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Short-Term Load Forecasting Using a Two-Stage Kalman Filter based Method

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ABSTRACT

In the smart grid era, Short-Term Load Forecasting (STLF) is the building block of a secure, reliable, and economical power system. Therefore, researchers have spent much time trying different methods to improve load forecasting accuracy. Despite the advances in the STLF area, load forecasting is still difficult. This difficulty comes from two facts: 1- The behavior of the electric load is complex and shows different levels of seasonality; 2- The electric load is strongly influenced by other external factors such as meteorological variables and calendar variables. To overcome these issues, in this paper, a two-stage Kalman filter-based method is used to enhance the accuracy of STLF. In the first stage of the proposed method, the Kalman filter and Rauch-Tung-Striebel smoother are applied to the short windows of the past electric load series to obtain an initial prediction of the load series. To produce the final forecast, in the second stage, the initial prediction of the load series along with other calendar and meteorological variables are used to form a load forecasting model whose parameters are obtained based on another Kalman filter. The effectiveness of the proposed method is evaluated by performing a case study on the real dataset from a power utility in Iran, which shows the excellent performance of the proposed method with 1.98% mean absolute error.

1. Introduction

Nowadays, Short-Term Load Forecasting (STLF), which provides electric load forecasts up to two weeks ahead, is a vital part of a secure, reliable, and economic power system. Accurate production coordination of electric generators in current power systems closely depends on the STLF accuracy. Also, STLF is crucial for designing and implementing proper demand-side response programs which avoid the cost of building new power generation and power transmission facilities by reducing power consumption during peak hours. Furthermore, with the deregulation of the power industry, the significance of the STLF task has become more pronounced for the electric utilities and retailers, which is due to the key role of STLF in purchasing the correct amount of required energy in power markets.

Due to the valuable benefits of the load forecasting and the fact that one percent growth in forecasting error approximately results in a 10 million Euro increase in operating costs per year (in 1984) [1], a large amount of research has been devoted to the load forecasting area, and therefore many techniques have been tried. These techniques can be classified into two major groups: 1- statistical and classical techniques: e.g., Multiple Linear Regression (MLR) [2], Auto Regressive Moving Average (ARMA) [3], exponential smoothing [4], Kalman filter [5], Markov-chain mixture distribution model [6], and 2- artificial intelligence techniques: e.g., Artificial Neural

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Network (ANN), Support Vector Machines (SVM) [7], gradient boosting machines [8] and fuzzy systems [9].

From the statistical techniques, MLR [10] and ARMA [11] models have received the most attention [12]. In MLR, the electric load is explained by combining some exogenous variables such as temperature and calendar variables, which is a great feature where there is a tangible relationship between temperature and electricity consumption. However, in the MLR models, some restrictive assumptions should be held that violating them leads to reduced forecasting accuracy. ARMA models are based on the electric load only. These models do not include other factors like temperature in the model, so this technique is suitable for regions where the load is not affected by other factors like weather conditions.

From artificial intelligence techniques, ANN [13] has received the most attention in the load forecasting area [14], which is partially due to the fact that ANN doesn't require much prior knowledge of the relationship between load and affecting variables; because ANN is a black box technique that can infer underlying relationships between input and output variables. In recent years, a class of ANNs called Recurrent Neural Network (RNN), and its variants like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) have been widely used for load forecasting. In reference [15], multiple time series are utilized to build a load forecasting system based on the RNN structure that can discover sequential information between continuous and discrete series; this method was tested on the polish power system dataset. Simple RNNs are prone to gradient vanishing or exploding, which refers to exponentially decrease (toward zero) or increase (toward infinity) in the norm of the error gradient, respectively [16]. Therefore, researchers are more interested in LSTM and GRU variants. In reference [17], the authors proposed an LSTM-based framework to forecast residential load. In reference [18], a load decomposition technique called Empirical Mode Decomposition (EMD) is used with the GRU network to increase STLF accuracy; it's shown that using highly correlated components with the primary load series instead of using all the decomposed components as the input features of the GRU network leads to enhanced performance. In reference [19], the authors have used a two-dimensional Convolutional Neural Network (CNN) to extract new features of the load series. They have fed these features to the bidirectional GRU and LSTM networks to perform hourly load forecasting. Also, a similar approach based on one-dimensional CNN and LSTM is proposed in reference [20], and it's used to forecast the electrical load of the Bangladesh power system. In reference [21], Deep Neural Network (DNN) is compared with shallow networks; in the end, the authors concluded that DNNs exhibit more accurate predictions and are more suitable for STLF. Successful implementation of DNN for STLF can be found in reference [22], where authors have proposed a variant of deep residual networks (ResNet) to enhance load forecasting.

Although ANNs have been extensively used in the field of load forecasting, they are prone to overfitting problems due to the high number of parameters [23], [24]; this problem exacerbates for deep networks or complex structures like LSTM where the number of parameters can reach thousands. In case of insufficient sample data in the training dataset, parameter estimation cannot be performed properly; therefore, one cannot expect good forecasting accuracy in practice. For example, in case of having significant events like changes in the size of the service territory, war, recession, or boom in the history of the service territory, only the load data after these changes can be used as the training data, which may not be enough for proper parameter estimation.

A review of STLF literature reveals that artificial intelligence techniques have dominated classical techniques for more than two decades. However, a recent paper [25] showed that the Kalman filter still has great capabilities in dealing with STLF problems. In reference [25], it's been demonstrated that the Kalman filter can outperform the prominent ResNet and LSTM networks and yield more accurate STLF results.

In this paper, a two-stage Kalman filter-based method is used to enhance the accuracy of STLF further. In the first stage of the proposed method, the Kalman filter and Rauch-Tung-Striebel smoother are applied to the short windows of the electric load series to capture the local behavior of the load series and obtain an initial prediction of it. Then in the second stage, the initial prediction of the load series along with other calendar and meteorological variables are used to form a load forecasting model whose parameters are obtained based on another Kalman filter.

The rest of the paper is organized as follows: Section II is devoted to a short introduction to the Kalman filter and Rauch-Tung-Striebel (RTS) smoother. Our proposed Kalman filter-based method for STLF is illustrated in Section III. Experimental results and comparisons with other methods are reported in section IV. Finally, Section V concludes the paper.

2. Theoretical Background

2.1. Kalman Filter

Introduced by Rudolf E. Kalman in 1960 [26], the Kalman filter addresses the problem of estimating the states of a linear discrete-time system which is defined as follows:

$$\begin{aligned} x_k &= F x_{k-1} + w_{k-1}, \\ y_k &= H x_k + v_k, \end{aligned} \qquad (1)$$

Where $\mathrm{x_k} \in \mathrm{R^n}$ is the state, $\mathrm{y_k} \in \mathrm{R^m}$ is the measurement, F is the transition matrix, H is the measurement matrix, $w_{k-1} \sim N(0, \mathrm{Q_{k-1}})$ is the process noise, and $v_k \sim N(0, \mathrm{R_k})$ is the measurement noise.

Kalman filter consists of two steps which are called prediction and update steps. The prediction step is needed for projecting forward the current state and error covariance estimates to obtain the a priori estimates for the next time step. The update step is required to include a new measurement into the a priori estimate to achieve an enhanced a posteriori estimate [27].

Kalman filter prediction step is:

$$\hat{x}_k^- = F \hat{x}_{k-1}^+ \qquad (2)$$

$$P_k^- = FP_{k-1}^+F^T + Q_{k-1}$$

Where $\hat{x}_k^-$ and P_k^- are a priori estimate and a priori covariance, respectively.

Kalman filter update step is:

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1} \quad (3)$$
$$\hat{x}_k^+ = \hat{x}_k^- + K_k(y_k - H\hat{x}_k^-)$$
$$P_k^+ = (I - K_k H)P_k^-$$

Where $\hat{x}_k^+$ and P_k^+ are a posteriori estimate and a posteriori covariance, respectively. The matrix K_k is called Kalman filter gain.

2.2. RTS Smoother

Kalman filter enables us to estimate the current state of a linear discrete-time system using the measurements obtained up to the current time. However, better estimates can be made using Kalman-based smoothers if future measurements are available. RTS smoother is a fixed-interval smoothing technique introduced by Rauch, Tung, and Striebel in 1965 [28]. This smoother allows us to refine estimates of previous states, in favor of the subsequent observations, in a more computationally efficient manner [29].

For a system defined in the form of Equ. (1), the RTS smoother algorithm is defined as follows [29]:

1- Initialize the forward filter as follows:

$$\hat{x}_0^+ = E(x_0) \quad (4)$$
$$P_0^+ = \mathrm{E}[(x_0 - \hat{x}_0^+)(x_0 - \hat{x}_0^+)^T]$$

2- For $k = 1, \ldots, N$, execute the standard Kalman filter, i.e., Equs. (2)& (3). Note that N is the final time.

3- Initialize the RTS smoother as follows:

$$\hat{x}_N^s = \hat{x}_N^+ \quad (5)$$
$$P_N^s = P_k^+$$

4- For $k = N - 1, \ldots, 1{,}0$, execute the following RTS smoother equations:

$$K_k^s = P_k^+ F^T (P_{k+1}^-)^{-1} \quad (6)$$
$$P_k^s = P_k^+ - K_k^s(P_{k+1}^- - P_{k+1}^s){K_k^s}^T$$
$$\hat{x}_k^s = \hat{x}_k^+ + K_k^s(\hat{x}_{k+1}^s - \hat{x}_{k+1}^-)$$

3. Proposed Method

Roughly speaking, there are two major issues regarding STLF which make accurate load forecasting a difficult task. 1- The behavior of the electric load is complex in nature and shows different levels of seasonality, e.g., hourly, daily, and weekly; 2- The electric load is strongly influenced by other external factors such as meteorological variables and calendar variables.

In this paper, a two-stage Kalman filter-based method is used to address the mentioned issues and enhance the accuracy of STLF. In the first stage of the proposed method, the Kalman filter and RTS smoother are used to obtain an initial prediction of the load series. To produce the final forecast, in the second stage, the initial prediction of the load series along with other calendar and meteorological variables are used to form a load forecasting model whose parameters are obtained based on another Kalman filter. These stages are further explained in the sequel of this section.

3.1. Stage I

In this stage, the idea is to build a state-space model that explains the local behavior of the electric load series. This model is assumed to be of the form defined in Equ. (1). In this stage, $\mathrm{x_k} \in \mathrm{R}^{24}$ is the hidden state, and $\mathrm{y_k} \in \mathrm{R}^{24}$ contains the observed hourly electric load values whose dimension corresponds to 24 hours of a day.

For building a state-space model that explains the local behavior of the electric load series, at first, F and H matrices of the linear discrete-time system should be estimated. Hence, Expectation-Maximization (EM) algorithm is used, which is a method for iteratively finding the Maximum Likelihood estimate of the parameters.

The EM algorithm for estimating F and H matrices is defined as follows [30]:

1- Start from an initial guess for F and H matrices.

2- Expectation step: Run RTS smoother algorithm (Equs. (4)-(6)) using the current values of F and H; then compute the following Equations:

$$\Sigma = \frac{1}{T}\sum_{k=1}^{T} P_k^s + \hat{x}_k^s[\hat{x}_k^s]^T \quad (7)$$
$$\Phi = \frac{1}{T}\sum_{k=1}^{T} P_{k-1}^s + \hat{x}_{k-1}^s[\hat{x}_{k-1}^s]^T$$
$$B = \frac{1}{T}\sum_{k=1}^{T} y_k[\hat{x}_k^s]^T$$
$$C = \frac{1}{T}\sum_{k=1}^{T} P_k^s {K_{k-1}^s}^T + \hat{x}_k^s[\hat{x}_{k-1}^s]^T$$

3- Maximization step: Find new values for F and H matrices using the following Equations:

$$F = C\Phi^{-1} \quad (8)$$
$$H = B\Sigma^{-1}$$

4- Return to step 2 for the next iteration of the EM algorithm. Or stop if the desired number of EM iterations is performed.

Note that, since we want to capture the local behavior of the load series, values of the load series for the last few weeks should be used in the EM algorithm. Our studies showed that two to four weeks of hourly electric load series would be fine for this purpose.

So far, we have built the desired state-space model. The following formula can be used to achieve an initial prediction for the load profile of the next day:

$$\hat{\boldsymbol{y}}_{k+1} = \boldsymbol{HF}\,\hat{x}_k^+ \tag{9}$$

Where $\hat{x}_k^+$ is obtained from the update step of the Kalman filter, i.e., Equ. (3). It should be noted that the initial prediction is obtained based on the electrical load values only. Therefore, further process is needed on the initial prediction to enhance its accuracy by taking into account external factors. This process is done in the second stage of the proposed method.

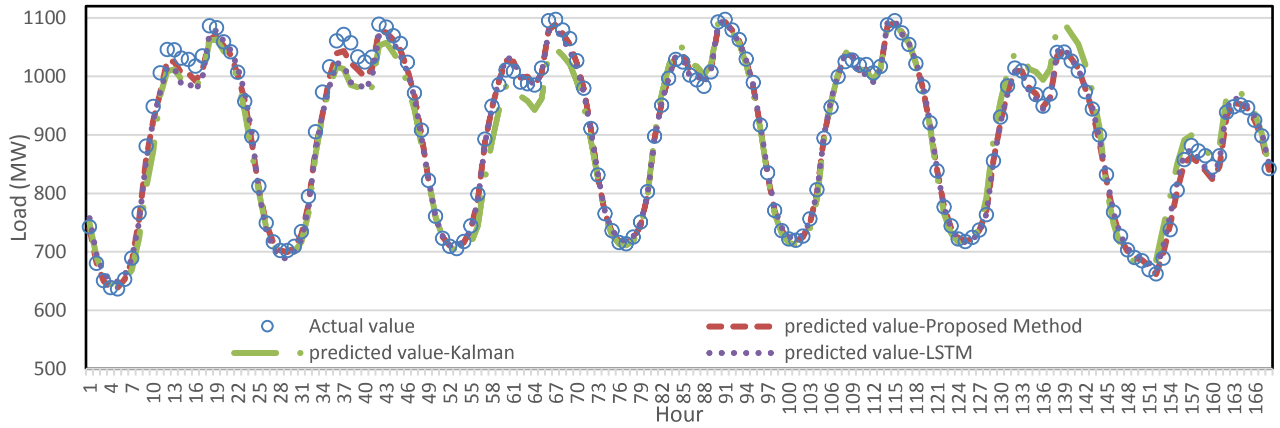

Fig. 4. Actual and Forecasted load profile of a sample week.

3.2. *Stage II*

Electric load consumption is highly dependent on other external factors such as meteorological and calendar variables. Among the meteorological variables, Temperature has the most effect on the electric load consumption that is due to the use of cooling and heating systems. In Fig. 1, the load profiles of three consecutive Tuesdays in June are depicted to better illustrate the effect of Temperature on the load consumption.

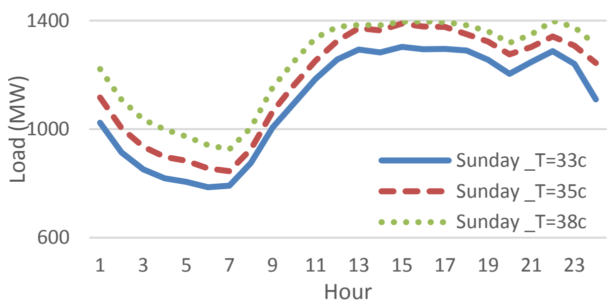

Fig. 1. Load profiles of three consecutive Tuesdays with different Temperatures (T).

As depicted in Fig. 1, for our considered region, the electric load consumption increases as temperature increases. In Fig. 1, the similar load during Hours 13- 17 for T=35 and T=38 are because of the activated Demand Response (DR) program, which reduces electric load consumption during peak hours. Among the calendar variables, holidays and days of the week have the most effect on the electric load consumption that is because of the different behavior of people in different situations. For example, schools and most offices are closed on holidays and weekends, which reduces electric load consumption. These issues are illustrated in Fig. 2 and Fig. 3.

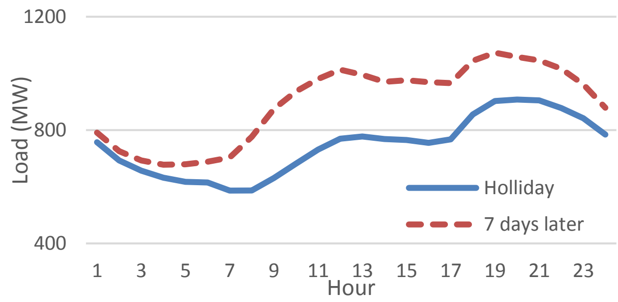

Fig. 2. Load profile of a Holiday and its seven days later.

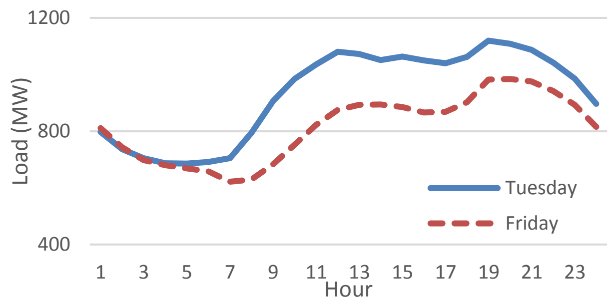

Fig. 3. Load profile of a Tuesday (working day) and its following Friday (weekend in Iran).

From the above discussion and Figs. 1-3, it can be concluded that external variables should be included in the forecasting model to perform accurate load forecasting. Moreover, since the electric load of each hour of the day has exclusive characteristics, therefore, in this section, twenty-four of the following single output linear models are used to produce the final load forecast for twenty-four hours of a day. Note that each of these 24 models, which correspond to each hour in a day, must be trained separately:

$$Y_i = \beta_0 + \beta_1 Month + \beta_2 Day + \beta_3 Month * T + \beta_4 Month * T^3 + \beta_5 L_{IF} + \beta_6 L_{IFi} * Day + \beta_7 Trend + \beta_8 Holiday + \beta_9 Holiday_d \tag{10}$$

In which $Month$ and Day are class variables that correspond to the month of the year and the day of the week, T is the average temperature of the forecasting day, L_{IF} is the load profile obtained from the initial forecast, L_{IFi} is the value of the initial forecast at the hour i, $Holiday$ and $Holiday_d$ are class variables which show national holidays of the forecasting day and the day before forecasting day, respectively, Trend is a natural number which captures the increasing trend of the load by assigning a separate number to each day in historical data, and Y_i is the final load forecast for hour $i = 1, \ldots, 24$.

To achieve accurate parameter estimation for the parameters of the forecasting models, these models should be written in the form defined in Equ. (1). Hence, in this stage, x_k is defined as the vector of unknown parameters, which is defined as follows:

$$x_k = [\beta_0 + \beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 + \beta_6 + \beta_7 + \beta_8 + \beta_9]^T \tag{11}$$

y_k is the predicted load (measure load in the parameter identification phase); F is an identity matrix, and H is defined as follows:

$$H = 1 + Month + Day + Month * T + Month * T^3 + L_{IF} + L_{IFi} * Day + Trend + Holiday + Holiday_d \tag{12}$$

Now that the forecasting model (Equ. 10) is rewritten in the form of a linear discrete-time system, we can use the Kalman filter to achieve parameter estimation for unknown parameters. Our studies showed that two to four years of data would be fine for accurate parameter estimation. After parameter estimation, the final load forecast can be obtained using $y_k = Hx_k$.

4. Experimental Results And Discussion

For validating the effectiveness of the proposed STLF method, in this section, the results of our case study on the real dataset from a power utility in Iran are presented and compared with two other STLF methods. For this purpose, five years of hourly electric load over the period of March 17, 2015, to March 16, 2020, has been gathered; the first four years of data are used for parameter estimation, and the last year of data is used for testing the accuracy of the proposed method.

To better illustrate the effectiveness of the proposed method, we have used two other STLF works as the competing methods. One of them is presented in Ref [25], which is based on the Kalman filter, and the other one is presented in Ref [31], which is based on LSTM neural network.

For the first stage of the proposed method, F and H are initially set as all-ones matrices. Also, Q and R are considered identity matrices with scale values of 1 and 10^{-2}, respectively. And the EM algorithm is performed for four iterations on the last three weeks of the hourly electric load series to estimate F and H matrices. In the second stage of the proposed method, F is an identity matrix, and H is defined as Equ. (12), Q and R are considered as identity matrices with scale values of 10^{-4} and 10^{-3}, respectively. Also, four years of data are used for parameter estimation.

In this paper, the load forecasting errors are reported in terms of mean absolute percentage error (MAPE) and root mean squared error (RMSE) which are defined as follows:

$$MAPE(\%) = \frac{1}{N} \sum_{n=1}^{N} \frac{|L_A(n) - L_F(n)|}{L_A(n)} \times 100 \tag{13}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^{N} \left(L_A(n) - L_F(n)\right)^2} \tag{14}$$

Where $L_A(n)$ and $L_F(n)$ denote the actual and forecasted load at the n^{th} hour, and N is the total number of the forecasted hours.

The results of our simulations with the proposed STLF method and two other competing methods are reported in Table I. For better illustrating the actual performance of the considered STLF methods, the results of a sample week in autumn of 2019 are shown in Fig. 4.

TABLE I

LOAD FORECASTING RESULTS

METHOD	MAPE(%)	RMSE
KALMAN FILTER [25]	3.56	44.9
LSTM [31]	2.26	26.5
PROPOSED METHOD	1.98	23.8

From the results of Table I and Fig. 4, it can be concluded that the proposed STLF method outperforms a recent work that was based on the Kalman filter. The achieved performance is primarily due to considering the effect of holidays in the proposed approach. In Fig. 5, load forecasting results of a holiday (Birth of Imam Mahdi) are depicted, which shows the superiority of the proposed method.

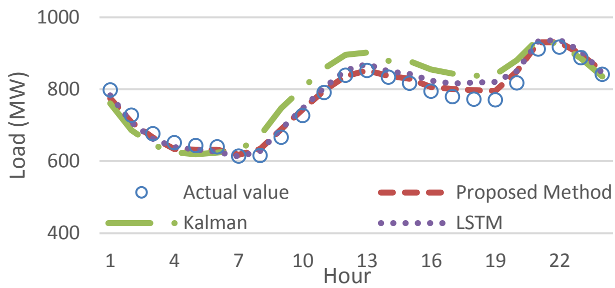

Fig. 5. Actual and Forecasted load profile of a Holiday

Furthermore, the present work not only outperforms our previous work, which was based on LSTM neural network (refer to Table I and Figs. 4-5), but also, it has significantly less computational time. The simulation time for running the present work on a laptop with an Intel Core-i7 processor and 8GB of RAM was 6 seconds, while it lasted 144 minutes for the LSTM –based method.

5. Conclusion

Nowadays, STLF is an essential component of a secure, reliable, and economic power system. Hence, in this work, a novel method based on the Kalman filter is presented to increase STLF accuracy further. The proposed method consists of two stages. In the first stage, a state-space model is built that explains the local behavior of the electric load series and produces an initial forecast. In the second stage, the initial forecast and other external variables are used to form the final load forecasting model that produces the final load forecast for the next day. In the end, through conducting a case study on the real dataset from a power utility in Iran, comparisons with two other STLF works have been made, which shows the effectiveness of the proposed method. For future work, instead of a simple Kalman Filter, one can use an Extended Kalman Filter or Unscented Kalman Filter in the proposed STLF framework.

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