Short-Term Load Forecasting Using Kalman Filter

M. M. Dixit[1], P.R. Chavan[2]

[1]PG Student, Electrical Engineering Department, Y.T.I.E.T, Karjat
Y.T.I.E.T. Bhivpuri, Karjat, Maharashtra, India

[2]Head of Electrical Engineering Department, Y.T.I.E.T, Karjat
Y.T.I.E.T. Bhivpuri, Karjat, Maharashtra, India

---***---

Abstract - *Short-term load forecasting (STLF) aims towards prediction of electricity loads for a period of minutes, hours, days or weeks. Accurate load forecasting will lead to appropriate scheduling and planning with optimize energy cost. The geographical location, population, social factors, and weather factors have different effects on load patterns. The models adopted for STLF mainly are of time series and casual models. The time series models include the methods based on Kalman filtering approach. In this paper hourly based load forecasting will be carried out by Kalman filter model. A 24-hour municipal load is being considered for the analysis.*

Key Words: Short-term load forecasting, Kalman filter, Municipal Load

1. INTRODUCTION

In recent years, with the opening of electricity markets, electrical power system load forecasting plays an important role for electrical power operation. Accurate load forecast will lead to appropriate operation and planning for the power system, thus achieving a lower operating cost and higher reliability of electricity supply. Short-term load forecasting (STLF) of electric power is important in operation scheduling, economic dispatch, unit commitment, energy transactions and fuel purchasing [1, 2]. Short-term load forecasting aims towards prediction of electricity loads for a period of minutes, hours, days or weeks. The quality of short-term load forecasts with lead time ranging from one hour to several days ahead has significant impact on the efficiency of any power utility [3]. In the developing countries like India the power sector is often unable to meet peak demands. It seems essential that the scheduling of generation is to be planned carefully since one has to work within stringent limits. Hence, suitable strategies are necessary for generation control and load management. For this purpose, short-term load forecasting has to be carried out as accurately as possible.

The objectives of STLF are [4]:

- To derive the scheduling function that determines the most economic load dispatch with operational constraints and policies, environmental and equipment limitations.
- To ensure the security of the power system at any time point.
- To provide system dispatchers with timely information.

The models adopted for STLF mainly belong to two classes: time series (univariate) models, modeling electric load as a function of only its past recorded values; casual models, modelling the electric load as a function of exogenous variables such as weather and social factors. The time series models include the methods based on Kalman Filtering approach[5, 6].

Owing to the importance of STLF, research in this area in the last years has resulted in the development of numerous forecasting methods [7]. These methods are mainly classified into two categories: classical approaches and artificial intelligence (AI) based techniques. Classical approaches are based on various statistical modeling methods. These approaches forecast future values of the load by using a mathematical combination of previous values of the load and other variable such as weather data. Classical STLF approaches use regression exponential smoothing, Box-Jenkins, autoregressive integrated moving average (ARIMA) models and Kalman filters. Recently several research groups have studied the use of artificial neural networks (ANNs) models and Fuzzy neural networks

(FNNs) models for load forecasting [8]. With the development of AI in recent years, people become able to forecast using FNN and ANN with the back propagation method. Although the back propagation method has solved a number of practical problems, its poor convergence and speed can somewhat deter engineers. Meanwhile, a conventional ANN model sometimes can suffer from a sub-optimization problem [9, 10].

In this paper, a STLF procedure based on a Kalman filtering model is illustrated in detail. The model is applied to the forecasting task of a municipal electrical utility hourly load shape. A simple method of error feedback has therefore, been devised to make corrections in the prediction, especially for the peak hours, by observing the deviations of the off-peak predictions from the measured values of the actual load at early hours of the day. Kalman filter algorithm was found particularly suitable for predicting the average local hourly loads, and the dynamic corrections were carried out subsequently. The forecasting results obtained are quite promising, thus demonstrating the good potentials of Kalman based approaches on such a kind of electric load.

2. Model Architecture

The models used for load forecasting mainly belong to two categories. In one, the weather variables which affect the consumption appear explicitly in the model. In the other, the observed load data are treated purely as a time-series, the effect of weather being implicit in the data. Weather variables affect load consumption significantly. This relationship may be expressed as *W(t) = f(T, H, P, . .)* where *W(t)* (which is a function of time *t)* is that part of the total load *L(t)* dependent on the weather, and f denotes the functional relationship between the weather-sensitive part of the load and temperature *(T),* humidity *(H),* precipitation *(P).*Variables such as wind speed, clouver etc. are other factors.

The forecasting procedure proposed by us is based on a Kalman filtering algorithm which is modified to give more emphasis on recent data as compared with past data. The more recent the data, the greater the weightage. The weighting function is exponential with a negative exponent (exp [-1/w) so that the filter 'memory' may be said to 'fade' exponentially. The 'fading memory' has been incorporated in the usual Kalman filter algorithm and the following set of equations was derived.

$$(I(T) = R(T) - D(T-1) \quad (1)$$

$$V(T) = \frac{\frac{I(T)^2}{T} + \frac{T-1}{T}V(T-1)}{P(T-1)} \quad (2)$$

$$K(T) = P(T-1) + FV(T) \quad (3)$$

$$D(T) = D(T-1) + K(T)I(T) \quad (4)$$

$$P(T) = (1/F)P(T-1)[1 - K(T)] \quad (5)$$

$$Rf(T+1) = D(T) \quad (6)$$

where

R(T) = measured value at time *T*

D(T - 1)= predicted value of *R(T)*

D(T) = predicted value of *R(T+ 1)*

I(T) = forecast error

V(T) = variance of *R(T)*

F = exp (-l/M) where M is the 'time constant'

K(T) = *P(T)/V(T)* = Kalman gain

Rf(T +1) = predicted value

It is observed that the load demand has a periodicity of a week (168h) within a season. The load demand at 10 o'clock on a Friday, for example, is different from the demand at 10 o'clock on other days of the week, but tends to repeat itself for a few consecutive Fridays, changing with the change in season. The load expected at a particular hour of the week can be predicted by filtering out the fluctuations from the load values observed at corresponding hours in previous weeks. The actual load observed fluctuates about these expected values. One of the factors contributing to these fluctuations is the weather. As has been mentioned, weather data are not easily available and therefore are not incorporated in this study. Their effects are however indirectly taken into account by a second stage correction of the forecast. It is assumed that the effects of the weather prevailing on a day are reflected in the load demand at early hours. The difference between the prediction and the actual measurement in the morning can be taken as an indication of how the predictions for the rest of the day need to be modified. The forecasting procedure thus comprises two stages. In the first stage, 168 separate filters are applied in parallel to 168 separate hour-of-the-week load sequences. The load values $L(t)$ observed at time t is represented as

$$L(t) = B(t) + E_1(t) \quad (7)$$

where $L(t)$ is the sum of the average (or base) load $B(t)$ and a stochastic fluctuation $E_1(t)$. The first stage filters out $E_l(t)$ and the resulting estimate $B(t)$ gives the one week ahead prediction of the expected load. The prediction errors for this lead time is equal to the value of $E_1(t)$.

In Stage 2, hourly corrections are carried out. As stated earlier, the deviations of the measured from the expected load on a particular day may be taken as the general tendency for the rest of the day and therefore, these deviations are used to correct the forecast for the forthcoming hour. The deviation $E_1(t)$ obtained for every hour from

$$E_1(t) = L(t) - B(t) \quad (8)$$

constitutes the observed sequence for the hourly fluctuations. This sequence is modelled as

$$E_1(t) = W(t) - E2(t) \quad (9)$$

based on the consideration that the deviation $E_1(t)$ consists of $W(t)$, the change in load demand due to weather change and $E_2(t)$, a residual random component. When the second stage of the filter is applied, $W(t)$ is abstracted from $E_1(t)$ based on the data at early hours of a particular day using the same filter. This is algebraically added to the expected load $B(t)$ obtained from the first stage filter with lead time of a week. The residual quantity $E_2(t)$ in eqn. 9 forms the prediction error with a lead time of 1 h.

For better load forecasts our approach provides the load variation forecasts, by using the load variation of the previous day. In this way the model improves forecast accuracy by reducing errors due to seasonal effects. Such estimate is finally optimized by including the electrical load variation of the previous week (because of the electrical load periodicity). The whole procedure as proposed is structured in two subsequent steps: in the first, the load variation is predicted through a Kalman filter in the form of predictor; in the second, the forecast is then used to determine the load value.

Forecast errors increase if there is excessive noise present in the data, and usually some smoothing technique is used to increase the signal to noise ratio for short- term load forecasting. With the Kalman filtering technique, smoothing is not really essential since the algorithm seeks the expected value despite the presence of noise.

3.ANALYSIS OF FORECASTING RESULTS

This method of short-term load forecasting based on the fading-memory Kalman filter algorithm. The fading memory Kalman filter algorithm provides variable weightage to past data. This is done by the factor exp $(-(T - t)/M)$ incorporated in the Kalman filter algorithm. If T is the instant of time at which the forecast is made, the weightage given to the data at time T - 1, T - 2, ... will be exp (-l/M), exp(-2/M), ..., so that the weightage keeps on reducing as we go back in time. The selection of M is done empirically so as to reduce the error of prediction. This was done by using the first six months' data. It was found that the value of M remains almost constant for a substation. Once the value of *M* is fixed, it can be used in the algorithm and does not need to be re-evaluated. For various values of *M,* the forecasting was carried out and the error in prediction calculated in each case. It can be seen that, as *M* is increased, the error keeps reducing up to a point beyond which it increases again. As *M* is increased the value of error seems to saturate and as *M* tends to infinity, the factor *F* will become one which gives the Kalman filter algorithm without the fading memory.

Various tests have been carried out on electric load time series available. As an instance of the results obtained, the hourly load forecasts for a Feeder of Thane City in Maharashatra. For each of these forecasting periods the forecasting errors have been determines as usual by calculating: - maximum value, in the week considered, of the forecasting error for each hour of the day.

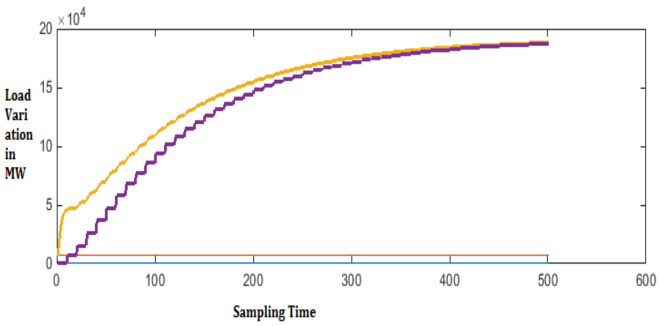

Chart -1: Forecasting graph

4. CONCLUSION

The paper has presented an application of a Kalman predictor to the Short-Term Forecasting of the load shape of a municipal electric utility. The basic model, main procedure and designing features are illustrated in detail. The obtained results show that the proposed architecture can be promising for the achieved forecasting accuracy. Furthermore, the Kalman filtering based approach allows very interesting possibilities in terms of integration and modification of both parameters and input data. Further improvements are expected from an extensive application to electric load data of further years jointly with the integration of data base with meteorological data.

REFERENCES

[1] M. Farahat and M. Talaat "A New Approach for Short-Term Load Forecasting Using Curve Fitting Prediction Optimized by Genetic Algorithms" IEEE, 14th International Middle East Power Systems Conference MEPCON'10, pp. 106-110, Egypt, 2010.

[2] Khotanzad, E. Zhou, and H. Elragal, "A Neuro-Fuzzy Approach to Short-Term Load Forecasting in a Price-Sensitive Environment", IEEE Transactions on Power Systems, Vol. 17, No. 4, (2002), pp. 1273-1282. [3]R. Sadowruk and E. Barbosa, "Short-Term Forecasting of Industrial Electricity Consumption in Brazil", Int. J. Forecast, Vol. 18, (1999), pp. 215–224.

[4] M. A. Farahat, Long – Term Industrial Load Forecasting and Planning Using Neural Networks Technique and Fuzzy Inference Method", 39th International Universities Power Engineering Conference UPEC'2004, University of West of England, Bristol, Vol. 1, 6 – 8 September (2004), pp. 368 - 372.

[5] G. Gross and F. D. Galiana, "Short term load forecasting," Proc. IEEE, vol. 75, no. 12, pp. 1558-1573, Dec. 1987.

[6] I. Moghram, S. Rahman, "Analysis and evaluation of five short-term load forecasting techniques," IEEE Trans. on Power Systems, Vol. 4, No. 4, October 1989.