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Research paper

Short term electricity load forecasting using hybrid prophet-LSTM model optimized by BPNN

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ABSTRACT

Electrical load forecasting plays a vital role in the operation and planning of power plants for the utility companies and policy makers to design stable and reliable energy infrastructure. Load forecasting is categorized in long-term, mid-term and short-term. Among them, short term load forecasting that monitors weekly, daily, hourly and even sub-hourly operations is gaining a lot of attention which saves time and cost while satisfying consumers' needs without interruption. Different models such as conventional, Artificial Intelligence (AI) and hybrid models have been developed to investigate short-term load forecasting. However, these models suffers various issues such as low speed convergence (conventional), high complexity (AI) and so on. Consequently, this work proposes a hybrid method using Prophet and Long Short Term Memory (LSTM) models to overcome the above limitations in an effort to predict accurate load. The Prophet model utilize linear as well as non-linear data to predict original load data but still some of the residuals are left which are regarded as non-linear data. Here, these residuals (non-linear data) are trained by employing LSTM, and finally both the forecasted data from Prophet and LSTM are trained by Back Propagation Neural Network (BPNN) to further enhance prediction accuracy. Elia Grid real time quarter hour based electrical load data from 2014 to 2021 has been utilized to verify working performance of proposed hybrid technique by computing Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Average Error (MAE). Results substantiate that proposed hybrid models outperforms the standalone models of Autoregressive Integrated Moving average (ARIMA), LSTM and Prophet model on the basis of reduced errors with least computation time.

1. Introduction

Electricity demand is increasing rapidly since the last decade because of urbanization and industrialization (Yu et al., 2019). However, electricity demand does not follow uniform pattern due to different customers' needs and their different energy usage patterns. This random pattern may lead to various issues such as unnecessary generating units, high consumption of fuel, and increase of operational cost (Jacob et al., 2020). Therefore, accurate energy forecasting is becoming very imperative to cope aforementioned issue. Energy/load forecasting not only provides crucial information to policy makers to assure efficient capacity planning but also helps in attaining optimal scheduling using unit commitment and economic dispatch. Electrical load forecasting is prediction of electrical load using load history, weather information etc.

Load forecasting is generally categorized in three types: short term (few hours to few weeks), mid-term (week to year) and long term (more than a year). Short term forecasting has garnered a lot of attention due to facilitate the utility companies and dispatchers to perform economic and secure operations on daily optimal operation of a power system (Almazrouee et al., 2020; Khwaja et al., 2015).

Load forecasting is generally performed either by employing conventional or artificial intelligence based models. Various conventional models such has multiple linear regression model (Charytoniuk et al., 1998; Saber and Alam, 2017), ARIMA model (Zhu and Shen, 2012) and exponential smoothing (Christiaanse, 1971) has been used for forecasting applications. All of these conventional methods are simple to use with high calculation speed. However, the accuracy efficiency of these methods falls short because of non-linear features of electrical load data. Therefore, a lot of recent works has shifted attention towards AI methods for accurate load forecasting by overcoming aforementioned issue. AI methods like Recurrent Neural Networks (RNN) (Tang et al., 2019; Zhang et al., 2020; Shi et al., 2017; Sehovac and Grolinger, 2020), Support Vector Machine (SVR) (Ahmad et al., 2020; Che and Wang, 2014; Ko and Lee, 2013), and fuzzy logic framework (Çevik and Çunkaş, 2015; Mukhopadhyay

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et al., 2017; Ganguly et al., 2017) have been utilized by numerous researchers for short term load forecasting. Though these models can accurately predict load, but they suffer various problems such as convergence issues, high complexity level, modeling of linear part and so on. In a nut shell, conventional methods complexity is lower than AI methods but AI methods accuracy is higher.

To combine advantages of both methods, in recent years, the hybrid methods have gained increasing attention. Ref. Rafi et al. (2021) employs Convolution Neural Network (CNN) and LSTM to predict short term load. This hybrid model is applied on Bangladesh power system and results substantiate higher accuracy in predicting electric load in comparison to non-hybrid models. Ref. Zhang et al. (2018) proposed combination of Multi-layer Perceptron (MLP) neural network, Adaptive Network-based Fuzzy Inference System (ANFIS), and Seasonal Autoregressive Integrated Moving Average (SARIMA) to forecast electricity load. Reduced MAPE with fast convergence speed depicts the superiority of the proposed model. Moreover, LSTM model along with Similar Days (SD) and Empirical Mode Decomposition (EMD) is proposed by Zheng et al. (2017) for Short Term Load Forecasting (STLF). The proposed SD-EMD-LSTM method had the ability to accurately anticipate the non-linear electric load. Other hybrid combinations like LSTM with XGboost (Li et al., 2019) and fractional ARIMA with improved Cuckoo search (Wu et al., 2020) has also been used for given problem. All of the above hybrid models CNN-LSTM, MLP-ANFIS-SARIMA and SD-EMD-LSTM outperforms any of the conventional (such as SARIMA, EMD and so on) or AI (such as CNN, LSTM and so on) models when used independently. These hybrids models have the ability of predicting load accurately by reducing AI complexity and increasing conventional methods accuracy by appending the advantages of both models while overcoming each other's limitations.

However, hybrid deep learning models (like CNN-LSTM) for the large and complex data sets operating on low configuration system not only suffers appropriate hyperparameter tuning but also results in slow computation speed. As far as conventional models are concerned, it highly depends on the stationary data for accurate forecasting and if data has multiple seasonality, it becomes very arduous to design. Therefore, in order to mitigate aforementioned issues for accurate load forecasting, this study proposes integrated prophet LSTM optimized by BP. The proposed work bridges the technological gap of load forecasting by covering the limitations of recent works including conventional, deep learning and hybrid models with the aid of prophet, LSTM and BPNN model on the real time data obtained from Elia grid. The major contributions of this work are:

- Real time quarter hour electrical load data of Elia grid is trained by using SARIMA and Prophet model while its performances are evaluated by evaluating MAPE, RMSE, and MAE.
- The residuals are considered to be the non-linear part of the electrical load data, which are trained by using deep learning LSTM model, then LSTM results is linearly added in forecast of optimal selected model.
- The final predicted values are optimized by using BPNN. The proposed hybrid technique can accurately forecast electricity consumption by inputting the self-history data without any additional data and handcrafted feature selection operation.

Rest of the paper is structured as follows. Section 2 elaborates methodology that includes model selection such as SARIMA model selection, LSTM model selection, and Prophet model selection. Section 3 provides results simulation and discussion while Section 4 concludes the paper.

2. Methodology

In this section, different criteria for selection of different models of electric load forecasting will be described. We will start with the most famous and widely used model in electrical load forecasting, such as ARIMA model. Then, LSTM and Prophet models will be briefly explored. Finally, the proposed novel hybrid Prophet-LSTM optimized by BPNN approach will be introduced.

2.1. ARIMA model selection

An ARIMA model is a statistics analysis model for electrical load forecasting, and is mainly consists of three stages and three sections that are: Identification, Estimation and Forecasting, while three main sections are Autoregressive (AR), Integration (I), and Moving Average (MA) respectively. The parameters for these three sections are p, d, and q, where p represents the autoregressive section order, d represents the differencing section order, and the q represents the moving average section order. In the first stage of operation of an ARIMA model which is identification stage the stationarity of the given electrical load data is checked. The most important requirement of the electrical load data before employing an ARIMA model is to check that either the data is stationary or not. Stationarity of any time series data is that statistical properties such as mean, covariance and variance of the data, which does not vary with respect to time. If electrical load data is non-stationary then it can be converted into stationary by differencing it (d) by times until the stationary data is obtained, and the value of this differencing order (d) is assigned to the integration parameter of the ARIMA model. Then, in the second stage of ARIMA model, estimation is performed on this stationary load data. In the estimation stage of ARIMA model, the best suitable values of rest of the other two parameters, i.e., (p) for the autoregression and (q) for movingaverage are selected. These two parameters can be selected on the base of different selection criterion, i.e. Maximum Likelihood, Sigma SQ, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) criterion. Then the final stage of forecasting is applied on this ARIMA model. ARIMA (p, d, q) model is as follows:

$$\begin{aligned} y_t = {} & \alpha + \theta_1 y_{t-1} + \theta_2 y_{t-2} \dots + \theta_p y_{t-p} + \varepsilon_t \\ & + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} \dots + \phi_q \varepsilon_{t-q} \end{aligned} \tag{1}$$

where y_t represents the value of current time; $\theta_1, \theta_2, \dots \theta_p$ represents AR coefficients of order p; $\phi_1, \phi_2, \dots \phi_q$ represents MA coefficients of order q; α is the constant term; ε_t represents the error term.

Eq. (1) can be transformed into the equation as follows:

$$y_t = \alpha + \varepsilon_t + \sum_{i=1}^{p} \theta_i y_{t-i} + \sum_{i=1}^{q} \phi_i \varepsilon_{t-i} \tag{2}$$

$$\theta(B) y_t = \alpha + \phi(B) \varepsilon_t \tag{3}$$

where B represents the back shift operator. For non-stationary sequences, the difference operator ∇^d is applied. Where ∇^d is given as follows:

$$\Theta(B) = \nabla^d = (1 - B)^d \tag{4}$$

Therefore final equation of the ARIMA (p, d, q) can be written as follows:

$$\theta(B) \Theta(B) y_t = \alpha + \phi(B) \varepsilon_t \tag{5}$$

SARIMA model is used when the electrical load data values display some seasonal behavior in it. SARIMA model is comprised of six parts which are autoregressive (AR), seasonal autoregressive (SAR), integration (I), seasonal integration (SI), and moving average (MA), and seasonal moving average (SMA). These parts are represented by p, d, q, P, D, Q respectively. Therefore, in general, SARIMA model can be written as SARIMA (p, d, q) (P, D, Q) $_{[m]}$, where m is the order of seasonal differencing. The SARIMA model is given as follows:

$$\theta(B)\Theta(B^m)(1-B)^d(1-B^m)^D y_t = \alpha + \phi(B)\Phi(B^m)\varepsilon_t \tag{6}$$

where y_t is the value electrical load at current time; $\theta(B)$ represents the non-seasonal AR coefficients of the order p; $\Theta(B)^m$ is the seasonal AR coefficient of order P with seasonal degree of order m; $(1-B)^d$ is non-seasonal differencing of order d; $(1-B^m)^D$ is the seasonal differencing of order D with seasonal degree of order m; α is constant; $\phi(B)$ is non-seasonal moving average; $\Phi(B^m)$ is the seasonal moving average and ε_t is the current time error.

2.2. LSTM model selection

LSTM is special type of the RNN, which is widely applied due to its extraordinary ability to retain and memorize long sequences of electrical load data. Before further explaining the LSTM, RNN shall be defined briefly as follows. RNN is the sequence based model designed to process the sequence dependencies. The mathematical dynamics of the associated RNN are as given below:

$$h_t = \sigma(Ux_t + V_h h_{t-1}) \tag{7}$$

$$y_t = W.h_t \tag{8}$$

where x_t is the sequential input to the model; U is relevant weight to input x_t; h_{t-1} is model internal short term memory; V_h is relevant weight to the short term memory h_{t-1}; σ is sigmoid activation function; W is the weight to the output.

One of the major drawbacks of employing traditional RNN model is the shortcoming of vanishing gradient that prevents them from updating the weights during training process, according to previous time lags. LSTM was introduced to address above problem. Internal cell structure, governing equations, and a quick description of the LSTM model is presented as follows. LSTM were first introduced by Sepp Hochreiter and Jrgen Schmidhuber in 1997 (Hochreiter and Schmidhuber, 1997). Internal cell body of LSTM is comprised of three computing gates called, input gate, forget gate, and output gate. Mathematical dynamics of these gates are given as follows:

$$i_t = \sigma(U_i x_t + V_i h_{t-1} + b_i) \tag{9}$$

$$f_t = \sigma(U_f x_t + V_f h_{t-1} + b_f) \tag{10}$$

$$o_t = \sigma(U_0 x_t + V_o h_{t-1} + b_o) \tag{11}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(U_{ia} x_t + V_{ia} h_{t-1} + b_{ia}) \tag{12}$$

$$h_t = o_t \odot \tanh(c_t) \tag{13}$$

where U, V are weight matrices; b are the bias values of the corresponding gates. The $\odot$ symbol represents Hadamrd's product (element-wise multiplication). The σ symbol represents the activation of the corresponding gates and is called sigmoid activation function, which is not only responsible for opening and closing of the corresponding gates but also enables the nonlinear capabilities of the LSTM model. The hyperbolic tangent function (tanh), on the other hand, is responsible for the regulating the outputs between −1 and 1 of the corresponding input activation and output gates. The internal structure of the LSTM is shown in Fig. 1. In the first step of the LSTM operation, the forget gate in the internal structure of the LSTM is responsible for either keeping or forgetting the contents of the previous cell state based on the sigmoid activation function. Next, the internal cell state of the LSTM is updated, by adding the product of the outputs of the forget gate and previous cell state with the product of the outputs of the input gate and input activation in the second step of the LSTM operation. In the final step of the LSTM operation, the output gate is responsible of maintaining or forwarding the output to the next cell in the LSTM structure. For this purpose, the decision made by the sigmoid activation function of the output gate is used. As a result, the output of the output gate and the regulated output with the hyperbolic tangent activation function of the updated cell state are multiplied and the final values are incorporated into the h_t. The cell state c_t and output h_t will be forwarded to the next stage. The next loop of the LSTM operation will repeat the same procedure stated above.

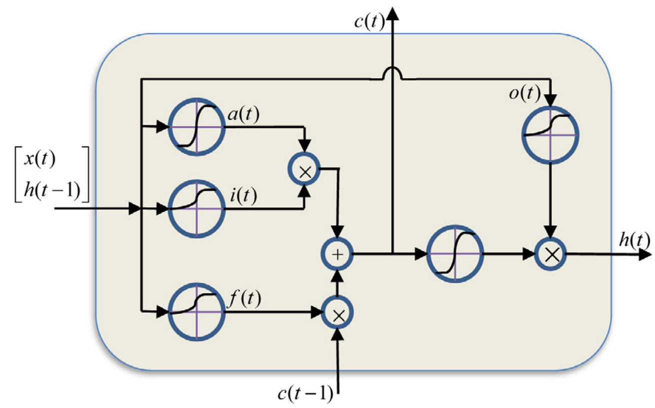

Fig. 1. Internal cell structure of LSTM.

2.3. Prophet model selection

The Prophet forecasting method considers electrical load data complicated features such as trend, seasonality and holidays. The mathematical dynamics are given as below:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon(t) \tag{14}$$

where $g(t)$ represents trend function responsible of modeling non-periodic changes in the electrical load data, $s(t)$ represents seasonality (daily, weekly, yearly), $h(t)$ represents holidays occurring on irregular schedules, and $\varepsilon(t)$ are the error terms unaccommodated by the model.

The trend function, $g(t)$, in Prophet model has two types: a non-linear saturating growth model and a piecewise linear model. Since electrical load data does not show any saturating growth, a piecewise linear model is opted. The mathematical dynamics are given as follows:

$$g(t) = (k + a(t)^T\delta)t(m + a(t)^T\gamma) \tag{15}$$

where k is the growth rate, m is an offset parameter, δ is the adjustment rate, and γ is the trend change points and set as $-s_j\delta_j$ to make the function continuous.

To represent daily, weekly and yearly seasonality of the electric load data, the seasonality function in the prophet model can be modeled by using Fourier series is given as follows:

$$s(t) = \sum_{n=1}^{N}(a_n\cos(\frac{2\pi nt}{P}) + b_n\sin(\frac{2\pi nt}{P})) \tag{16}$$

where P is the period of the seasonality, for yearly seasonality $P = 354.25$ and for weekly seasonality $P = 7$. Holidays and special events do not follow any periodic cycle, to model the holiday function $h(t)$, user can provide the specific matrix containing the dates and the details of these holidays.

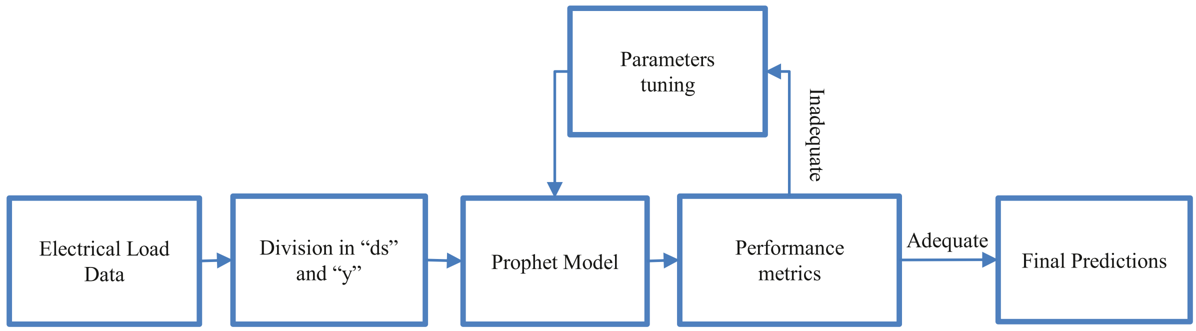

Fig. 2. Modeling flowchart of the Prophet model.

2.4. Proposed methodology

With above models, the proposed methodology is explained step-wise which is given below.

2.4.1. Step 1: Data collection

In data collection step, historical electric load data of Belgium based Elia Grid data is downloaded, missing values in the data are checked. By observing the trend in historical load pattern, these missing values are adjusted. Thus by the filling the missing values in the load data, a complete data set is obtained, which has very low impact on the performance of the forecasting. For the evaluation of the proposed model, the load data is divided into training and testing set.

2.4.2. Step.2: Modeling linear components of electrical load data

Generally, an electrical load data is considered to be composed of linear and non-linear components. Different models has been used to train the linear and non-linear parts of the load data individually and collectively. Among which the most common models to train the linear component of load data is ARIMA model which has been excessively reported in the relevant literature (Radziukynas and Klementavičius, 2016; Deng and Jirutitijaroen, 2010; de Andrade and da Silva, 2009). Additionally, it was proven to be very effective in forecasting electric energy consumption with high accuracy. However, designing and tuning of hyperparameters for the selection of suitable ARIMA model is found to be very challenging task and also requires strong technical knowledge background related to statistical models. As the model selection criteria stated in Section 1, the stationarity of electrical load data was checked by using Autocorrelation Function (ACF) plot. Because seasonal and nonstable trend was found in the electrical load data, so the SARIMA model was adopted. Seasonal and non-seasonal parts of the SARIMA model were investigated by using ACF and Partial Autocorrelation (PACF) plots respectively. Then based on AIC and BIC, optimal SARIMA with lowest values of AIC and BIC is selected. P value of the white noise test to check the validation of selected model is above 0.05 value accrediting the validation of model.

The Prophet model used for forecasting short term electric load is a relatively new forecasting model that designed to have automatic tuning of parameters without prior knowledge of underlying model. The Prophet model is robust against missing data, thus data interpolation to this missing data is not required. Before employing the load data to the model, it is the requirement of the Prophet model to divide the data into time-stamp (ds) column, containing the details of time and date, and logged of load values (y) column. The trend function as described in the section above is manually tuned by changing the trend changepoints prior scale (τ), the grid search on the τ hyperparameter is done by tuning it in the range of $\tau \in \{0.5, 0.1, 0.01, 0.05 , 0.06\}$ to fit the model well on the load data. Holidays in the load data is modeled by calling the built-in function available in prophet library in R software. Furthermore, to address the seasonality with multiple periods in the load data, as described in the section, Fourier series is used. The default values of Fourier components to address the yearly and weekly seasonality are 10 and 3 respectively. However, increasing the number of Fourier components may risk overfitting of model. The modeling flow chart of the Prophet forecasting is shown in Fig. 2 and the modeling flow chart of the proposed hybrid model is given in Fig. 3. Here in our case, we took total 7 seven years of historical data, first 5 years of historical data was fed to Prophet and ARIMA model as training data, remaining data was given to these models as testing data. The accuracy of both models is measured by comparing the original test data with these forecasted data by using MAPE, RMSE, and MAE metrics. Lower error forecast model is considered to be the optimal model and the error terms assumed to carry the non-linear tendency of electrical load data also known as remainders from this model is forwarded next to deep learning LSTM model.

2.4.3. Step.3: Modeling non-linear components of electrical load data

The residual from the optimal model is considered to have non-linear tendency, thus are fed to LSTM model for training to improve the forecast. In this part, these non-linear components of the load data are given to LSTM model. Before employing LSTM model to train non-linear component of load data, it is normalized and transformed into a range between 0 and 1. The normalization is done by using method given below:

$$x_{norm} = \frac{x - \mu(x)}{\sigma(x)} \tag{17}$$

where μ is mean and σ is standard deviation.

Different number of neurons in hidden layer and epochs are tried to tune the hyperparameters. After multiple attempts, optimal LSTM model was obtained that coincidently was the default model in the MATLAB deep learning toolbox. Adam algorithm is the optimizer and number of epochs was set to 250.

2.4.4. Step4: Optimization of final forecasting values

Classical BPNN is utilized to optimize the final forecast load values. This network is comprised of three sections, named as: an input layer section, hidden layer section, and output layer section (FaizanTahir, 2016). Each layer contains several nodes also called neurons, each node take information from other node through connection weights (Samuel et al., 2016; Tahir et al., 2020; Mitchell et al., 2017). The BP neural network has forward and backward process also called forward propagation and backward propagation respectively. During the forward propagation, the input information propagates from input layer to output layer via hidden layer. If outputs are closed to desired output, the algorithm propagate backward. During the backward propagation, weight and threshold values are adjusted and then cycle of

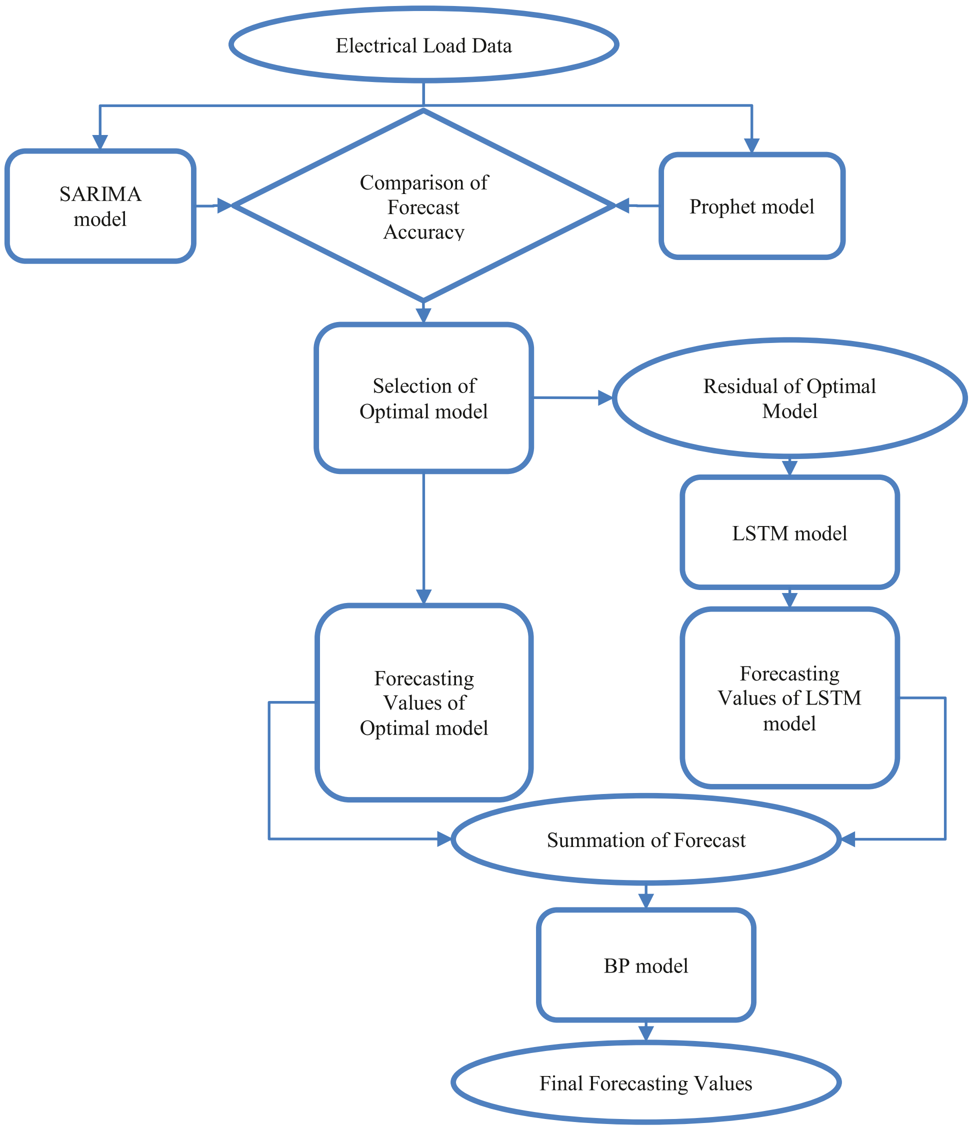

Fig. 3. Modeling flowchart of the proposed hybrid model.

working process of BP algorithm is repeated as mentioned above. The functionality of BPNN here in our hybrid model is to optimize the forecast from optimal model and residual of optimal model forecasted by the deep learning LSTM model.

3. Results and discussions

To verify the effectiveness of proposed method, one year load data is utilized to compare predicted results with other methods

3.1. Prediction outcome

The Prophet model is implemented in R software, and ARIMA, LSTM, BPNN models are implemented in MATLAB, using real time electrical load data with 15-minutes time interval collected from ELIA grid from jan-2014 to sep-2021. The combination of proposed hybrid models can forecast load over different time horizons such as 24 h, one week, and one month at 15-minutes time interval. The time series load data from 2014 to 2021 contains 271 681 no. of total data points. First six years of load data set (i.e. from January 2014 to December 2019) is selected for training and remaining load data set (i.e. from January 2020 to September 2021) is selected for testing.

3.2. Evaluation metrics

To check the statistical performance and accuracy of the proposed methodology, integrated prophet LSTM model optimized by BP, forecasting results are compared with the forecasting results of single ARIMA, single prophet, single LSTM, and integrated Prophet LSTM optimized by BP in terms of evaluation metrics. In this work, various validation metrics i.e. MAPE, MAE, and RMSE, are used. The lower values of these metrics indicate the better forecasting results. The mathematical dynamics of these metrics are given below.

$$MAPE = \frac{\sum_{L=1}^{N} \left| \frac{(F_L - O_L)}{O_L} \right|}{N} \times 100 \tag{18}$$

$$MAE = \frac{1}{N} \sum_{L=1}^{N} |(F_L - O_L)| \tag{19}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{L=1}^{N} (F_L - O_L)^2} \tag{20}$$

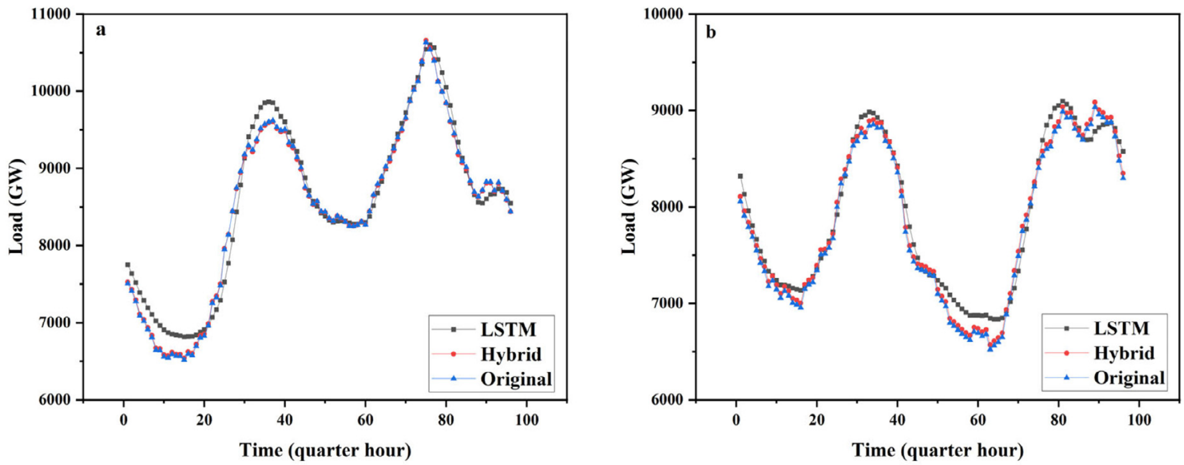

Fig. 4. Comparison of load prediction of results using different networks for 21 February 2021 (a) and 12 May 2021(b).

Table 1
Comparison of RMSE, MAPE, and MAE using different models.

Name	RMSE	MAPE (%)	MAE
ARIMA	592.52	5.19	396.98
LSTM	335.43	3.72	198.25
Prophet	471.04	5.21	391.57
Hybrid ARIMA SVM (Karthika et al., 2017)	204.58	2.47	184.94
Proposed hybrid	35.79	0.49	46.05

where N, is the total number of data points in forecasted load, F_L is the value of forecasted load, and O_L is the value of original load at any instance.

3.3. Performance calculation using error metrics

By comparing the values of MAPE, MAE, RMSE, obtained by different forecasting methods, it is found that the proposed integrated model outperforms the single LSTM, single ARIMA, and single Prophet models in all three-time horizons.

Note that a computer utilized to carry out these simulations has following specification — Processor: Intel(R) Core(TM) i5-7400 CPU @ 3.00 GHz 3.00 GHz, RAM: 16.0 GB. The run time for the proposed hybrid model is half an hour which is relatively less compared to other models took to complete the computations.

The performance of single ARIMA model, single Prophet model, single LSTM model, and Hybrid ARIMA SVM model, and proposed hybrid model are compared in Table 1

3.3.1. Comparison of error metrics for 24 h

The performance of the hybrid model is compared with single ARIMA, single Prophet and single LSTM models by utilizing 24 h load data, and forecasted load data by these models in terms of RMSE, MAPE, and MAE in Table 2. Comparison plots of day ahead forecast is plotted in Fig. 4.

For example, on 01 October 2020, RMSE of LSTM model forecast is 861.17 while the proposed hybrid model has lower value which is 137.32. Similarly on 08 November 2020, RMSE of proposed hybrid network forecast is 180.93 while LSTM network has 884.44 value which is greater than RMSE value of hybrid model. This trend can be seen on other forecasting values too. Overall, on average, hybrid network provides 442.79, 1.44%, and 742.65 less RMSE, MAPE, and MAE respectively. This found out to be more effective than other employed networks for short term load forecasting.

3.3.2. Weekly comparison of error metrics

Weekly comparison of the error metrics for proposed hybrid network and single ARIMA, single LSTM, and single Prophet models are shown in Table 3. The comparison of forecasting of these different models for different time horizon on weekly basis is depicted in form of graph in Fig. 5.

For example, on week 01–07 October 2020, MAE for single LSTM network provides 59.46, while the proposed hybrid network offers 34.32. Similarly, the proposed hybrid network provides less MAE in week 08–14 November 2020. This similar trend can also be seen in other weeks. On average the proposed hybrid network provides 150.82, 0.92%, and 64.42 less RMSE, MAPE, and MAE respectively than LSTM network.

3.3.3. Monthly comparison of error metrics

Table 4 demonstrates monthly comparison of the error metrics for single ARIMA, single LSTM, single Prophet, and proposed hybrid model (see Table 4).

For instance, with the forecasted data in month of October 2020, the proposed hybrid network offers a MAPE 1.12%, while the single LSTM network provides a MAPE of 3.17%. Similarly the proposed hybrid network offers less MAPE in November 2020. This similar trend can be seen in other forecasting results too. On average, the proposed hybrid method provides 192.24, 1.87%, and 139.36 less RMSE, MAPE, and MAE respectively than LSTM network. The forecasting comparison of the proposed hybrid network and single LSTM networks is illustrated in form of graphs in Fig. 6.

4. Conclusion

In this paper, a hybrid method consisting of Prophet model, ARIMA model, and LSTM model, and BPNN model is presented to forecast short-term electrical load. The proposed methodology takes the advantage of each model to forecast by utilizing not only linear trend of the electrical load but also utilizes the non-linear trend present in electrical load to improve the forecasting accuracy. The performance of the proposed model is validated by forecasting real time Elia Grid electrical load data. Simulation results corroborate that the proposed hybrid model has the lowest value of RMSE, MAE, and MAPE in comparison to standalone models like LSTM, ARIMA and Prophet as well as hybrid models such as hybrid ARIMA SVM. The proposed hybrid model in day ahead forecast time horizon on average forecasts 81.36 (RMSE), 0.91% (MAPE), and 80.11 (MAE). Similarly, the proposed hybrid model forecast on average 89.04 (RMSE), 0.91% (MAPE), 71.23 (MAE), in

Table 2
Comparison of RMSE, MAPE, and MAE for day ahead forecast using different models.

Day	RMSE				MAPE (%)				MAE			
	ARIMA	LSTM	Prophet	Hybrid	ARIMA	LSTM	Prophet	Hybrid	ARIMA	LSTM	Prophet	Hybrid
01-Oct-20	805.12	861.17	495.09	137.32	5.98	1.97	4.47	1.44	614.09	177.80	429.39	137.25
08-Nov-20	753.05	884.44	413.74	180.93	7.20	2.22	3.84	2.07	631.30	193.01	339.91	180.15
13-Dec-20	1966.56	1037.67	625.55	301.91	19.84	4.84	5.74	3.18	1872.10	454.40	548.81	301.70
03-Jan-21	1284.77	976.91	518.97	125.14	14.11	5.41	4.87	1.46	1195.83	441.75	401.69	123.37
21-Feb-21	586.97	880.77	548.59	18.24	5.86	2.85	5.77	0.19	492.98	232.75	471.82	15.96
19-Mar-20	790.89	879.50	1346.89	26.53	8.18	3.73	14.35	0.23	638.76	290.79	1075.10	19.43
03-Apr-21	556.19	118.79	1317.06	21.65	5.27	0.86	11.57	0.25	468.28	76.66	1071.32	21.59
12-May-21	657.08	185.94	938.19	48.63	7.33	1.85	9.58	0.63	575.74	141.52	704.24	48.62
15-Jun-21	1431.55	95.03	573.83	21.99	11.83	0.78	5.61	0.23	1066.17	67.27	498.56	20.21
27-Jul-21	1157.27	114.39	661.12	32.86	10.24	1.15	7.58	0.40	848.38	92.37	619.60	32.66
05-Aug-21	967.91	72.67	1009.28	15.85	13.47	0.71	11.44	0.22	907.63	75.69	736.88	15.24
30-Sep-21	798.64	182.50	456.94	45.33	7.14	1.81	5.31	0.57	561.87	143.07	408.73	45.12
Average	979.67	524.15	742.11	81.36	9.73	2.35	7.51	0.91	822.76	198.92	608.84	80.11

Table 3
Comparison of RMSE, MAPE, and MAE for week ahead forecast using different models.

Week	RMSE				MAPE (%)				MAE			
	ARIMA	LSTM	Prophet	Hybrid	ARIMA	LSTM	Prophet	Hybrid	ARIMA	LSTM	Prophet	Hybrid
01–07 Oct-20	537.52	84.71	541.81	34.33	4.69	0.66	4.97	0.38	441.76	59.46	456.17	34.32
08–14 Nov-20	966.63	339.05	533.35	44.75	8.42	1.11	4.62	0.47	778.66	104.82	433.29	44.64
15–21 Dec-20	577.56	229.33	657.03	202.47	5.12	1.85	5.28	1.57	497.78	181.75	547.85	157.21
01–07 Jan-21	882.87	390.33	718.10	89.95	7.87	1.22	6.29	0.96	723.01	116.55	562.54	85.52
08–14 Feb-21	849.75	187.66	1129.08	21.51	6.97	1.49	9.89	0.21	664.84	150.62	988.35	21.49
15–21 Mar-20	985.89	147.34	1072.31	134.19	8.16	1.38	10.82	1.27	671.23	111.74	881.51	108.54
22–28 Apr-21	1179.96	529.72	1425.26	171.34	12.45	4.75	15.86	1.77	904.77	324.28	1125.94	123.78
01–07 May-21	1297.24	170.91	1208.42	11.11	13.36	1.86	12.53	0.14	984.38	141.06	913.44	11.08
08–14 Jun-21	735.07	295.40	1126.71	93.45	8.02	1.45	12.67	0.54	570.03	99.19	905.86	36.86
15–21 Jul-21	1242.88	272.24	1541.93	136.13	16.91	3.61	20.87	1.74	922.16	206.16	1144.77	114.04
22–28 Aug-21	833.67	104.29	1018.24	35.31	10.26	1.16	11.04	0.49	701.94	83.09	708.77	33.58
01–07 Sep-21	851.21	127.39	1106.51	93.91	9.86	1.38	12.36	1.27	672.63	91.91	778.16	83.70
Average	911.68	239.86	1008.81	89.04	9.34	1.83	10.6	0.91	711.09	135.65	787.22	71.23

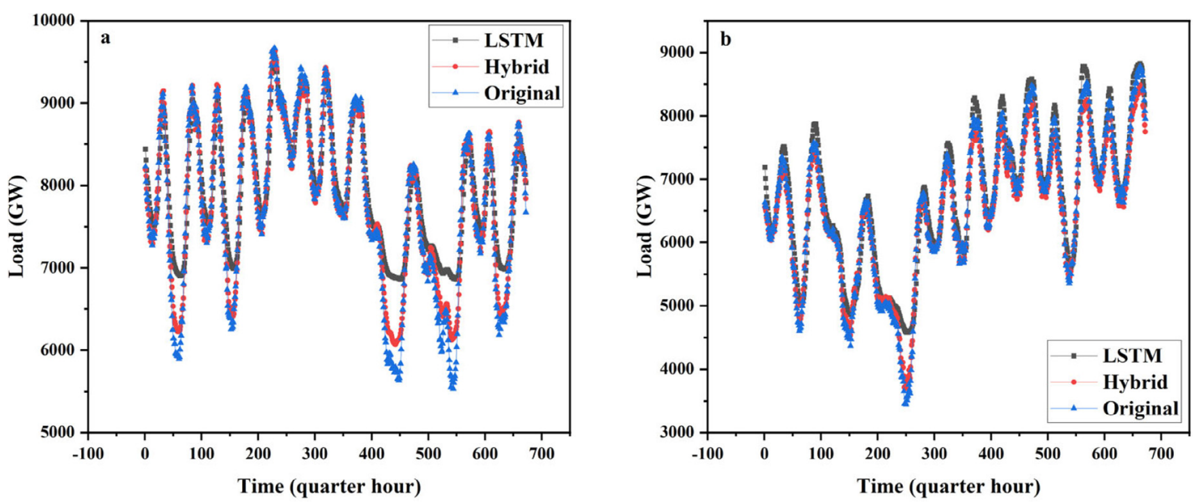

Fig. 5. Comparison of load prediction of results using different networks for 22–28 April 2021 (a) and 15–21 July 2021 (b).

Table 4
Comparison of RMSE, MAPE, and MAE for month ahead forecast using different models.

Month	RMSE				MAPE (%)				MAE			
	ARIMA	LSTM	Prophet	Hybrid	ARIMA	LSTM	Prophet	Hybrid	ARIMA	LSTM	Prophet	Hybrid
Oct 20	742.4	376.74	511.37	143.41	6.62	3.17	4.68	1.12	637.53	275.52	427.65	103.42
Nov 20	606.84	286.15	576.02	178.03	4.94	2.34	4.81	1.39	471.23	224.76	470.89	136.4
Dec 20	1048.14	348.71	748.58	302.18	8.52	2.72	5.99	2.19	803.63	274.68	618.22	220.74
Jan 21	1531.42	386.34	775.84	315.16	13.53	3.24	6.85	2.63	1231.51	307.25	634.22	242.10
Feb 21	1704.33	636.89	1247.95	425.51	15.60	5.66	11.51	3.84	1286.12	459.42	948.28	326.56
Mar 20	1947.2	656.19	1205.84	133.33	20.54	6.76	13.37	1.50	1747.23	433.38	907.48	109.66
Average	1263.38	441.84	844.26	249.60	11.63	3.98	7.87	2.11	1029.54	329.17	667.79	189.81

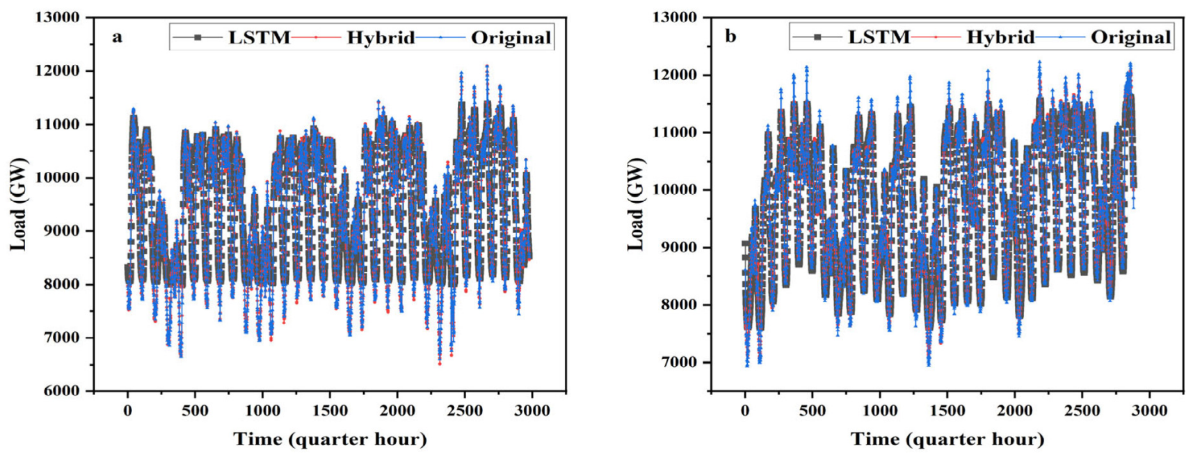

Fig. 6. Comparison of load prediction of results using different networks for October 2020 (a) and November 2020 (b).

week ahead time horizon and in month ahead time horizon on average forecasts 249.60 (RMSE), 2.11% (MAPE), 189.81 (MAE). These forecasted values are lower than the other models. Other than electric load forecasting, the proposed hybrid model can be extended to predict different application like weather forecasting, sales forecasting, and stock price forecasting. Besides, evaluating parameters on the basis of reduced error, least computational time with fast convergence, systems can also be analyzed in terms of cost-effectiveness.

CRediT authorship contribution statement

Tasarruf Bashir: Problem formulation, Acquisition of data and results simulation, Writing – original draft. **Chen Haoyong:** Conception and design of study, Writing – original draft. **Muhammad Faizan Tahir:** Writing – original draft. **Zhu Liqiang:** Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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