Energy Proceedings
Vol 55, 2025
ISSN 2004-2965

Assessing the Impact of Climate Change on Long Term Load Forecasting for Electric Utilities#

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ABSTRACT

This paper presents a comparison of different statistical and machine learning models using five groups of input features to forecast the future demand of a region, comprising 5 adjacent cities (Lahore, Sheikhupura, Kasur, Okara, Nankana), managed by a single government-operated utility. The proposed methodology was constructed using hourly data of electricity load in MW and hourly data of three weather variables with the highest correlation with load, for more than 10 years i.e. from July 2013 to Dec 2023. We have applied LM, SVM, and LSTM models, the most widely used techniques in literature for long term load forecasts. In three years of out-of-sample forecasts with 26041 timesteps, the SVM model performed best with a MAPE value of 2.98% applying ARIMA with Kalman smoothing to fill missing load values for 4 months. However, LSTM performed 2.5 times better than LM and SVM if input features are only weather variables and historical hourly load is not provided as input to training and test sets.

Keywords: Power System planning, Load Forecasting, climate change

NOMENCLATURE

ARIMA	Auto Regressive Moving Average
LSTM	Long Short term memory
SVM	Support Vector machines
LM	Linear Regression Model
GA	Genetic Algorithms

Symbols	
h	hour
MW	mega watts

1. INTRODUCTION

The main objective of power system planning is to meet the energy demand reliably in a sustainable way. All investment decisions in the power sector are based on the statistics of addition in generation capacity, expansion in transmission network, and enhancement in distribution facilities which in turn depend on accurate load forecast [1]. Electric utilities sign future contracts for profit maximization with reduced risk [2]. Generation contracts are long term and require the most accurate forecasts for optimal investment decisions. Even small improvements in electricity forecasted value save millions of dollars. A study found that a mere 1% reduction in forecast error led to a £10 million decrease in annual operating costs for an electric utility in the United Kingdom [3]. Inaccurate load forecast results in over or under investment that causes higher tariffs or load management respectively. Electricity demand forecasting models are developed to study forecasting for different time horizons. The time horizon is classified into 4 categories that are very short term which is less than an hour, short term which ranges from 1 hour to several days, mid-term is from 1 month to a season and long term is from a year to several years. [4]. As forecasting becomes very challenging in the long term due to its complexity, difficulty in gathering and processing data, and uncertainty due to the large time horizons involved, most of the research on predicting future loads is now focused on short term load forecasting. There is more need to work on long term forecasts with novel techniques to improve forecasting errors and reduce model run time so that utilities can make the least cost generation, transmission, and distribution plans. Most researchers work on monthly granularity for long term forecasting [5].

This is a paper for the 16th International Conference on Applied Energy (ICAE2024), Sep. 1-5, 2024, Niigata, Japan.

Load forecasting models can generally be categorized into two broad classes: classical statistical techniques and modern machine learning (ML) approaches. These techniques include regression, multiple regression, exponential smoothing, iterative reweighted least squares, adaptive load forecasting, stochastic time series autoregressive, ARMA model, ARIMA model, support vector machine-based models, soft-computing based models, genetic algorithms, fuzzy logic, neural networks, and knowledge-based expert systems, etc. Each technique has merits and demerits [6]. From the works reported so far, it can be inferred that demand forecasting techniques based on soft computing methods are gaining major advantages for their effective use. The use of deep learning techniques has grown with the rise in computational power and the availability of big data [7]. RNN-LSTM models are used to model sequential data, such as time series data, as they store contextual information from past inputs. For predicting future load based on nine years of historical data, the results show that deep learning could predict the load demand more accurately than SVM and RF [8].

In the context of climate change, the temperature-power consumption response function in Beijing was evaluated, and power consumption was predicted in the next 40 years under different shared socio-economic paths (SSPS) [9].

Statistical and machine learning models used for long term load forecasting use different input features such as socio-economic factors e.g. GDP, population, historical electricity demand, etc., and weather features e.g. temperature, humidity, and wind speed for long term forecasts. In this paper, a decade long new data set of a large utility at hourly resolution is used for long term load forecast. Using historical electricity load and weather variables as input features, we have compared three models based on their respective MAPE values.

The rest of the paper is structured as follows: In Section 2, Data description and selection of models, input features, and performance measures are described. Section 3 describes the complete methodology, from feature engineering to training of the proposed model. Subsequently, the performance metrics have been included in Section 4. This has been further illustrated with plots. The paper has been recapitulated in Section 5 and potential future works are also described.

2. Data Processing

This section comprises data description Section 2.1 which identifies the data type, resolution, and processing. The selection of input features, models, and performance measures is described in Section 2.2

2.1. Data Description

We have gathered historical electricity load data at hourly resolution, of a large utility, Lahore Electric Supply Company having presently 6464887 customers, from 2013 to 2023. The unique aspect of this research is that this data is being used for the first time in any research. The values of electricity load are actual consumption values recorded at hourly resolution and not the true electricity demand values. This happened due to forced and planned load management from 2013 to 2023 in the region under study. Observing the behavior of load patterns over a decade, we can see that load has a large variation during the year. Hourly load varied from 354 MW to 5503 MW in 2023. Peak load occurs in summer due to the addition of air conditioning load.

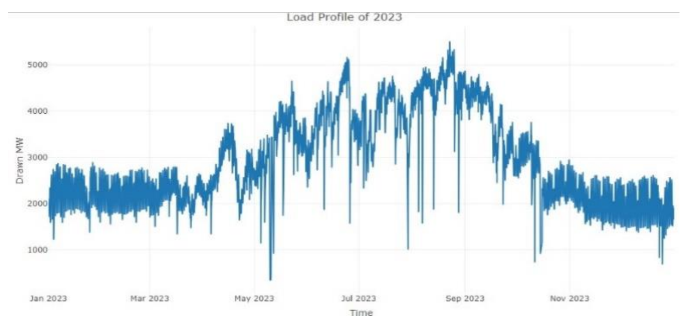

Figure 1 Load Profile- 2023

The decade long electricity data was supposed to be influenced by global climate change impact over the past decade. For incorporating climate change impact of weather on electricity usage, weather data of the same region, same period, and resolution as of electricity load data was downloaded online from a weather API by providing latitude 31.1072 and longitude 73.32542. The weather features downloaded were temperature at 2 m (°C), relative humidity at 2 m, dew point at 2 m (°C), apparent temperature(°C) , rain(mm), precipitation (mm), cloud cover, wind speed at 10 m (km/h), wind speed at 100m (km/h) [10]. Based on P values of Pearson correlation of these weather parameters with hourly load over a decade, we have selected 3 weather variables having the highest correlation namely apparent temperature (℃), temperature at 2 m (℃) and dew point (℃).

The load data collected was mostly clean, however, there were some zeros, duplicate values, and missing values in the data set. Duplicate values were removed, zeros and and missing values of hourly electricity load for approximately 4 months from 18th Sep 2015 to 15th Jan 2016 were filled by two methods. The first method MVFill_1 fills hourly load missing values based on corresponding apparent temperature values. Apparent temperature has the highest correlation with load among all weather variables. The value to be filled against the missing load value is calculated by taking the mean of all values of hourly load in the whole data set of more than 10 years at the same apparent temperature value as the missing load value. The second method applied to fill in missing load values uses ARIMA lag regression and Kalman smoothing to fill in missing values of electricity load.

For all the models, 70% of the data is used for training and 30% for testing.

2.2 SELECTION OF MODELS, INPUT FEATURES AND PERFORMANCE MEASURES

The research community uses different models, input features, and performance measures to forecast electricity load. Energy demand models can be classified in several ways such as static versus dynamic, univariate versus multivariate, and time series versus hybrid models [11]. These models can also be differentiated based on different input features, modeling methods, and performance measures. There is a research gap in using any scientific methodology for choosing forecasting models, input features, and performance measures. We have observed that any set of models, features, and performance measures are selected on a hit-and-trial basis. To fill this research gap, we have used the ABC classification technique for the selection of models, input features, and performance measures based on 35 latest relevant research papers. There are three classes, A, B, and C each for forecasting models, input features, and performance measures. The criterion chosen for classification is that Class A contains 70 %, class B contains 20% and Class C contains 10% of modeling techniques used in the literature. The same criterion is used for the classification of features and performance measures. As a first step based on this scientific methodology, we have selected the most widely used models and performance measures from Class A for our research. We have selected SVM, LM, and LSTM as the most commonly used modeling techniques in the literature. We have compared LM, a statistical method, SVM, a machine learning method, and LSTM, a deep learning method. Due to the complexity of the problem in long term forecasting involving weather, socioeconomic and other factors, time series analysis can be applied. Linear Regression (LR) is the earliest form of least-squares estimation in classification [12] and has been used extensively for long term load forecasts. Support Vector machine is based on statistical learning theory [13]. In SVM, the empirical risk minimization principle employed in Artificial Neural Networks is replaced by the structural risk minimization principle. SVM is equivalent to solving a linear constrained quadratic programming problem having a unique and globally optimal solution [14]. LSTM was introduced as a more efficient architecture compared to traditional RNNs addressing the problem of vanishing gradient [15]. Recurrent Neural Networks (RNNs) are one of the most widely used models for performing time-series predictions. However, they suffer from an inherent problem of vanishing gradient descent. To overcome this problem and additionally formulate long term dependencies between training samples, LSTM-RNN is used which significantly increases the precision of the proposed model [16].

The performance measures used by researchers most frequently are MAPE, RMSE, and MAE subsequently. For this research, we have used MAPE as a performance measure to compare models with different sets of input features.

Similarly, a large variety of input features have been used in literature, like previous electricity consumption at different aggregation levels e.g. monthly load, daily load; weather features e.g. mean temp, wind speed, cloud cover, etc. and socio-economic features such as GDP, population, etc. The input feature most frequently used in literature is daily electricity load, however, we have not used daily load as input, instead, we have used historical load at hourly resolution as the input feature. With the growing shift towards renewable energy generation and greater integration of electricity into primary energy consumption, the necessity for higher resolution of precise long-term load forecasting is essential [17]. This selection was made due to the increasing trend in future load demand variations [18]. This is happening due to the climate change phenomenon and rapidly changing socio-economic factors [19]. In this scenario, electricity service providers can get better insight from hourly resolution of forecast for better decision making to use their money wisely. Features are selected not only based on the most frequently used features by the researchers but also on the correlation value with electricity load. The electric load of previous hours in MWs is selected based on autocorrelation values.

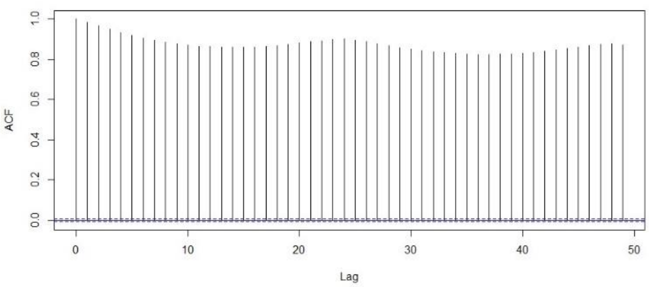

Figure 2 ACF graph of hourly load (MW)

We have selected the previous hour load namely Lag_h1, one hour before previous hour load as Lag_h2 and 3 hours earlier load as Lag_h3. Similarly, 24h ago load is taken as Lag_24h and one week ago load as Lag_168h. ACF graph is shown in Figure 2.

As per ABC classification, Mean, max, min temp, and wind speed are among the most used weather features of class A. However, we have used Pearson correlation values of weather features with electricity load for selection of weather features for this research. Three weather variables with the highest correlation values are selected as input features for this research and are shown in Figure 3. The apparent temperature has 0.648, the temperature has 0.606, and the dew point has 0.577 correlation values with load. All other weather variables have less than 0.16 correlation values with load, relative humidity has -0.15, rain and precipitation have 0.03, cloud cover has -0.006, wind speed at 10 meters has 0.12, and wind speed at 100 m has 0.13 correlation value with the load.

Year-wise correlation values of selected features are also shown in Figure 4, the values vary from 0.53 for the dew point in 2022 to 0.82 for the apparent temperature in 2019.

We can see that correlation values of selected variables also show a strong correlation with load on a yearly basis for the past 10 years, averaging at 0.7.

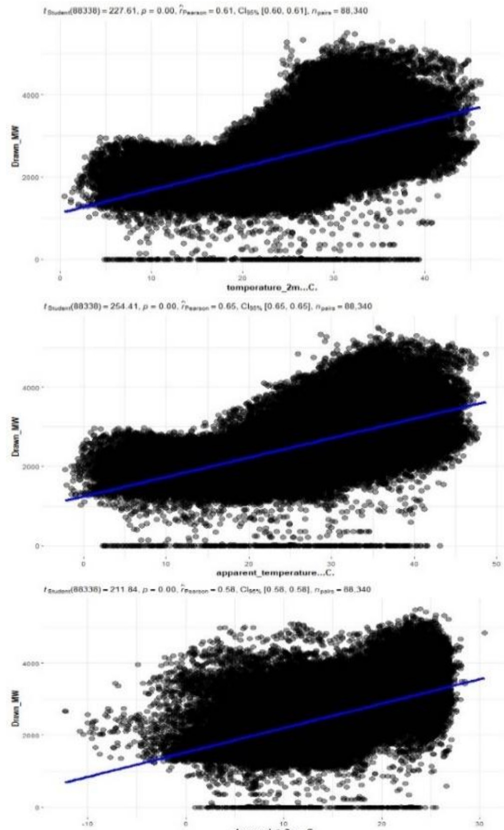

Figure 3 Apparent Temperature, Temperature, and Dew point graphs respectively have highest Pearson correlation with load

machines, and long-short-term-memory network based Recurrent Neural Network (LSTM-RNN) model for forecasting electricity demand for a period of three years. LM assumes a linear relationship between input features and can underfit if the true relationship is non-linear. LM is sensitive to outliers. This model is the simplest to apply among the three models and requires less time to train the data. LM assumes that features are independent.

SVM is computationally expensive compared to LM. SVM can overfit with small data sets and can perform poorly with large data sets in terms of speed and memory usage. SVM is sensitive to noisy data [20]. The application of SVM and LM was easy, however, the parameters setting for the LSTM model application was not simple. LSTM model is applied for time series data and has advantages in managing complex or non-linear patterns in electricity data. Having smaller training data sets compared to model complexity or choosing too many lag values for forecasting can cause the overfitting problem in LSTM. Too many epochs can cause overfitting whereas not training the model for enough epochs results in underfitting [21].

The parameters used for LSTM are mentioned in Table 1.

Parameters	Layer 1	Layer 2
Layer type	Bidirectional LSTM	Dense
Nodes	32	
Activation	Tanh	Linear
Output Size		1
Optimizer	ADAM	
Epochs	40	
Batch Size	100	

Table 1 LSTM model parameters

LSTM model parameters can be further tuned for improved results. The optimal number of time lags and LSTM layers can be selected using GA.

Each model has 2 variants of results based on 2 different techniques to fill in missing values in the data set of electricity load. Thus 3 models have 6 variants. Each variant has further 5 types of output based on grouping of selected input features. The variables selected as input features are based on Pearson correlation values.

We have selected two types of input features: historical load values and weather variables. We have also selected 3 load values at the previous three hours, load at a day ago hour, and load at a week ago hour i.e. Lag_h1, Lag_h2, Lag_h3, Lag_h24, and Lag_h168. The other type of input feature is hourly weather variables: temperature, apparent temperature, and dew point. These two types of features are grouped into five groups of features.

Group1 has only 3 weather variables i.e. temperature, apparent temperature, and dew point, Group2 has 3 lag values of electricity load with the highest correlation i.e. load values at each of the previous 3 hours, Group 3 has 5 lag values of load having the highest correlation with load i.e. Lag_h1, Lag_h2, Lag_h3, Lag_h24 and Lag_h168, Group 4 has all features of Group1 and Group2 and Group5 has all the three weather variables and 5 lag variables as input features. The total number of input features in each group is also different. Group1 and 2 have 3 input features, Group3 has 5, Group4 has 6 and Group5 has 8 input features. Thus, each of the 3 models has 2 variants and each variant is further divided into 5 subtypes. Accordingly, error estimation based on MAPE values for all the 10

		SVM		LM		LSTM	
Feature Groups	***Input Features***	***MVFill_1***	***MVFill_2***	***MVFill_1***	***MVFill_2***	***MVFill_1***	***MVFill_2***
Group1	***Temp_h0, App Temp_h0, Dew Point_h0***	**23.03**	**23.31**	**22.60**	**22.95**	**9.35**	**12.04**
Group2	***Lag_h1, Lag_h2, Lag_h3***	**3.15**	**3.06**	**3.45**	**3.25**	**6.78**	**6.69**
Group3	***Lag_h1, Lag_h2, Lag_h3, Lag _h24, Lag_ h168***	**3.09**	**3.00**	**3.41**	**3.19**	**8.08**	**7.53**
Group4	***Lag_h1, Lag_h2, Lag_h3, Temp_h0, App Temp_h0, Dew Point_h0***	**3.09**	**3.03**	**3.29**	**3.13**	**7.43**	**8.54**
Group5	***Lag_h1, Lag_h2, Lag_h3, Lag _h24, Lag_h168, Temp_h0, App Temp_h0, Dew Point_h0***	**3.03**	**2.98**	**3.23**	**3.08**	**8.77**	**7.57**

Table 2 Comparison of SVM, LM, and LSTM based on MAPE value for all groups of features.

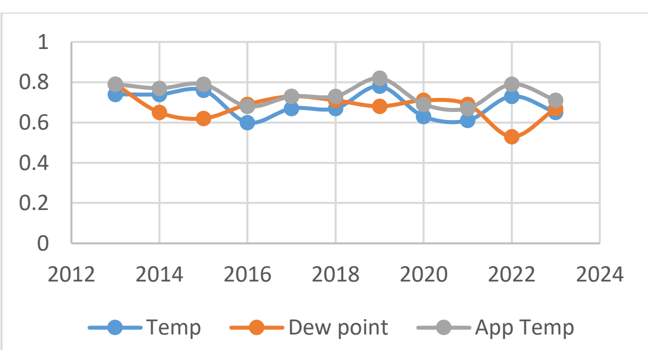

Figure 4 Year-wise correlation of selected weather features.

versions of each of the 3 models is presented in Table 2. The forecasted values are hourly electricity load values which are more useful for utilities in present times where abrupt changes occur at more frequent rates.

3 Results and Discussion

Comparing MAPE values in Table 2 for 3 models, it can be observed that the results of SVM are better than other techniques LM and LSTM for input features groups: Group2, Group3, Group4, and Group5. The best performance of the SVM model with the lowest MAPE value of 2.98 is for Group5 input features and with the MVFill_2 technique to fill missing values. It means for long term load forecasts; utilities must consider weather features with the highest correlation with load along with a load of the previous three hours, load of one day before, and a week ago load. It is also shown that for any missing historical load data, ARIMA lag regression along with Kalman smoothing gives better estimated values.
The climate change impact incorporated by considering most correlated weather variables for the past decade has shown improvement in forecasted load values. Considering missing values fill techniques, for LM and SVM, results have much resemblance of pattern as for input features groups; Group2, Group3, Group4, and Group5, MVFill_2 performed better than MVFill_1. Whereas, for Group 1, the MVFill_1 technique performed better than the MVFill_2.

Group 1 which contains only 3 weather variables, and no electricity load lag variable has shown very interesting results. All modeling techniques performed better with MVFill_1 compared to MVFill_2. If we compare the results of SVM and LM with LSTM for Group 1 only, we can see that LSTM performed 2.5 times better than both classical techniques for MVFill_1, and for MVFill_2, LSTM results are about 2 times better than classical techniques. This means if we do not need to give load lag values as input features to predict future load values then LSTM gives better results than other techniques.

When we compare the results of different input feature groups (except group 1) and missing value fill techniques for SVM and LM, it is obvious that results are not very elastic for any group of input features and missing value fill techniques. MAPE values of all the 15 variants of SVM range from 2.98 to 3.15 whereas for LM, it ranges from 3.08 to 3.45. The most interesting result of this study is that in Group 1 where only three highly correlated weather features are taken as input, without considering any value of historical consumption, LSTM resulted in a 9.35 MAPE value which is about 2.5 times better compared to LM and SVM. This indicates that LSTM outperforms the best techniques reported in literature if we only take weather variables as input features. We can say that for the purpose of studying only the climate effects of weather on electricity load without giving additional features of historical consumption as input, LSTM is far ahead of other techniques reported in the literature. So, we can train our model only on three highly correlated weather features and can forecast future load with a 9.35 MAPE value at hourly resolution.

For example, when we forecast two years ahead load, we need future loads at all hours till 2 years which involves inaccuracies and errors. If we do not need that load and can forecast our future load which is not in the near future, by providing weather variables, errors and inaccuracies of only the weather variables involved will affect the forecasted load results. Simply, we do not require forecasted electricity consumption data for long term forecasts of years ahead. Without considering any feature of historical electricity load, LSTM has outperformed LM and SVM with significant difference in MAPE values.

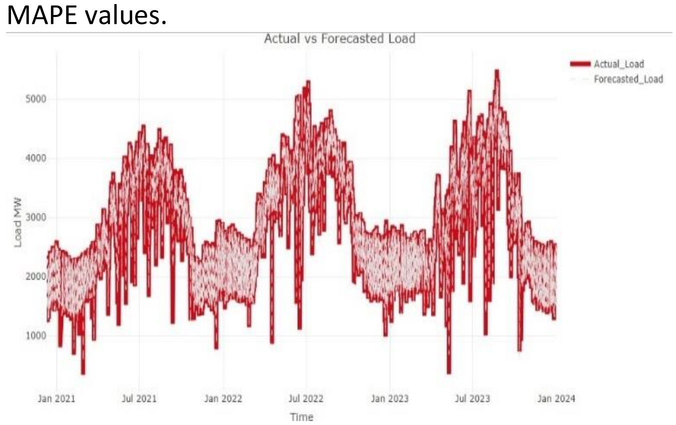

Figure 5 Actual vs Forecasted Load

3. Future Work

The work presented here was aimed at long term load forecast, however, it can also be used for short time horizons. As we have presented our work in hourly resolution, we can forecast the load of the next hour, two hours, three hours, and so on which means we can predict the load of the next hour which is short term load forecasting. Similarly, we can forecast load at any hour after one month or after more than one month which is termed as medium term load forecasting. This shows the same study can be used for short term and medium-term forecasting as well. The results can be improved by considering socio-economic variables as input features. The socio-economic variables could not be considered input features in this research as only a single value of GDP and population was available for the region under study for the past decade. However, the results can be improved if socio-economic data is made available at a greater resolution. Since this research was conducted with data at hourly resolution, we assume that GDP and population data could not be made available at one-hour resolution, so we can take the mean of hourly loads and weather variables for monthly or annual values to incorporate those socio-economic variables. We can further improve the results by assigning appropriate weights to historical load and weather variables based on the time gap between the input variables and the forecasted load.

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