAPE	MAE	RMSE	MSE
Daily	0.434869	3.9769	4.0145	8.16803	66.7168
Weekly	0.31008	10.294	11.30656	16.01586	256.5079
Monthly	0.27836	11.97092	13.3075	17.34778	300.9457
Season-Vise	0.83801	17.75232	11.894	16.6907	278.581

Polynomials with order 3, 5 and 7 were applied to the model for line fitting. It can be observed from Figure 8 that the 7th order polynomial well fitted the data as compared to other degree polynomials due to the nonlinearity of our data.

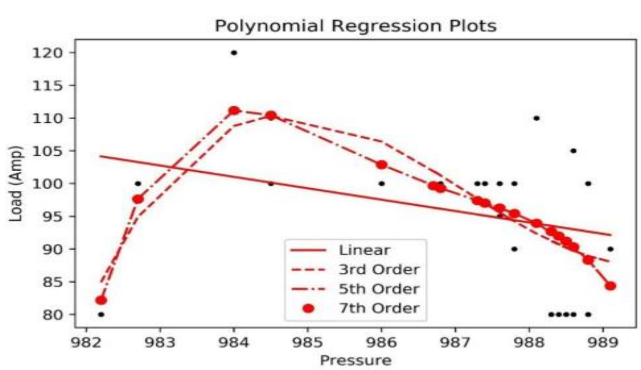


Figure 8. Line Fitting Plot for January 15, 2015

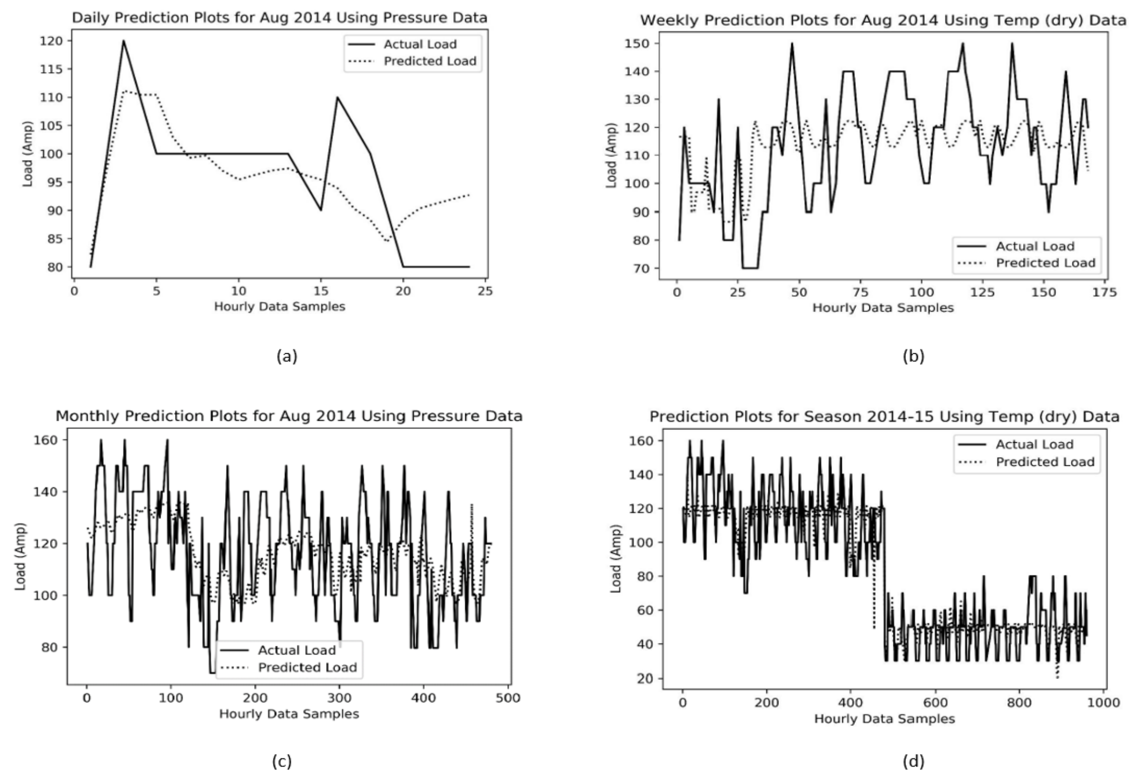


Figure 9. (a) PR Predictions for August 15, 2014. **(b)** PR Predictions for Week in August 2014. **(c)** PR Predictions for Month of August 2014. **(d)** PR Predictions for Season 2014-2015

Table 3. Polynomial regression prediction results

Parameters	R-squared	MAPE	MAE	RMSE	MSE
Daily	0.454894840	6.91901136	6.427675	8.0220129	64.352692
Weekly	0.23656	12.63149	13.5173	16.8476	283.8430
Monthly	0.287195	12.779	14.1387	17.2412	297.261
Season-Vise	0.82006	18.155	12.7592	16.3316	266.7228

Conclusion

This paperwork aimed to develop short-term and medium-term forecasts for the electrical load. We have tested our models by using actual electrical load utilization from a 220 KV Grid Station of D.G Khan City. We used four years of data. We split our data in an 80% to 20% ratio for all types of forecasting horizons (daily, weekly, monthly, and season vise) in all the models mentioned above. The target output in this work was electricity load for next year, while four weather variables like dry temperature, wet temperature, humidity, and pressure from the past year's data were considered input parameters. The SVR model achieved the overall performance for short-term forecasting. For future work, the previous year's data with power break down periods (in case of faults) and data with load shedding periods can be incorporated to obtain better accuracy. The population density factor can also be introduced to keep track of the variations in the population of a particular region to determine the most appropriate load demand, resulting in better prediction outcomes.

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Conflicts of interest. There is no conflict of interest.

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