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One-Day-Ahead Load Forecasting using nonlinear Kalman filtering algorithms

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Abstract

In this paper, we consider the problem of 24-hour ahead short-term load forecasting; the formulation is based on the nonlinear Kalman filtering. Our formulation takes into account weather conditions as well as previous trends. Effects of weather as well as prior consumptions are nonlinear functions; hence our choice. We compare our proposed method with the standard Kalman filtering approach and with the state-of-the-art echo state network. Experiments are carried out on the well known REDD dataset. We show that our proposed nonlinear Kalman filtering algorithm outperforms all prior techniques.

Keywords: short-term; load forecasting; one-day-ahead; kalman filters; echo state network; extended; unscented; nonlinear systems

1. Introduction

In today's scenario, with the advent of smart grids, electricity demand forecasting has become one of the leading areas of research. There is a great need to accurately forecast the load and energy requirements for the better management of the utility companies. Load forecasting provides the most important information for power delivery and planning.

In the smart grid infrastructure, high quality demand side techniques have become indispensable to control the energy delivery by utilities. It is required for budget planning, maintenance scheduling and fuel management [1,2]. Prior studies have also used prediction (rather deviations from predictions) to identify the anomalous behavior. Having said that, an accurate forecast is challenging due to the following reasons; 1) the electric load time series is highly complex and nonlinear, 2) several external factors can have significant impact on the daily load curve.

Load forecasting [3] can be divided into three categories: short-term load forecasts (STLF) [4,5] which is usually from one hour to one week, medium-term forecasts [6] which is from one week to one year and long-term forecasts [7] which is more than a year. The methods end use and econometric approach are used for medium- and long-term load forecasts whereas variety of methods including similar day approach, time series, various regression models, neural networks, and statistical approaches are used for short-term forecasts [3]. The forecasts for different time horizons are significant for different operations in the utility company. Long-term forecasts are needed for capacity planning and maintenance scheduling, medium-term forecasts are required for power system operation and planning and the short-term predictions are used for control and scheduling of power. Transmission companies also require short-term forecasts when a self-dispatching market is in operation.

Several utility companies have adopted methods for forecasting the power load. In these methods, models are formulated based on the relationship between load power and factors influencing load power. The factors that affect the system load behavior can be categorized as given below.

1. Weather: This is the most crucial externality. It includes temperature, humidity, precipitation, wind speed, etc. The change in these factors directly leads to the change in the usage patterns of the appliances such as air conditioners, heaters, coolers, etc.
2. Time: Time factor influences load at different periods of the day, holidays, weekdays/weekends and seasons of the year. The load variation with time can reflect the lifestyle of the people, that is their work schedule, sleeping pattern, leisure time, etc.
3. Economy: In the deregulated market, economic factors such as variable price of electricity, load management policy have a significant impact on the system load growth/decline trend.
4. Random disturbances: The start-up and shutdown of the large loads such as steel mill, wind tunnels will lead to an impulse in the load curve. The other anomalous days/events events which are known in prior but whose effect on load is uncertain, also fall in to the category of random disturbance.
5. Customer factors: It includes the type of consumption (residential, commercial, agricultural and industrial), size of building, number of employees, and number of electric appliances.

In this work, we do not engage in the social/ economic factors, i.e. points 3 & 5. Neither do we want to model anomalies; however our forecasting model can be used to estimate deviations and detect anomalies – but this is beyond the scope of this paper. We only consider the physical factors, i.e. points 1 (weather) and 2 (time).

This paper is organized as follows: Section 2 reviews various existing methods to perform short-term load forecasting and also describes the research gap in the existing field of work. To overcome this gap, Kalman filters (KF) and its nonlinear variants are proposed in section 3. Section 4 and 5 describe the experimental setup and the results obtained after comparing our technique with the state-of-the-art [10]. Finally, section 6 includes discussion and concluding remarks.

2. Short-Term Forecasting Methods

Short-term load forecasting has gained importance since the rise of the competitive energy market. The methods for solving load-forecasting problems use either statistical techniques or artificial intelligence approach such as regression, fuzzy logic, neural networks and expert based systems [8,9]. In [10], the author uses ensemble neural network (ENN) to predict the load series. The ENNs are useful in enhancing the generalization capacity of neural networks. There is a great deal of research on using neural networks for short-term load forecasting but it is not easily updatable to changing conditions over a course of season. The retraining of the entire network is costly and leaves no time with the utility to confirm the forecast in a short span of time. The other problem is the interpretability; even though neural networks are known to yield good results, they cannot be analyzed. A review on variants of artificial neural network for the purpose of short-term load forecasting can be found in [11]. A hybrid approach of using SVM with ANN was used by [12] to predict the 24-hour ahead load.

Traditional short-term forecasting approaches rely on time series analysis technique. In this approach, the model is built using past load and/ or weather data. On the basis of this model the forecasting of future load is done. The techniques used for the analysis of linear time series load signal are KF method, box jenkins or autoregressive integrated moving average method, regression model, etc. A short-term forecasting method [13] is based on state-space and KF approach. It shows that the model produces robust and accurate forecasts as compared to other techniques. Echo state network (ESN) [9] predicts the future value of the load for time horizon of 10 min and 24 hours. They compare their approach with the standard autoregressive integrated moving average model (ARIMA) and claim to outperform it [14].

Very few statistical studies have modeled non-linearity in the short-term load forecasting problem; one such study is [15]. Others like [16] rely on the nonlinear activation function of neural networks.

3. Proposed Approach

In this paper, we consider the problem of short-term load forecasting by modeling the problem's non-linearity and non-stationarity [17]. As mentioned before, we account for two factors – weather and prior temporal trends. There is no reason for either of them to have linear effects on the consumption pattern; therefore we do not overtly simplify our model using the often-used linearity assumptions.

Instead of using the popular ARIMA forecasting models, we leverage the KF [18] and its nonlinear variants to address the problem at hand. KF is considered as the optimal filter (in the least square sense) for data prediction and trend matching. However, owing to the aforesaid non-linearities, the standard KF is not an ideal choice. We resort to its nonlinear variants.

3.1 Kalman Filter

We have used standard Kalman filter for 24-hour-ahead load prediction of the residential houses. KF give optimal estimates of parameters of interest from indirect, inaccurate and uncertain observations. They are recursive in nature as they compute the best estimate of state and covariance by updating the previous estimates with new measurements. The dynamics of KF is governed by Markov process. They are widely used in forecasting applications like stock price prediction, navigation, tracking, etc.

In our application, we have used a discrete time linear dynamic system with the latent state vector x representing the hidden state of the appliances and observation vector y representing the smart meter readings. The delayed estimator generates output estimates y[k|k-1] and state estimates x[k|k-1] using measurements only up to y[k-1]. This works in a two-step process, predictor and corrector as shown in figure 1. In the prediction step, the filter estimates the current state of the load based on its previous state along with its uncertainty (covariance). Once the smart meter reading is observed, the estimated state is updated using a weighted average, with more weight being given to estimate with higher certainty. This is a recursive process and it works in real time. The state and observation equations of a standard linear Kalman filter are shown in equations 1 and 2. To explore the nonlinearity of the problem, we have used the nonlinear versions of the KF called the Extended Kalman filter (EKF) and Unscented Kalman filter (UKF) for our problem [19].

State equation: $x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}$, (1)

Observation equation: $y_k = Cx_k + v_k$, (2)

where **A**, **B**, **C** are matrices representing state transition, control input and observation model, u is the input to the system (temp, wind speed), **w** and **v** are the process and measurement noise vectors respectively.

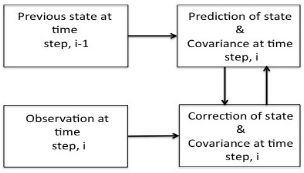


Fig. 1. Two step process of Kalman filter

3.2 Nonlinear Extension – EKF

Extended Kalman filters were developed for nonlinear discrete-time processes. It gives an approximation of the optimal estimate. The nonlinearities of the system's dynamics are approximated by the linearized version of the nonlinear system model around the last state estimate. For the approximation to be valid, this linearization (done using first order taylor series) should be a good approximation of the nonlinear model in the entire uncertainty domain associated with the state estimate. EKFs may face difficulties from its use of linearization such as implementation issues, difficulty with tuning, reliability issues, etc. To overcome these, unscented transformations (UT) were introduced to propagate mean and covariance information through nonlinear transformations [19]. The flaws in the EKF and its improvement through UKF can be reviewed here [20]. This work also extends the application of UKF to areas like machine learning, neural networks, nonlinear system identification, dual estimation, etc.

- In the extended Kalman filter, the state transition and observation models don't need to be linear functions of the state but may instead be differentiable functions.
- System equations are given as,

  State equation: $x_{k+1} = f(x_k, u_k) + w_k$,

  Observation equation: $y_k = h(x_k) + v_k$,
- The function f can be used to compute the predicted state from the previous estimate and similarly the function h can be used to compute the predicted measurement from the predicted state. However, f and h cannot be applied to the covariance directly. Instead a matrix of partial derivatives (the Jacobian) is computed.
- At each time step, the Jacobian is evaluated with current predicted states. These matrices can be used in the Kalman filter equations. This process essentially linearizes the non-linear function around the current estimate.
- The predict equations are,

  State estimate: $\hat{x}_{k|k-1} = f(\hat{x}_{k-1|k-1}, u_k)$,

  Covariance estimate: $P_{k|k-1} = F_{k-1} P_{k-1|k-1} F'_{k-1} + Q_k$.

  The update equations are,

  Measurement residual: $\tilde{y}_k = z_k - h(\hat{x}_{k|k-1})\tilde{y}_k$,

  Residual variance: $S_k = H_k P_{k|k-1} H_k^T + R_k S_k$,

  Kalman gain: $K_k = P_{k|k-1} H_k^T S_k^{-1} K_k$,

  State estimate: $\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \tilde{y}_k$,

  Covariance estimate: $P_{k|k} = (I - K_k H_k) P_{k|k-1}$,

  where the state transition and observation matrices are defined to be the following Jacobians,

$$F_{k-1} = \left.\frac{\partial f}{\partial x}\right|_{\hat{x}_{k-1|k-1}, u_k},$$
$$H_k = \left.\frac{\partial h}{\partial x}\right|_{\hat{x}_{k|k-1}}.$$

3.3. Model Formulation

- Dataset: The following datasets were used in our work.
  1. Energy dataset: For energy, we used a publicly available Reference Energy Disaggregation Dataset (REDD)[1]. This dataset is anonymously collected from greater Boston area in US. It contains average power readings from mains and individual circuits of six houses along with the corresponding timestamps. We used the mains data from house 1 to house 6, except house 5 for our experiments. For mains, the data was logged at the frequency of once a second and once every three seconds for the individual circuits.
  2. Weather dataset: The weather dataset used here was retrieved from the website[2]. The dataset contains 14 attributes consisting of timestamps, temperate, humidity, dew point, sea level pressure, visibility, wind

[1] http://redd.csail.mit.edu/
[2] https://www.wunderground.com/

Table 1. Percentage of missing data (REDD)

Houses	Missing (%)
House 1	37.8
House 2	52.7
House 3	43.4
House 4	46.9
House 5	80.85
House 6	12

direction, wind speed, precipitation, gust speed, events and conditions. As the REDD dataset is anonymously recorded from the greater Boston area during the months of April, May and June, the weather corresponding to these months is relatively colder (highest temperature being 13°C, 19°C and 24°C for the respective months), hence we chose temperature and wind speed as the input to the system.

- Data Pre-processing: For the purpose of the research, the data was preprocessed using the following steps.
  1. Missing data: This dataset contains a lot of missing data. The missing values, (NaNs) were replaced by the previous non-NaN values. Since 5th house has lot of missing values, it was not included in our experiments. The percentage of missing data for different houses in REDD is given in table 1.
  2. Inconsistent data: The dataset was inconsistent with the specified format of the attributes.
  3. Data aggregation: Aggregation of data from both the datasets, i.e. previous load values and weather data (Temperature and Wind Speed) was performed at the hour-level.
- Input/ output of the model: We have compared three combinations of past load (L), past temperature (T), and wind speed (W). In the first case of figure 2, the input to the model is previous days' load (L) and temperature (T); in the second case, the input is past load (L) and wind speed (W) and in the third case, the input is just the historic load. The output of the model is the one-day-ahead load forecast.
- Implementation: To implement the nonlinear Kalman filters, we had used the matlab toolkit called **Re**cursive **B**ayesian **E**stimation **L**ibrary (ReBEL)[3].

4. Experimental Setup

The first experiment is to predict the 24-hours ahead load forecasting of the residential houses using the standard linear Kalman filter. The baseline method used is echo state network (ESN) [9]. Using both the techniques, we recorded the (n+24)*th* hour ahead estimate at every n*th* hour. The results recorded in this setup used all three inputs; past load, temperature and wind speed data. The mean absolute percentage error (MAPE) calculated for all the houses using linear KF and ESN are shown in table 2.

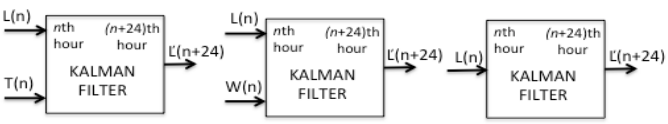


Fig.2. Input/ output cases of nonlinear Kalman filter

Table 2. 24-hours ahead load forecasting (MAPE)

Houses	ESN	KF
House 1	178.60	49.17
House 2	39.72	24.91
House 3	144.29	26.97
House 4	215.84	68.34
House 6	607.96	215.79

[3] http://www.pdx.edu/biomedical-signal-processing-lab/signal-point-kalman-filters-and-the-rebel-toolkit

The second experiment is to perform 24-hour ahead load prediction using nonlinear Kalman filtering algorithms, EKF and UKF. In this experiment, we recorded the estimates for three different input-output cases as shown in figure 2. For each hour, the results from the three cases are noted using both the techniques (EKF & UKF). The number of iterations in this experiment was fixed to 50.

5. Simulation Results

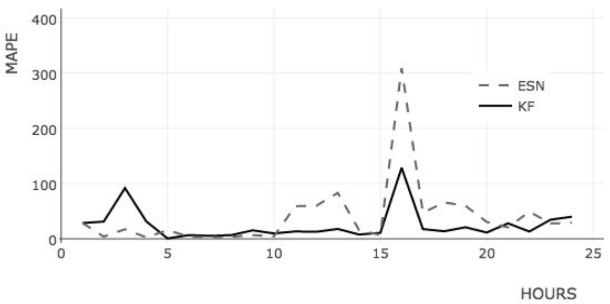
- In table 2, Kalman filter clearly performs much better than echo state network. The performance of the Kalman filter can be attributed to the fact that each iteration tries to minimize the mean square error and move towards the estimate with higher certainty. In case of ESN, the recurrent neural network is less generalized as it easily over fits the training data.

- The relative variation in the error values of KF is much lesser as compared to ESN. This pattern can be resulted due to the sudden spikes/ surges in the signal, making the prediction using ESN change abruptly. Figure 3a and 3b show the comparison of MAPE for house 2 using ESN vs. KF and EKF vs. UKF.

- The model performs better when exogenous inputs are taken into consideration during prediction. We also observe that between the two nonlinear techniques (EKF and UKF) used, UKF performs slightly better in terms of accuracy. In figure 4a, the bar chart represents the MAPE using EKF and UKF (only load input case) for different periods of the day. The comparison between different houses of REDD is shown in figure 3b. The resulting graph depicts the MAPE using EKF on 5 different houses. Figure 3c gives a better comparison between different input cases of the nonlinear Kalman filter. It can be seen that using past load with temperature gives better performance. The bar chart shown for the morning and evening period gives the performance of the UKF and EKF respectively.

Conclusion

In our dataset, the readings were collected from the greater Boston area, therefore we chose temperature and wind speed as the exogenous inputs. We clearly see that, both the inputs in conjunction with the past load make the model perform better than otherwise. Therefore, careful selection of parameters is of prime importance in case of short-term load forecasting. The forecasting accuracy is a combination of good data, good process and a good model. Also, if we compare the linear and the nonlinear techniques, then nonlinear techniques perform better in terms of accuracy though the variance is higher. For house 2, the average MAPE using EKF and UKF was 8.43 and 8 respectively.



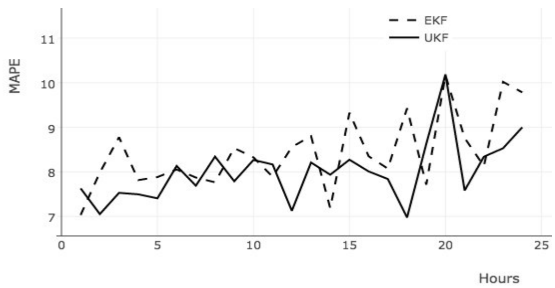


Fig. 3. MAPE of house 2 (a) using ESN & EKF (b) using EKF & UKF

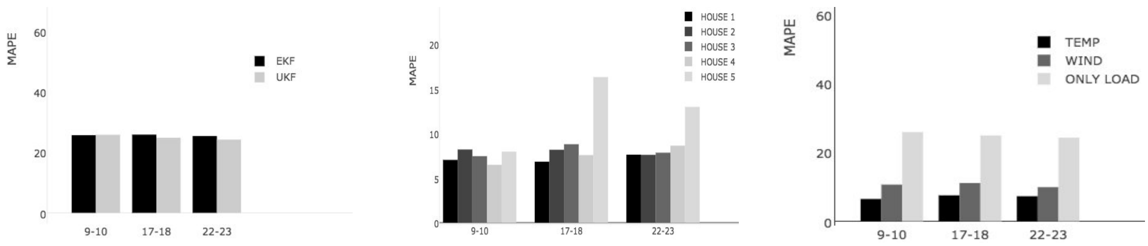


Fig. 4. (a) MAPE for load only input case (b) MAPE using EKF on different houses (c) Different input cases on house 3

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