An efficient approach for short-term load forecasting using historical data

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Abstract
Price modeling has become a fundamental input to an energy company's decision-making and strategy development. Short Term Load Forecasting (STLF) plays an important role in electric power system operation and planning. Forecast of the total load demand is necessary for Unit Commitment and Economic load Dispatch of generating units along with system security.
This paper presents a study of short term half-hourly load forecasting with the help of previous day data and current day data. The proposed model for short term load forecasting (STLF) in the electricity market has been applied to DVC grid which is operating under arena of Eastern Region Load Despatch Centre (ERLDC), India.
Keywords: Load forecast; Time series; Mean Absolute Percentage Error (MAPE); Short Term Load Forecasting (STLF).

1. Introduction

In the deregulated regime Power producers are facing new challenges due to introduction of competition in power sector. The basic quantity of interest here is typically the half hourly total system load. However, load forecasting is also concerned with the prediction of hourly, daily, weekly and monthly values of the system load and peak system load. The forecasts for different time horizons are important for different operations within a company. Load forecasting may be classified in terms of the planning horizon's duration, as short term (STLF), medium-term (MTLF) and long-term load forecasting (LTLF).

Short-term load forecasting has become increasingly important since the rise of competitive energy markets.

STLF can help to estimate load flows and to make decisions that can prevent overloading and reduce occurrences of equipment failures. This in turn has propelled research in electricity price modeling and forecasting.

When bidding for spot electricity in an auction-type market, players are requested to express their bids in terms of prices and quantities. Buy (sell) orders are accepted in order of increasing (decreasing) prices until total demand (supply) is met. A power plant that is able to forecast spot prices can adjust its own production schedule accordingly and hence maximize its profits. Since the day-ahead spot market typically consists of 24 hourly (or 48 half-hourly) auctions that take place simultaneously one day in advance, STLF with lead times from a few hours to a few days is of prime importance in day-to-day market operations.

For some time power engineers have been familiar with both scheduling and dispatching units in the system and load forecasting. With the restructuring of the electric power industry, it has been very natural for the engineers to adapt these models for price forecasting under the new economic conditions.

Depending on the objectives of the analysis, a number of methods for modeling price dynamics have been proposed, ranging from parsimonious stochastic models to fundamental and game theory approaches. It was only a question of time before these methods were put into use in the power markets.

We know several straightforward averaging methods can be applied for data smoothing in many ways including the mean, simple moving average, double moving averages and higher-order moving averages. In all cases the objective is to make use of past data to develop a forecasting system for future periods. Other factors like power plant availability, grid traffic (for zonal and modal pricing) or weather data (although these are generally included already in load forecasts) could also be considered.

We have to remember, though, that no matter how good our forecasting model is, if the inputs to the model are poor, it will be difficult or impossible to come up with good predictions.

In this paper, the work presents a study of short term half-hourly load forecasting with the help of using previous day data and current day data. The proposed novel model for short term load forecast (STLF) in the electricity market applied to DVC grid operating under ERLDC, India. The prior electricity demand data are treated as time series. The proposed model is processed using historical data. The development of forecast engine involves 3 steps. The first step involves study of system behaviour. The second step training of historical data available. The next step is formulation of the mathematical model and implementation of statistical analysis to study its efficacy.

This model gives load forecasts half an hour in advance.

2 Overview & Classification of load forecasting techniques:

Load forecasting has become one of the most significant aspects of electric utility planning [1-6]. The economic consequences of improved load forecasting approaches have kept development of alternate, more accurate algorithms at the forefront of electric power research [7-10]. Thus the significance of the subject in power systems has drawn alarming interests of many researchers, and to date a number of load forecasting approaches have been developed [11-16].

Generally, load forecasting models can be classified into two categories: time-of-day models and dynamic models. Time-of-day model is a non-dynamic approach and expresses the load at once as discrete time series consisting of predicated values for each hour of the forecasting period.

The second classification involves the dynamic model that recognizes the fact that the load is not only a function of the time of the day, but also of the load most recent behaviour.

The various methods used for load forecasting are similar day approach, regression models, time series, neural networks, expert systems, fuzzy logic, statistical learning algorithms, etc. [17-18] and their classification is in terms of their degrees of mathematical analysis used in the forecasting model.

In most cases historical data are insufficient or not available at all, yet it is anticipated for planners to accurately forecast, thus qualitative forecasting methods are generally used. Among others methods include Delphi method, curve fitting and technological comparisons.

Other forecasting techniques such as decomposition methods, regression analysis, exponential smoothing, and the Box-Jenkins approach are quantitative methods [19-22].

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3 Factors Affecting Load Patterns

The forecasting accuracy depends not only on the numerical efficiency of the employed algorithms, but also on the quality of the analyzed data and the ability to incorporate important exogenous factors into the models. For STLF, several variables should be considered, such as time factors, weather data, electricity prices, social events and possible customers' classes.

3.1 Time Factors

The time factors influencing the system load include the time of the year, the day of the week and the hour of the day.

3.2 Weather Conditions

Apart from time factors, weather conditions are the most influential exogenous variables, especially for STLF. Various weather variables could be considered, but temperature and humidity are the most commonly used load predictors.

3.3 Other Factors

Components or factors related to electricity prices can also be included in load forecasting models. For non-residential and cost-sensitive industrial or institutional consumers the financial incentives to adjust loads can be significant. At low prices, load elasticity is negligible, but at times of extreme conditions, price-induced rationing is a likely scenario. Many social and behavioral factors can come into play and the accuracy of short-term forecasts can be at times severely curtailed. Major social events like TV programs (World Cup) or special events (death of a charismatic leader, severe terrorist attack) can have a dominating influence on consumption over very short-term intervals. Some of these factors are known in advance and can be taken into account, but some are not.

Nevertheless, residential loads are easier to forecast than industrial loads because of the large number of residential customers. If one customer does something strange, the impact of his actions on the whole system is negligible. On the other hand, a large industrial customer may behave unpredictably enough to deceive forecasts by, for example, adding an extra work shift or shutting down a production line. Since most electric utilities serve customers of different types they often distinguish load behavior on a class-by-class basis. The electric usage pattern is different for customers that belong to different classes but is somewhat alike for customers within each class. An alternative approach that electric utilities can take is to transfer the volumetric risk to the industrial consumer. At the cost of reducing the margin for delivery of electricity the financial consequences of the fluctuations in consumption are passed on directly to the consumer.

4 Problem statement: *To develop optimised-historical data based model for Short-Term Load Forecasting and apply this to a real life case study to evaluate the performance of the proposed approach and provide half an hour ahead forecast for the data of DVC power system network operating under ERLDC, India.*

Load Characteristics

The load forecasting problem has been solved using Historical data method. Equations devised for load forecasting are as given below:

$$L_t^F = L_t^{pd} + \left(\Delta L^{\sim}_{t\frac{1}{2}} + \Delta L^{\sim}_{t\,1} \right) \qquad (1)$$

$$\Delta L^{\sim}_{t\,1/2} = \left|\left(L^{pd}_{t-1/2} - L^{cd}_{t-1/2}\right)/2\right| \qquad (2)$$

$$\Delta L^{\sim}_{t\,1} = \left|\left(L^{pd}_{t-1} - L^{cd}_{t-1}\right)/2\right| \qquad (3)$$

Where,

L_t^F=Actual forecast load of current day at required time.

L_t^{pd}=load of the previous day at the same time.

$L^{pd}_{t-1/2}$=load of the previous day half hour before the current forecast time.

L^{pd}_{t-1}=load of the previous day one hour before the current forecast time.

$L^{cd}_{t-1/2}$=load of the current day half hour before the current forecast time.

L^{cd}_{t-1}=load of the current day one hour before the current forecast time.

$\Delta L^{\sim}_{t\frac{1}{2}}$= Absolute average value of difference of half hour values.

$\Delta L^{\sim}_{t\,1}$= Absolute average value of difference of hour values.

This supervised historical data model can make predictions based on the relationships of processed data of previous day and data available for the current day.

In this paper, the proposed STLF method has been developed and tested on DVC load data in which the forecast has been made based on load data at a particular time of the previous day in steps of half hour and one hour and corresponding load data of the current day of the previous half hour and one hour.

The assessment of the prediction performance of the different soft computing models was done by quantifying the prediction obtained on an independent data set. The mean absolute percentage error (MAPE) was used to study the performance of the trained forecasting models for the testing time samples. MAPE is defined as follows:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\{[L_t^{AL} - L_t^{F}]/L_t^{AL}\} * 100 \qquad (4)$$

Where L_t^{AL}= actual load of the current day at the same time and N represents the total number of data (interval hours=48) & L_t^{F}=Actual forecast load of current day at required time.

5. RESULTS & DISCUSSION: The new devised method was applied for very short term load forecasting for the one week time span from 8th to 14th of January and graphs were plotted with number of samples representing half hourly duration for the whole day in the x axis and corresponding actual load and forecast load on y axis. From the Fig.1to Fig.7, it is observed that forecast load is very close to actual load and the calculated % error was found to be negligible and within limits.

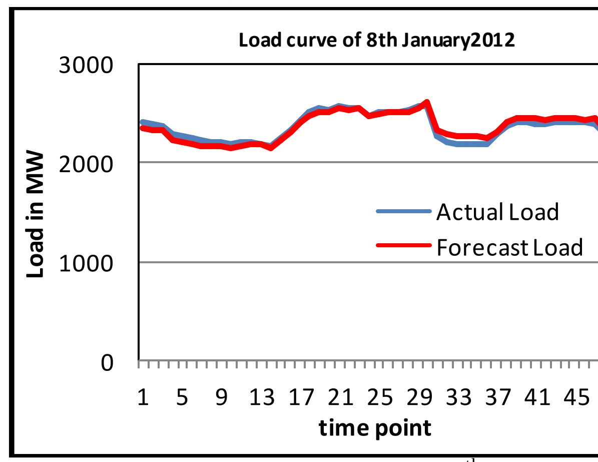

Fig.1: Actual Load ~ Forecast Load on 8th Jan'2012

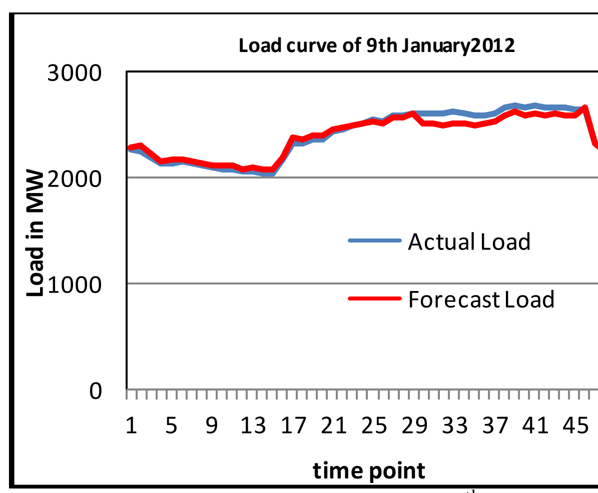

Fig.2: Actual Load ~ Forecast Load on 9th Jan'2012

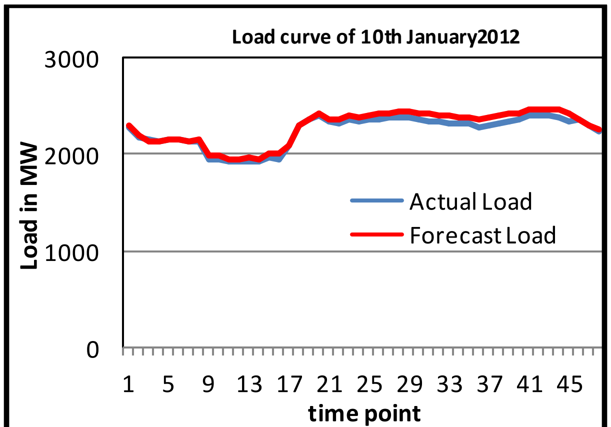

Fig.3: Actual Load ~ Forecast Load on 10th Jan’2012

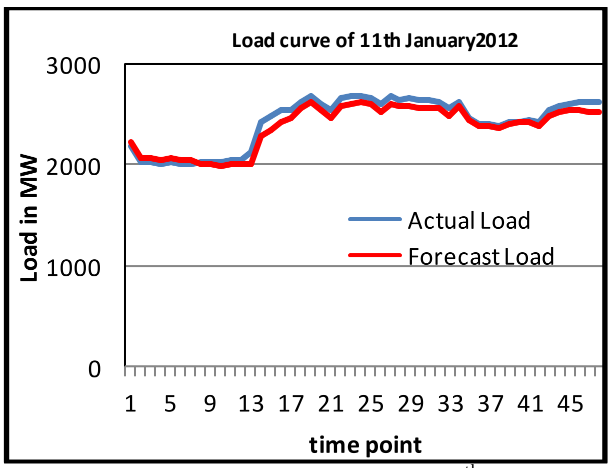

Fig.4: Actual Load ~ Forecast Load on 11th Jan’2012

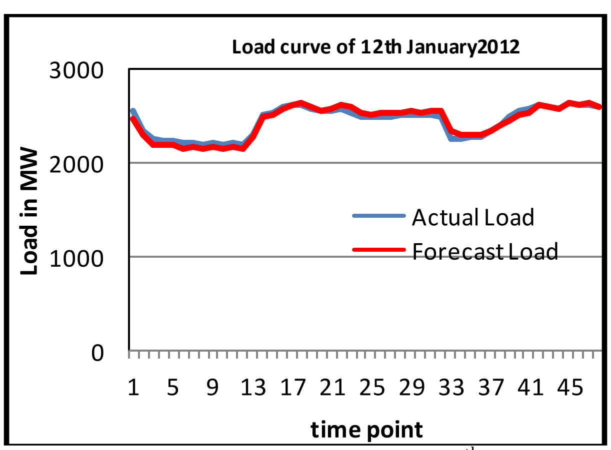

Fig.5: Actual Load ~ Forecast Load on 12th Jan’2012

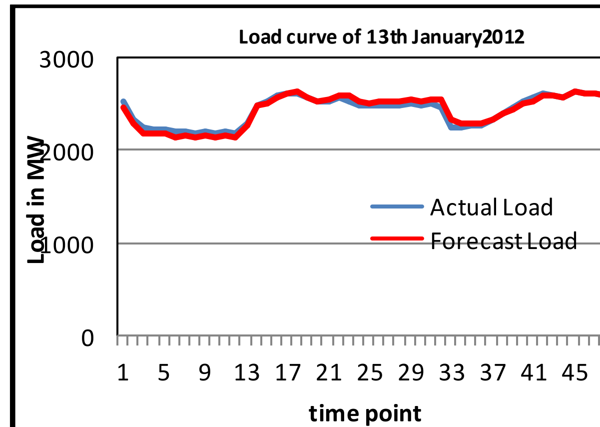

Fig.6: Actual Load ~ Forecast Load on 13th Jan’2012

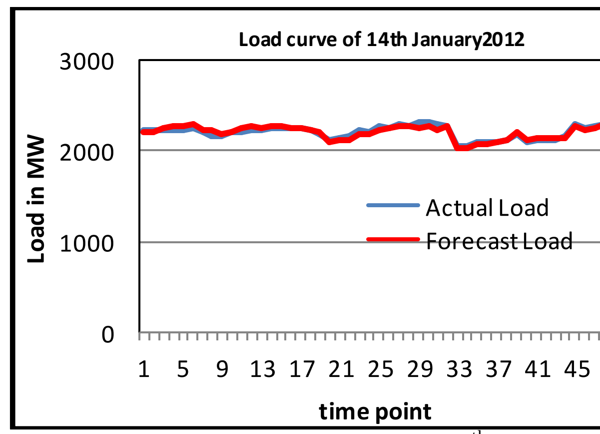

Fig.7: Actual Load ~ Forecast Load on 14th Jan’2012

The Mean Absolute Percentage Error (MAPE) for the proposed method was calculated and compared with other proven methods like Holt's Two-Parameter Method (HTPM), Brown's One-Parameter Quadratic Method (BOPQM), and Chow’s Adaptive Control Method (CACM), shown in Table-1. Subsequent plots were also plotted and are shown in the fig.8 to fig.15 below. It has been observed that error depends on several factors such as the homogeneity in data, the choice of model, the network parameters, and finally the type of solution. From the above results, it is observed that the predicted values are in good agreement with exact values and the calculated error is very small. Also, the results obtained clearly demonstrate that the proposed technique/method is reliable, accurate and effective for short term load forecasting. It is observed that this method can perform good prediction with least error.

Table 1- Comparison of %MAPE of different methods with Proposed Method for the period 8th Jan'12 to 15th Jan'12.

Name of the Method	8th Jan '12	9th Jan' 12	10th Jan' 12	11th Jan' 12	12th Jan' 12	13th Jan' 12	14th Jan' 12
HTPM	6.51	4.92	5.13	7.81	7.57	3.04	2.73
BOPQM	3.66	2.83	3.4	4.14	4.19	2.29	2.1
CACM	2.63	2.07	2.27	2.81	3.49	1.8	1.06
PROPOSED METHOD	**1.7**	**1.77**	**1.86**	**2.27**	**1.29**	**1.75**	**1.02**

(HTPM - Holt's Two-Parameter Method, BOPQM - Brown's One-Parameter Quadratic Method, CACM - Chow's Adaptive Control Method.)

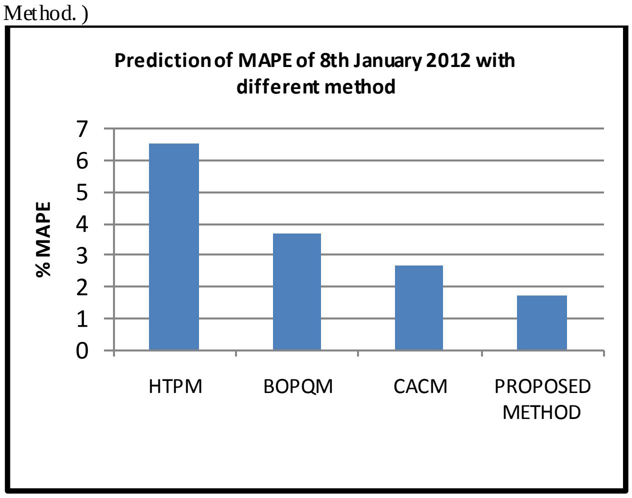

Fig.8: Comparison of Proposed method's MAPE with other method on 8th Jan'2012

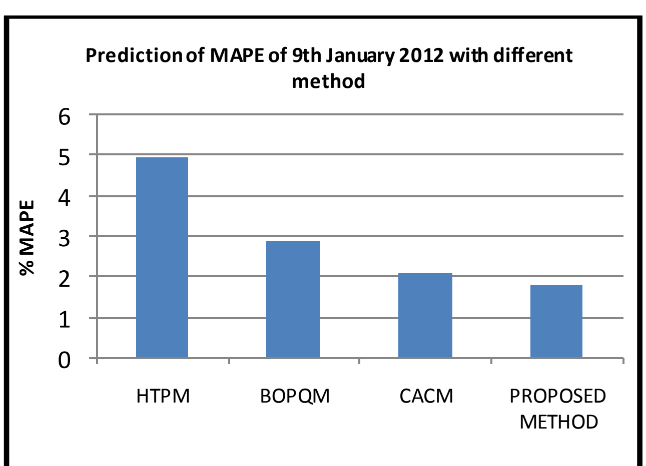

Fig.9: Comparison of Proposed method's MAPE with other method on 9th Jan'2012

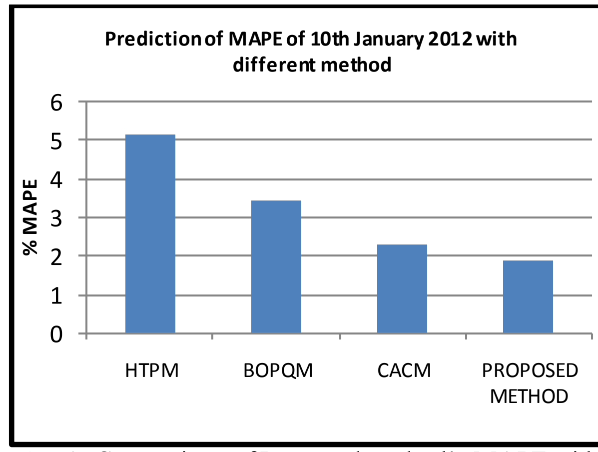

Fig.10: Comparison of Proposed method's MAPE with other method on 10th Jan'2012

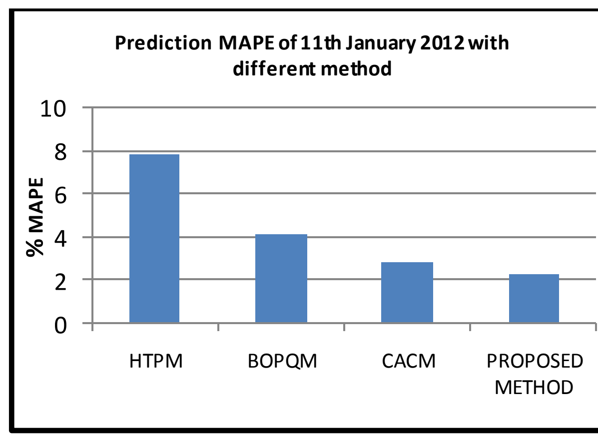

Fig.11: Comparison of Proposed method's MAPE with other method on 11th Jan'2012

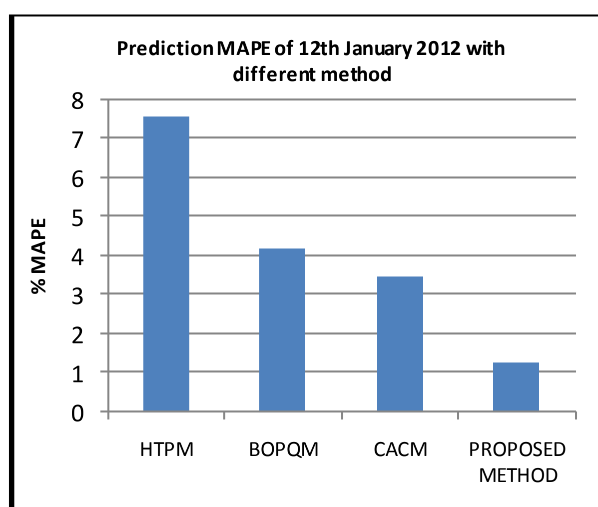

Fig.12: Comparison of Proposed method's MAPE with other method on 12th Jan'2012

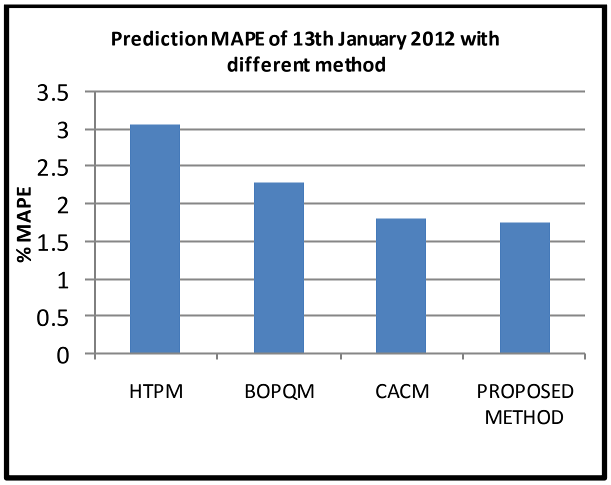

Fig.13: Comparison of Proposed method's MAPE with other method on 13th Jan'2012

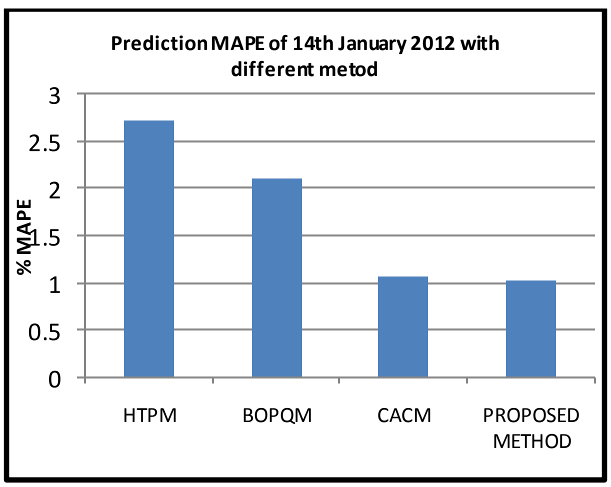

Fig.14: Comparison of Proposed method's MAPE with other method on 14th Jan'2012.

CONCLUSION

Price forecast has become a fundamental input to an energy company's decision-making and strategy development. The results obtained for the proposed model of STLF using historical data was applied to DVC power system network operating under ERLDC, India and confirm the applicability as well as the efficiency of the proposed method in short-term load forecasting.

The proposed method was able to forecast the load in the next half an hour. The forecasting reliability of the proposed method was evaluated by computing the Mean Absolute Percentage Error between the exact and predicted values and performed good prediction with least error and Results are very encouraging. On detailed study of the proposed forecast model, the calculated Mean Absolute Percentage Error (MAPE) of the forecasted data is 1.02(minimum) which is reasonable. Hence proposed methodology is generic enough to be applied to forecasting problem of other distribution companies (DISCOM) / utilities of its novelty, simplicity, efficacy and accuracy.

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