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Load Forecasting Model Using LSTM for Indian State Load Dispatch Centre

Rashmi Bareth[1], Matushree Kochar[1], Anamika Yadav[1], Mohammad Pazoki[2]

[1]Department of Electrical Engineering, National Institute of Technology, Raipur, India
[2]Damghan University, School of Engineering, Damghan, Iran

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ABSTRACT

This paper presents an approach to address the critical challenge of load forecasting in the Indian state of Odisha. Motivated by the necessity for accurate predictions to support efficient planning and operation of the power system network, the work focuses on developing a reliable load forecasting model according to the unique characteristics of Odisha's electricity consumption patterns and environmental influences. To handle this problem, a Long Short-Term Memory based model is proposed with the ability to capture long-term dependencies and handle non-linear dynamics in time-series data. Historical load datasets are collected from the Odisha State Load Dispatch Centre, and meteorological datasets are collected from the National Aeronautics and Space Administration site. The work aims to accurately forecast power demand at 15-minute intervals for both short-term (next week) and medium-term (next month) horizons. Through comparative analysis with traditional methods such as Gaussian Process Regression and Artificial Neural Network, the proposed approach demonstrates superior performance in terms of accuracy and reliability. One year of the dataset (from January to December 2022) is considered as a training dataset to forecast next year's January 2023 load demand at every 15-minute intervals. The LSTM model achieves an absolute error range of ±10 MW during testing, with a mean absolute error of 5.9443 MW and a Mean Absolute Percentage Error of 0.2134%, outperforming the existing models. This research contributes to advancing the reliability and efficiency of power system operations, offering valuable insights for optimizing load forecasting strategies in Odisha and similar regions.
Index Terms— Load forecasting, long short-term memory, energy consumption

I. INTRODUCTION

The world faces two significant challenges today: global warming and energy security. Addressing these issues is not just crucial; it is a matter of utmost importance, and energy efficiency is a key part of the solution. Numerous countries are continuously striving to enhance their energy efficiency. Renewable energy sources, such as solar and wind power, have been proven to be effective in reducing harmful emissions. By utilizing renewable energy sources, countries can increase their energy security and efficiency while reducing their reliance on fossil fuels, thereby significantly mitigating the adverse effects of global warming. Furthermore, electricity demand analysis is a complex process, and the demand variability presents a challenge to the electrical grid. This variability can lead to imbalances between electricity supply and demand, posing a significant threat to grid stability [1]. Accurate load forecasting is essential in addressing this issue and ensuring that the electrical grid operates reliably. By predicting energy consumption patterns, grid operators can balance supply and demand in real-time, reducing the need for backup power plants and improving overall grid efficiency.

Machine learning algorithms are increasingly being used in electrical power systems to address load forecasting problems [2]. Studies have shown that meteorological variables have a significant relationship with electricity load consumption and are frequently used as inputs for machine learning algorithms [3].

To predict electrical power load demand for the day ahead in the European Network of Transmission System, a simple processing pipeline method is applied for preprocessing raw power data, which is gathered at discrete and separate time intervals [4]. Secondly, a Gated Recurrent Unit (GRU), which is a lightweight type of recurrent neural network, is selected to yield the multi-step forecast. A new transformer model called the transform graph, and the Graph Convolutional Network (GCN), is developed to predict electric load [5]. The predicted load values

Corresponding author:
Mohammad Pazoki

E-mail:
pazoki.m@du.ac.ir

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are generated using a feedforward neural network that takes the outputs of the transform graph as input. In ref. [6], for day-ahead grid system-wide level load forecasting, the Long Short-Term Memory (LSTM) algorithm is used. An improved complete empirical mode decomposition with adequate noise technique is used in ref. [6] to obtain the input of net load decomposition. In ref. [7], separate load forecasting models for net load and PV generation are proposed for a 66/13.2 kV power substation located in the north of Spain; it uses 64 variables as input to Cubist and random forest models to estimate the load demand with 5—7% Mean Absolute Percentage Error (MAPE). A mid-term load forecasting technique utilizing both load data and environment data for Australian and Indian datasets is proposed in ref. [8]. In ref. [9], a hybrid short-term load forecasting model has been proposed for the smart grid. The model consists of feature engineering and adaptive grasshopper optimization, as well as a locally weighted Support Vector Regression (SVR) forecaster. In ref. [10], a novel temporal convolution network-LSTM load forecasting model is proposed that incorporates mobility data and multi-tasking learning. The combination of different methods used in refs. [9] and [10] imposes more complexity compared to single-method-based models. Support Vector Regression and Artificial Neural Network (ANN) in ref. [11] are used to forecast the electrical load demand for the period from July 16 to July 22, 2010. Between March and July 2010, the local electrical distribution company is the source of data that they use. The findings show that the SVR model is better than the ANN model. In ref. [12], the electric load consumption in the Nepool region of New England is predicted between 2004 and 2008 using an ANN model. The research discovers that weather variables like temperature and wind speed affect forecast accuracy. Similarly, in ref. [13], an ANN model for analyzing the electrical load data for 2019 in Macedonia is proposed. An ensemble model for short-term load forecasting in the Australian National Electricity Market (NEM) that employs an Extreme Learning Machine (ELM) is proposed in ref. [14]. The proposed model consists of several single ELMs that are trained using random input parameters and hidden nodes within a specified range to generalize the randomness of the individual ELMs. In ref. [15], a hybrid load forecasting model employing Vibrational Mode Decomposition (VMD), Empirical Mode Decomposition (EMD), Fast Fourier Transform (FFT), stepwise regression, Similar Days (SD) selection method, and ANN is proposed, but owing to the deployment of numerous methods, this model complexity is quite high, which leads to higher computation time.

In ref. [16], a comparative analysis of 19 machine learning models for short-term load forecasting is done using a dataset from Maharashtra, India, for July 2022. In terms of forecasting accuracy, the study revealed that the exponential Gaussian process Regression (GPR) performed better than the other models. Further, a combined Prophet and LSTM model is proposed to forecast the load data. This model uses both linear and nonlinear data to predict the original load data, and the non-linear residuals are trained using LSTM [17]. An LSTM model with a combination of Recurrent Neural Network (RNN) deep neural network models used 24- and 168-hour records for day- and week-ahead prediction with the help of historical load and weather data, indicating an accuracy in terms of MAPE as 1.01% [18]. Similarly, a Convolutional Neural Network (CNN) and LSTM (CNN–LSTM) hybrid model is proposed for STLF with a 6-year historical load data training dataset to predict 12 days' load with a MAPE of 3.5% [19]. Ultra-load demand prediction for several hours is proposed by using the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) concept and LSTM neural network; a total 4-year dataset (2014–2017) is applied for training purposes, and the result is compared with Autoregressive Moving-Average (ARMA), LSTM single-prediction, Ensemble Empirical Mode Decomposition (EEMD) and LSTM, and CEEMDAN-LSTM models [20]. A model using a multi-stage-based method for short-term zonal load probabilistic forecasting is proposed [21]. In this method, highly correlated features with electricity load are provided, and an LSTM model integrates a temporal attention-based decoder and pinball loss function for probabilistic forecasting. It is clear from the previous discussion that historical load data and weather information are two crucial kinds of features that can affect the accuracy of load forecasting. Additionally, good performance in load forecasting has been affirmed in the past using machine learning-based methods. However, Indian load patterns have not been analyzed in research articles; therefore, in this paper, a load forecasting model using LSTM is proposed for the Indian State Load Dispatch Centre.

The proposed model has the following main contributions:

- Developing a forecasting model that is driven by data for the Odisha Load Dispatch Centre.
- Investigating the effect of past load and weather information on load forecast. Temperature, relative humidity, dew point, wet bulb, and wind speed are the weather variables taken into account in this research.
- Assessing how well GPR, ANN, and LSTM work in predicting the electrical load. For the evaluation of the performance of different models and to determine the most accurate model, MAPE is calculated and compared.

II. FRAMEWORK OF LOAD FORECASTING MODEL

The first step of load forecasting is gathering the required input dataset for building load forecasting models and organizing them. The framework of load forecasting is shown in Fig. 1. Data, information, and knowledge acquisition are of utmost importance in the area of data analysis. Further, to forecast load demand accurately by machine learning algorithms, it is necessary to preprocess and clean the data before feeding it to the learning algorithms.

Arranging and combining the collected historical load data with other elements produce various load characteristics, which can be visualized and analyzed to achieve the desired knowledge. Later, this knowledge can help with the decision-making process of feature selection.

The study focuses on determining the effect of meteorological variables on load forecast accuracy by using different features. Various features are collected and compared to identify the most effective set of features for accurate predictions. Studies have shown that meteorological variables have a significant relationship with electricity load consumption and are frequently used as inputs for machine learning algorithms [3]. Because load patterns are frequently predictable, historical load information, such as past energy consumption, can significantly affect load forecasts. The proposed work's datasets consist of historical load data as well as meteorological data.

In this paper, the load forecasting model is developed for Tata Power Southern Odisha Distribution Limited (TPSODL) using the electricity load data provided by the State Load Dispatch Centre, Odisha [22] for the year 2022 (January–December) and 2023 (January). The dataset also includes six meteorological features: block, temperature,

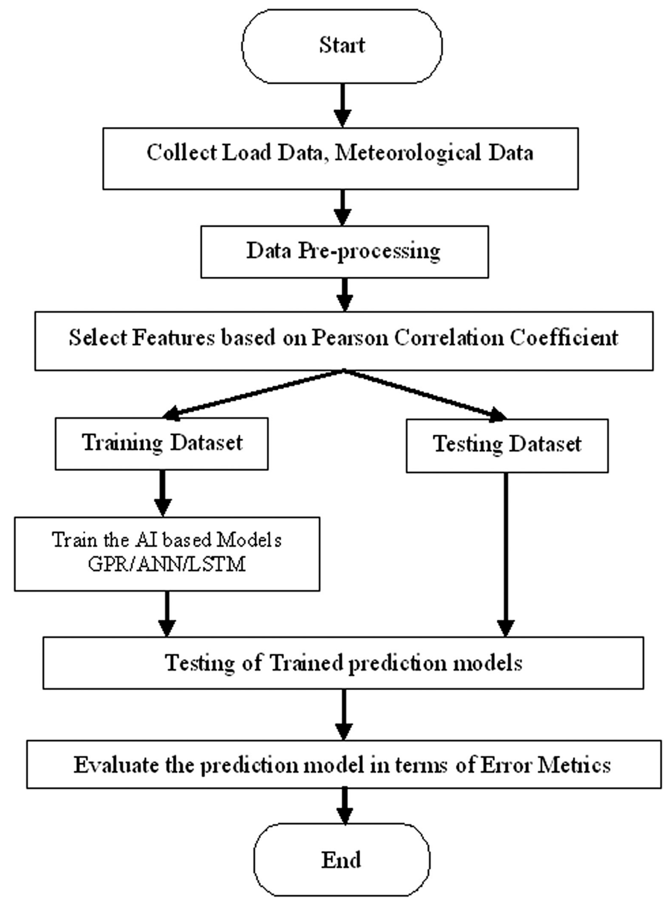

Fig. 1. Framework to forecast the load.

relative humidity, dew point temperature, wet bulb temperature, and wind speed, along with load demand data consisting of 96 data points for a day collected at every 15-minute time interval. The meteorological features are collected from the National Aeronautics and Space Administration (NASA) website available online at https://power.larc.nasa.gov/ [23]. The dataset from the year 2022 is used to train and validate the models and test them using the dataset of January 2023. For the load forecasting model, the final dataset is prepared using a variety of data preprocessing methods. These methods include gathering data, data cleaning, data monitoring, missing data filling, and data normalization. The chosen features are further analyzed based on the Pearson correlation coefficient.

The Pearson correlation coefficients are used to measure the correlation between two variables. It can be calculated by using (1) as:

$$\rho_{x_{Weather},x_{load}} = \frac{\mathrm{cov}(x_{Weather} x_{load})}{\sigma_{Weather}\sigma_{load}} \tag{1}$$

Where σ_{Weather} and σ_{load} represent the standard deviations of the weather variable x_{Weather} and the load value x_{load} and cov is the covariance. The feature that has a high score (close to 1) is highly correlated with load demand and selected for further forecasting steps. Table 1 indicates the correlation coefficient values of the variables (if the current day is "k" then previous day's load demand (day k–1), block (day k), temperature (day k), relative humidity (day k), dew point (day k), wet bulb (day k), and wind speed (day k)) with the actual load for the year 2022. Artificial neural network-based algorithms assign weights to variables, thereby reflect the influence of input variables and the assigned weight on the forecasted load. The model might assign a higher weight to a historical variable if it is found to have a strong correlation with load demand. This approach ensures that the model produces accurate and reliable predictions that can help energy companies make informed decisions regarding management and planning. As depicted in Fig. 2, there is a strong correlation between the previous day's load demand and the current day's load demand, as the Pearson coefficient value is 0.99. Similarly, additional feature correlations can be recognized through the visual representation in Fig. 2.

Further, the total dataset is split into training and testing sets with different ratios, say 70–30%, 80–20%, and 90–10%. In order to get the most accurate results, the machine learning algorithm to forecast load must be chosen carefully. This paper uses GPR, ANN, and LSTM to provide load forecasting models, where the training data is utilized to teach machine learning techniques. To evaluate the accuracy of the predictive model, the test set is employed. Evaluation metrics are an essential part of measuring the performance of any model. In this particular case, the evaluation is done based on MAPE. The percentage difference between the actual and predicted values is measured by MAPE. This metric is particularly useful when evaluating models that predict values with different scales. The important parameters for simulation work are basically related to system configuration and model parameters. The proposed approach is carried out on a workstation with a 64-bit operating system, ×64-based processor, and 16.0 GB RAM. All three models are simulated in MATLAB/Simulink software for different basis functions with validation. Gaussian Process Regression is simulated with different kernel functions, and the ANN and LSTM models are trained by selecting an appropriate number of layers and neurons for each model. For ANN, two hidden layers are considered with 30 neurons in each layer and one neuron in the output layer, whereas the LSTM model simulated with 400 hidden neurons and one neuron in the output layer with a hyperbolic tangent activation function and Adam optimizer.

III. DECISION-MAKING TOOLS

Three decision-making tools are selected to develop load forecasting models. These techniques are: GPR, ANN, and LSTM. These techniques are discussed in the subsections hereunder.

TABLE 1. PEARSON CORRELATION COEFFICIENT VALUES

Input Variables	Pearson Correlation Coefficient Values	
Load demand (day k–1)	0.99	With respect to load demand of the current day (day k)
Block (day k)	0.188	
Temperature (day k)	0.447	
Relative humidity (day k)	0.011	
Dew point temperature (day k)	0.423	
Wet blub temperature (day k)	0.493	
Wind speed (day k)	0.332	

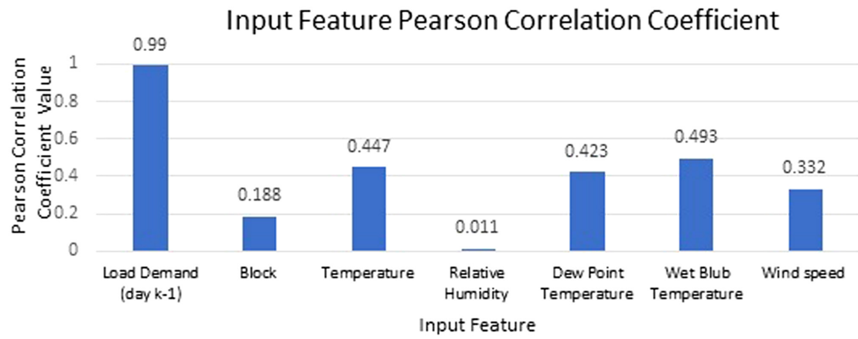

Fig. 2. Input features correlation with load.

A. Gaussian Process Regression

A non-parametric Bayesian estimation method called GPR applies a Gaussian Process prior to a collection of hidden functions. This prior distribution can be updated as new data becomes available, allowing the model to adapt and improve its prediction over time. When dealing with complex and noisy datasets, this approach can be particularly beneficial. By capturing the uncertainty in the data, it can provide a measure of confidence in the predictions. Additionally, the non-parametric nature of this method allows for flexibility in the model, which can lead to more accurate and robust predictions.

At a specific time, *t*, a set of denoted by $x_t = \left[x_t^1, x_t^2, \ldots, x_t^D\right] \in R^D$ which includes *D* as exogenous variables that provide information on weather and calendar as the input.

In addition, let $y_t \in R$ represents the total power consumption that is being measured, and this defines the output variable. $X = \left\{x_1, \ldots, x_N\right\} \in R^{N \times D}$ and $Y = \left\{y_1, \ldots, y_N\right\} \in R^N$ can capture the historical data of the previous *N* measurements of both the input and output variables. This information can be used to develop a Gaussian Process (GP) model that makes predictions about future values of the output variables based on input variables. By using this model, we can capture the underlying trends and patterns in the data and make informed decisions about power consumption based on this information. The GP model can be formulated as follows:

$$\begin{aligned} & f(x) \sim GP\left(0, k(x, x')\right) \\ & y_t \mid f(x_t) \sim N\left(f(x_t), \sigma^2\right) \end{aligned} \tag{2}$$

The Gaussian Process regression uses the variance of the estimation error σ^2 and the variance of the latent function *f*(*x*) to make predictions. The covariance function, denoted as *k* (*x*,*x*′), is used to capture the similarity between different input points in the dataset. By using this model, the relationship between input and output variables can be estimated without having to make any assumptions about the underlying functional form [24].

B. Artificial Neural Network

The biological neural networks found in the human brain are mimicked by a computational model called ANN. It consists of many interconnected processing units known as neurons, which collaborate to process and analyze information. The Multi-Layer Perceptron (MLP) is a popular type of ANN used in machine learning and pattern recognition [25]. Multiple layers of neurons are used to process the output of the previous layer until a final output is obtained.

In an MLP, neurons are organized into layers, with each neuron receiving input from the neurons in the previous layer and producing an output that is sent to the neurons in the next layer. The first layer is the input layer, the last layer is the output layer, and the hidden layers are the layers in between. A weighted sum of inputs is calculated by every neuron in an MLP, and then an activation function is applied to produce its output. The weights and biases of the neurons are adjusted during training using algorithms like backpropagation to enhance the accuracy of the network's predictions.

In this research, the selection and identification of the optimal number of hidden layers for the ANN model are accomplished through a trial-and-error process that aims to maximize accuracy. The best results are achieved by setting the number of nodes equal to the number of input features to determine the most suitable number of hidden layers. The calculation of the model output is derived using (3) for a single hidden layer.

$$y_i = \alpha_0 + \sum_{j=1}^{n} \alpha_j f\left(\sum_{i=1}^{m} \beta_{ij} y_{t-i} + \beta_{0j}\right) \tag{3}$$

The equation (3) is used to calculate the model output, which involves several parameters, including "*m*" representing the number of input layer nodes, "*n*"' denoting the number of hidden layer nodes, *α*, *β* are weights, and "f" as the transfer function. In this paper, a log-sigmoid function is used.

C. Long Short-Term Memory

Hochreiter and Schmidhuber proposed LSTM in 1997, and it has been improved by several researchers to become a highly effective architecture for RNNs. The primary purpose of LSTM is to address the issue of vanishing gradients, which occurs in standard RNNs when they attempt to handle long-term dependencies. The structure of a typical RNN is made up of a series of similar modules, each of which contains a straightforward hidden network, like a single sigmoid layer. In contrast to the normal RNN, the LSTM's hidden layers have a more intricate structure. In each concealed layer of the LSTM, a gate and a memory cell are specifically introduced. LSTM's memory block is made up of four parts: self-connected memory cells C, an output gate o, an ignore gate f, and an input gate I. The output gate is responsible for filtering and sending pertinent cell activations to the following network, while the input gate is responsible for entering activations into the memory cell.

The network can reset the memory cells and ignore previous incoming data thanks to the forget gate. In order to mitigate the

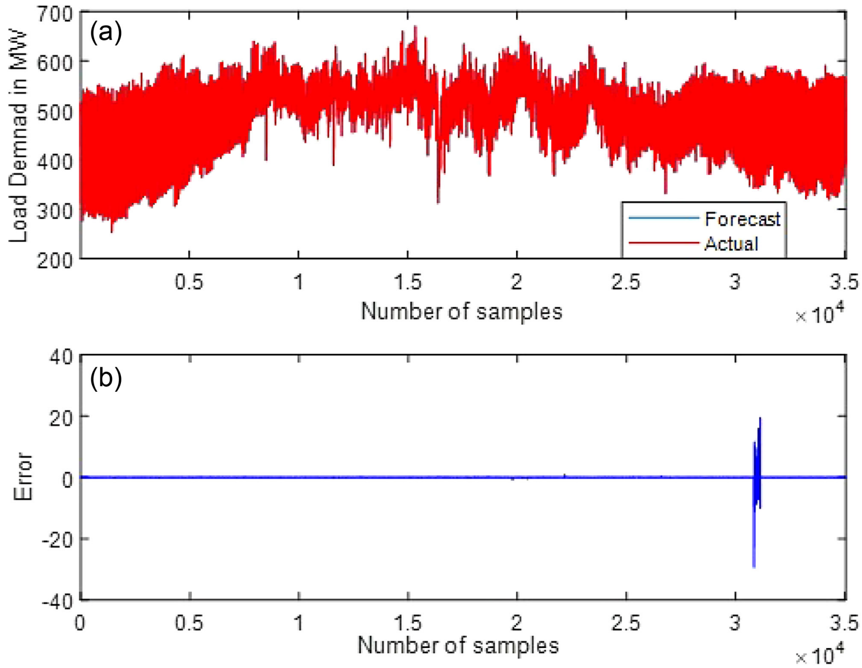

Fig. 3. Training of GPR-based LF model for the year 2022 dataset (365 × 96 = 35 040 data points). (a) Actual and predicted load. (b) Error.

vanishing gradient problem, multiplicative gates are also used to enable memory cells to access and store data for lengthy periods of time [26]. Because of this, LSTM is an appropriate architecture for tasks with long-term dependencies. The model faces several challenges, one of which is the inherent "black-box" nature of LSTMs. This characteristic makes it difficult to interpret the internal workings of the model and understand the logic behind specific predictions. Additionally, effective training of LSTMs often demands a substantial amount of data, particularly when dealing with long-term dependencies. The tuning of hyperparameters, including the number of layers, hidden units, and learning rates, is another challenge associated with LSTMs.

VI. RESULTS

Three prediction tools, GPR, ANN, and LSTM, have been selected to develop load forecasting models in this paper. The training and testing results of each tool are discussed in subsequent subsections.

A. Results Obtained by Using GPR

The load dataset from Southern DISCOM of Odisha for the year 2022 has been used to develop a GPR-based load forecasting model. A training dataset selected from the database is used to train the model using a GPR model with exponential kernel functions and a constant basic function. The training plot of estimated load and actual load along with error for the complete 2022 year dataset consisting of 35 040 data points is shown in Fig. 3. It signifies that the forecasting model is fitting the training data well. In other words, the model is able to learn the patterns and hidden relationships, and trends in the training data and produce forecasted values that are very close to the actual values for that period. The histogram plot of error during training is shown in Fig. 4, which highlights the distribution of errors made by the forecasting model during the training phase. The difference between the actual values and the forecasted values for the electrical load is typically the reason for the error. To test the model, the dataset for January 2023 is used as the testing dataset. The testing results are presented in Figs. 5 and 6, which show the estimated load and actual load along with error, and the histogram plot of error during testing, respectively.

It has been observed that the predicted load and actual load pattern variations match and overlap each other, which signifies that the model is capable of capturing the underlying patterns and trends in the data and is able to make accurate predictions based on available information. By analyzing the histogram of errors during testing, we can identify areas where the forecasting model needs to be improved and determine if the model is suitable for its intended use. Additionally,

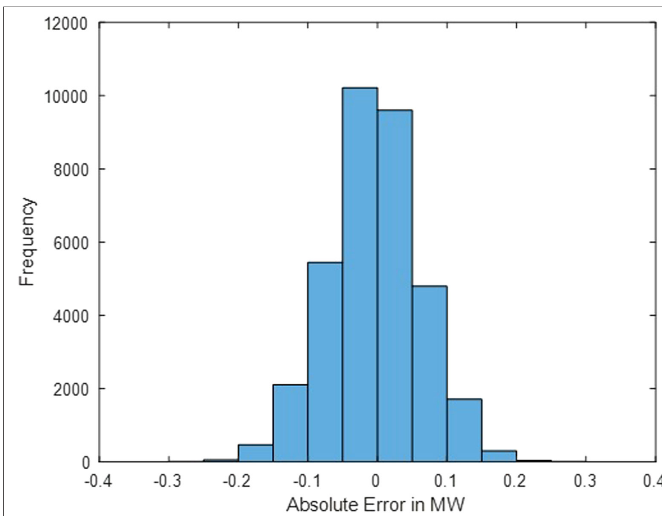

Fig. 4. Error histogram of load prediction during training of GPR-based LF model for the year 2022 dataset.

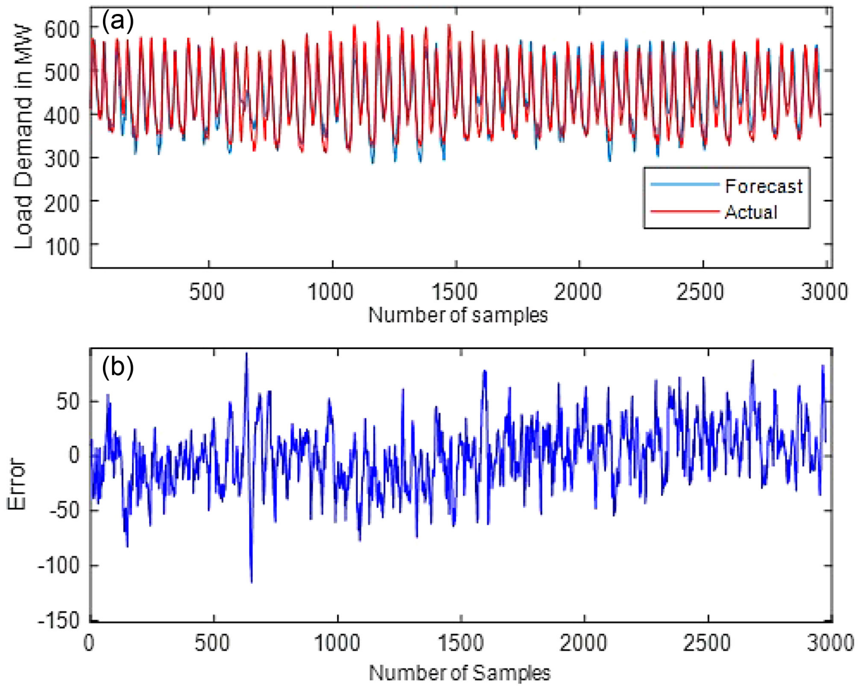

Fig. 5. Testing of GPR-based LF model with January 2023 dataset. (a) Actual and predicted load. (b) Error.

the histogram of errors can be used to set appropriate thresholds for alerts when the forecasted load deviates from the actual load beyond an acceptable margin. It is clear from Fig. 3 that the absolute error in the prediction of load demand using GPR is in the range of ±20 MW during training, whereas during testing with the January 2023 dataset, it is ±50 MW as depicted in Figs. 5 and 6. The MAPE of the corresponding model for January 2023 is calculated as 0.6201.

B. Results Obtained by Using ANN

Artificial neural network has been trained with a training dataset from the year 2022 to estimate the load demand with one hidden layer, thus forming a multilayered network with seven input features or seven neurons in the input layer, 30 neurons in the hidden layer, and one neuron in the output layer representing the day-ahead load demand every 15 minutes. Furthermore, a log-sigmoid activation function is used for all layers, and ANN is trained with the Levenberg–Marquardt training algorithm. The learning curve of the ANN model for the train, test, and validation dataset is shown in Fig. 7, wherein *x*-axis represents the number of epochs and the *y*-axis represents the Mean Square Error obtained during training. The training results are presented in Figs. 8 and 9, which depict the actual and forecasted plot of load demand in MW and the error histogram plot in MW, respectively. It is implied that actual and

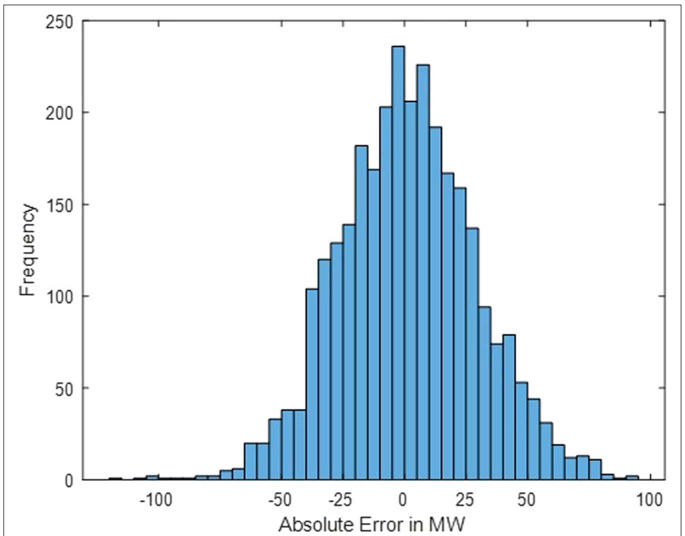

Fig. 6. Error histogram of load prediction during testing of GPR with January 2023 dataset.

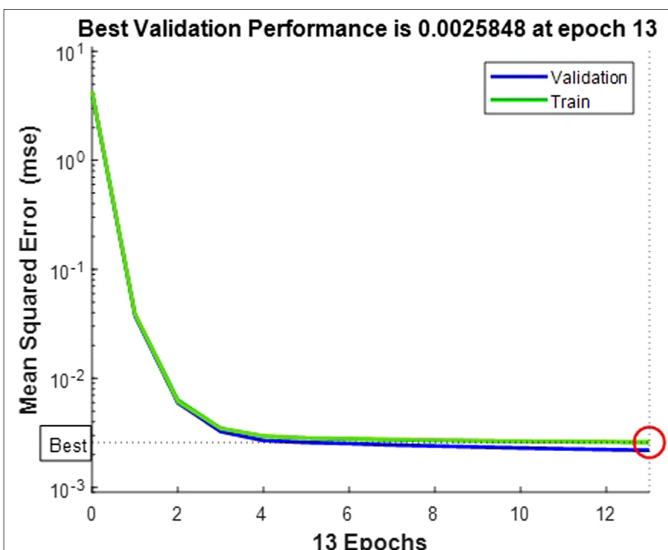

Fig. 7. Learning curve of the ANN model for train, test, and validation dataset.

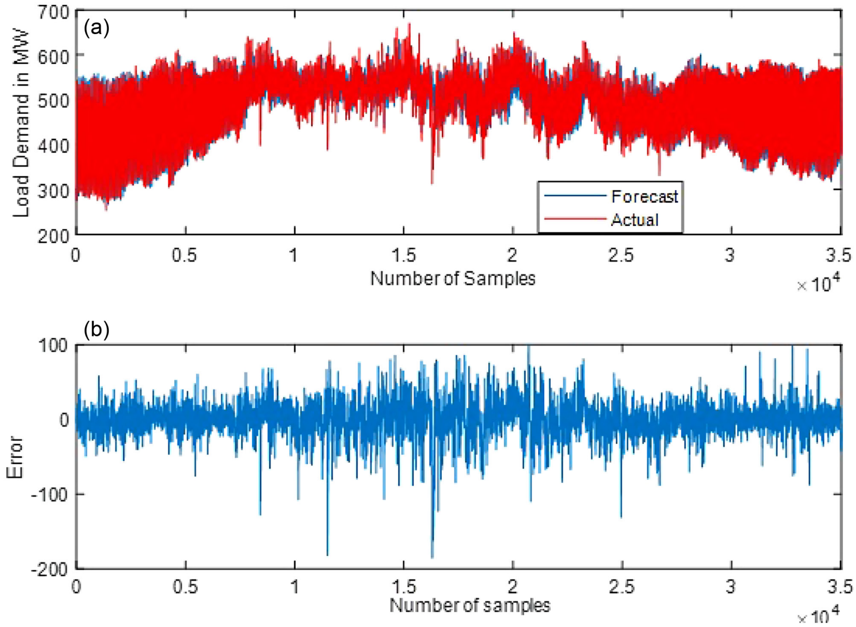

Fig. 8. Training of ANN for year 2022 dataset. (a) Actual and predicted load (b) Error.

forecasted plots should overlap as much as possible, indicating that the model is able to accurately predict the electric load based on the available data. During training, it's important to monitor both actual and predicted loads as well as histogram plot of error to ensure that the model is learning from the training data and making accurate predictions. It is clear from Figs. 8 and 9 that the absolute error in the prediction of load demand for the complete 2022 year dataset consisting of 35 040 data points using ANN is in the range of ±100 MW during training, whereas during testing it is ±50 MW as depicted in Figs. 10 and 11. By analyzing these plots, adjustments can be made to the model's architecture or training parameters to improve its performance.

The trained neural network has been tested with the year 2023 testing data to assess its performance, which is entirely different from the training dataset. The actual and forecasted loads have been compared in Fig. 10, while an error histogram plot of testing data is shown in Fig. 11. It is important to note that the testing data has not been used in the training of the neural network. This ensures that the performance of the model on new and unseen data can be accurately assessed. Fig. 10 demonstrates that the neural network has performed reasonably well in forecasting the load for the testing period. However, it is evident that the actual load values deviate from forecasted values, indicating that the model may not be fully accurate.

Fig. 11 provides a histogram plot of the error, which shows the distribution of the actual load values. This plot can be used to assess the accuracy of the neural network's forecasted value, which shows that the absolute error lies in the range of approximately ±60 MW. The MAPE of the ANN during testing is evaluated as 0.2567%.

C. Results Obtained by Using LSTM

The primary objective of an LSTM network is to learn from data with both long-term and short-term dependencies, which is crucial for accurate predictions and forecasts. However, the effectiveness of the learning process is heavily influenced by the type of input data that is used. If the input data is insufficient or leads the network in the wrong direction, the LSTM will not be able to accurately predict or forecast future data. In this specific case, one input feature (historical load) is used as input data which consists of 35 040 datapoints, thus forming a 1 × 35 040 input dataset for the LSTM network. The model is trained using 12 months of historical data, and one month is used for validation purposes to assess the accuracy of the forecast by Adam optimizer with LSTM layers of 400 hidden units followed by one fully connected layer having one neuron. The optimizer by default selects Root Mean Squared Error (RMSE) as the loss function in the regression process. Fig. 12(a) and (b) illustrates the learning curve of the LSTM model obtained during training, where Fig. 12(a)

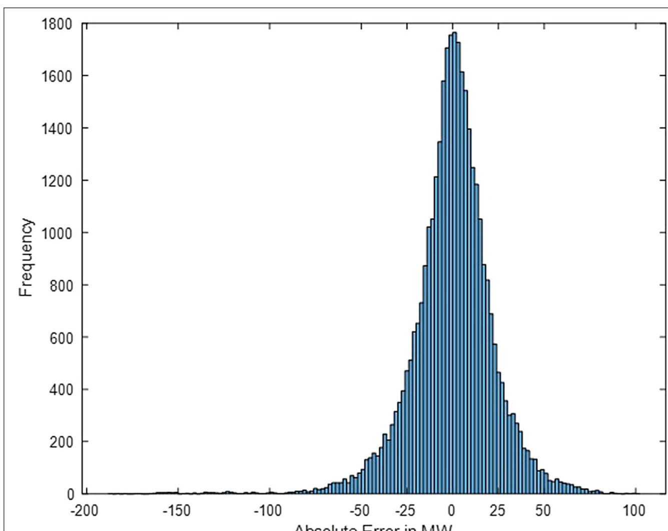

Fig. 9. Error histogram of load prediction during training of ANN for year 2022 dataset.

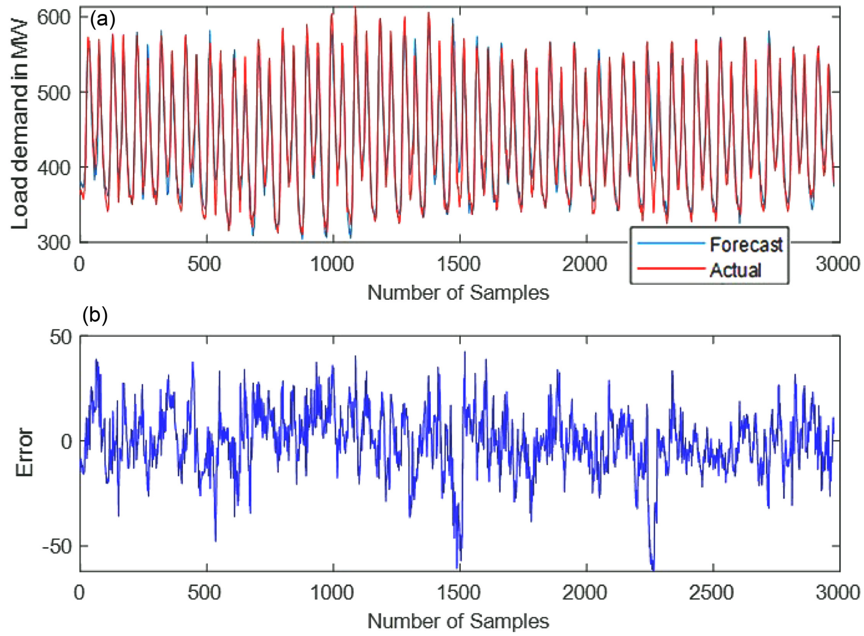

Fig. 10. Testing of ANN with the January 2023 dataset. (a) Actual and predicted load. (b) Error.

represents the RMSE and Fig. 12(b) represents the loss function in the case of training and validation dataset. It shows a decreasing trend, approaching zero; here, the dotted lines indicate validation performance, whereas smooth lines illustrate training performance at each iteration. The proximity of the loss to zero throughout training suggests accuracy in the model's performance on the training and validation dataset.

Fig. 13 displays the training progress of both actual and predicted load for the complete 2022 year dataset consisting of 35040 data points, as well as the associated error. To ensure that the LSTM can effectively learn the relevant features and patterns in the data, it is important to select and process the input data carefully. Fig. 14 depicts a histogram of RMSE during the training phase. It is clear from Figs. 13 and 14 that the absolute error in the prediction of load demand using the LSTM model is in the range of ±50 MW during training; however, for most cases, it is between ±25 MW.

In the testing phase, Fig. 15 displays both the actual and predicted load along with error, and Fig. 16 shows a histogram plot of the absolute error during testing, which confirms the error values between ±10 MW approximatly. During training, Fig. 13 shows how well the LSTM model is able to fit the training data. A high degree of overlap signifies how well the model fits the data. The histogram in Fig. 14 is used to monitor the model's performance during training and to identify any areas where the model needs to be improved.

During testing, Fig. 15 shows how well the LSTM model is able to generalize to new, unseen data. It can be observed that the predicted load and actual load pattern variation are matched and overlap each other. This signifies that the model is able to capture the underlying patterns and trends in the data and make accurate predictions based on available information. Fig. 16 shows the distribution of error ranges between actual and forecasted load during the testing phase, which lies within ±10 MW. The MAPE during testing is calculated as 0.2134%.

As accurate results are obtained by using the LSTM, further 1-day and 1-week predictions can be observed for more clarification of the load forecasting using LSTM. Figs. 17 and 18 show the actual and forecasted load pattern along with error for 96 data points of 1 January 2023 and 31 January 2023, respectively. Similarly, Fig. 19 shows the comparison of actual and forecasted plots along with error for the first week of January, which is 672 data points. It can be observed that the predicted load and actual load pattern variations are matched and overlapped each other.

A separate dataset is prepared to test the proposed model for 1-day load forecasting of 22 March 2023. Fig. 20 illustrates the prediction of load demand for 22 March 2023 using the LSTM. In testing, 1-week load data from 15th to 21st March 2023 has been taken for predicting the load demand of 22nd March 2023.

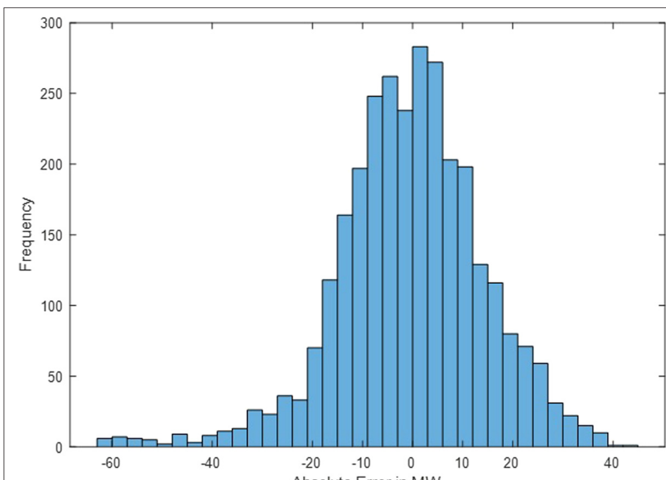

Fig. 11. Error histogram of Load Prediction during testing of ANN with the January 2023 dataset.

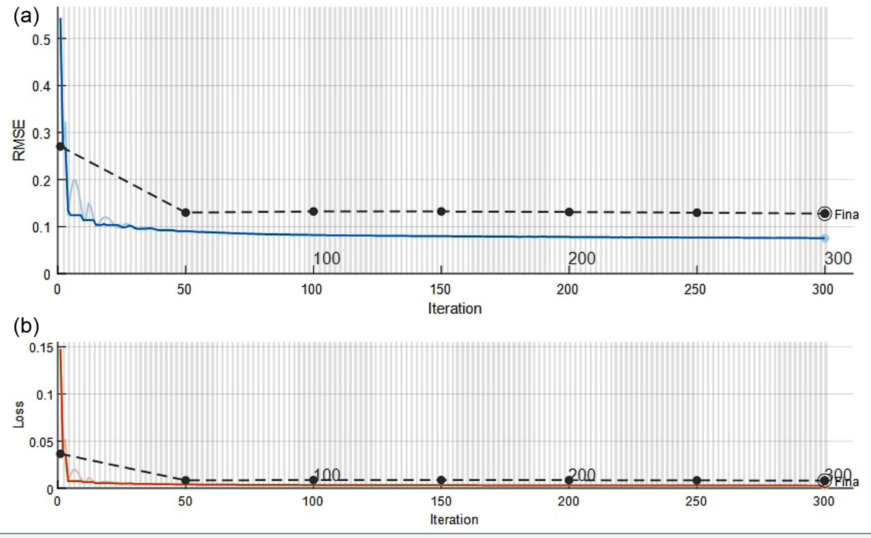

Fig. 12. (a) RMSE value curve of LSTM model during training and (b) loss function curve of LSTM model during training (dotted line = validation, smooth line = train).

V. COMPARISON

The three models can be compared based on their computational complexity. The GPR generally requires more time to train the data compared to ANN and LSTM models, which typically have shorter training times. Additionally, LSTM models may require higher system memory compared to the other two techniques due to their architecture and memory cell structures. These factors are important considerations when evaluating the performance and practicality of each model for a given application. Table 2 indicates that the LSTM model is superior to the GPR and ANN models in terms of load forecasting accuracy, as demonstrated by its lower Mean Absolute Error (MAE) and MAPE. Specifically, the LSTM model achieves 5.9443 MW of MAE, which is significantly lower than the ANN model's 11.1976 MW and the GPR model's 22.0412 MW with "exponential" kernel function, 19.9441 MW with "squared exponential" kernel function, 21.3106 MW with "rational quadratic" kernel function, and 20.9792 MW with "Matern 5/2" kernel function. Furthermore, the MAPE obtained using the LSTM is the least of 0.2134% as compared to 0.2567% with ANN and 0.3877% with GPR. Similarly, RMSE is also the least using the LSTM. It is important to note that the comparison of different models is dependent upon various factors such as datasets, input parameters, training and testing data sizes, and evaluation metrics.

In this paper, the success ratio is calculated based on various performance plots and metrics, which are shown in Figs. 15–20; these metrics provide a comprehensive evaluation of system performance in achieving its objectives, which include:

- Error plots: An error plot is the difference between actual and forecasted values of loads that indicate model performance.
- MAE: Measures the average absolute difference in regression tasks presented in Table 2 for all models.

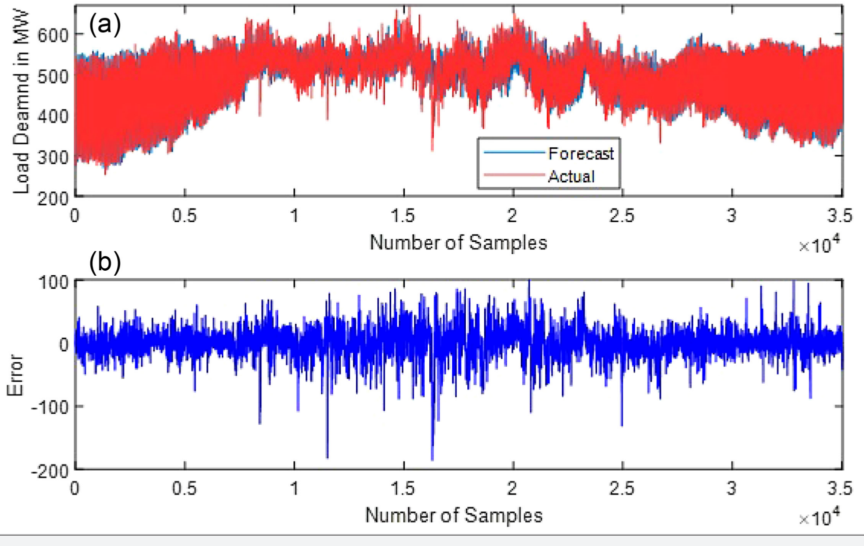

Fig. 13. During training of LSTM for the 2022 year dataset. (a) Actual and predicted load. (b) Error.

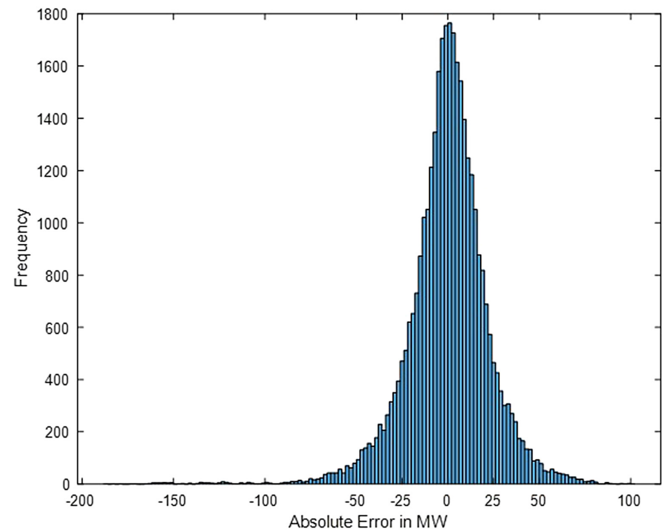

Fig. 14. Absolute error histogram of load prediction during training of LSTM for the year 2022 dataset.

- MAPE: Measures average absolute percentage in regression tasks presented in Table 2 for all models.
- The *R*-squared (R^2) value is determined by comparing actual and predicted load demand, which provides an indication of the forecasting model's performance. A higher R^2 value, closer to 1, suggests a better fit of the forecasting model to the actual data. The R^2 value obtained for the different models is depicted in Table 3, wherein the LSTM offers the highest R^2 value of 0.959 as compared with other models of ANN and GPR. Thus, it is clear that LSTM outperforms the other two models.

In particular, Fig. 15 depicts that the actual and the forecasted load demand plots during the testing phase overlap with each other, and the absolute error is within ±10 MW.

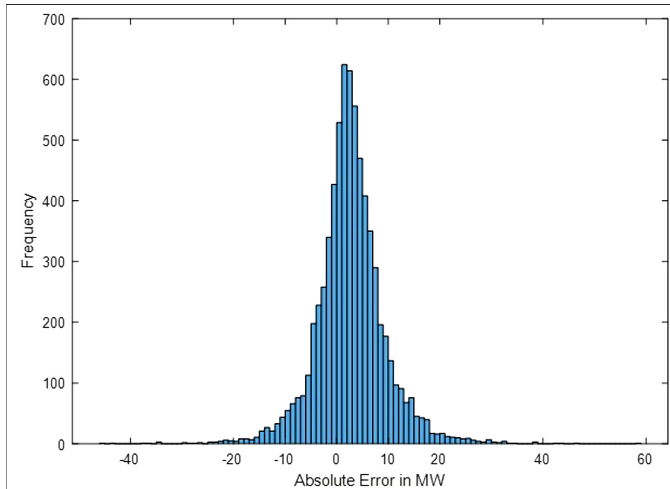

Fig. 16. Histogram plot of error during testing of LSTM.

Thus, a comparative study with existing schemes is done and reported in Table 4. Furthermore, when compared to other load forecasting models from the literature [4, 14, 15, 17–20], the LSTM model appears to have the lowest error metrics, as illustrated in Table 4. From Table 4, the proposed LSTM-based model achieves the highest prediction accuracy by using the minimum number of input features. It is imperative to mention here that the proposed scheme simply uses the raw signals of meteorological data and previous day load data collected at 15-minute intervals and then applies the input features to the LSTM model to predict the next day's load demand at every 15-minute interval. Therefore, there is lower computational complexity involved only in running the LSTM model compared with hybrid methods. Moreover, the proposed model does not need auxiliary methods to optimize the tuning parameters. Results shown in Tables 2, 3, and 4 confirm the efficacy of the proposed model.

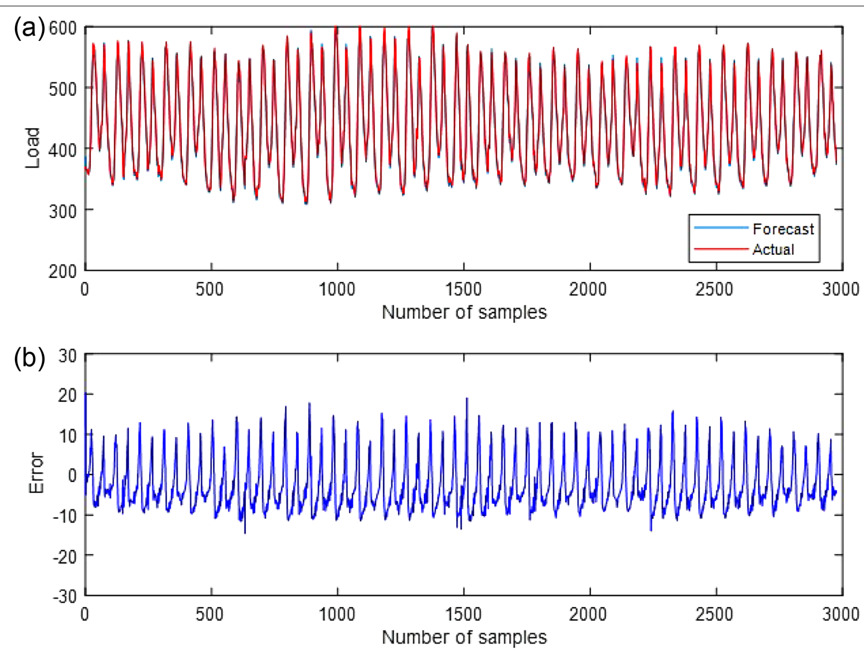

Fig. 15. During testing of LSTM with January 2023 dataset. (a) Actual and predicted load. (b) Error.

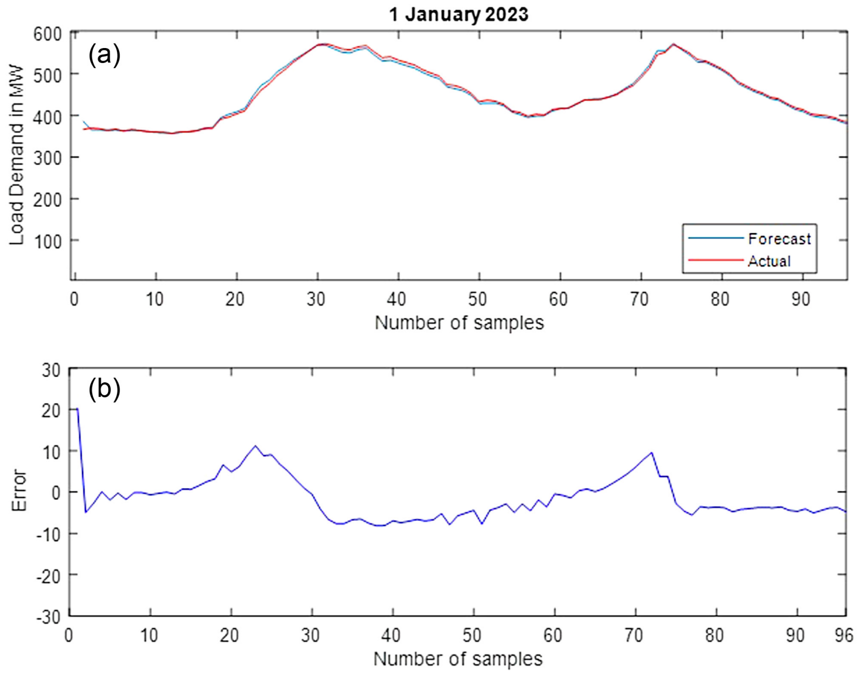

Fig. 17. On 1stJanuary 2023. (a) Actual and predicted load plot and (b) error.

VI. CONCLUSION

This paper develops load forecasting models utilizing GPR, ANN, and LSTM methods, and these are applied to real-time datasets collected from the Load Dispatch Centre of Odisha, an Indian State. The model considered historical load and meteorological data from 2022-2023, and the performance of all three models is assessed to determine which indicates the most accurate load predictions. The absolute error obtained using LSTM is in the range of ±10 MW during the testing phase, as compared with ±50 MW obtained using GPR and ANN. The LSTM model achieves the least MAE of 5.9443 MW. Furthermore, the MAPE in the prediction of load demand

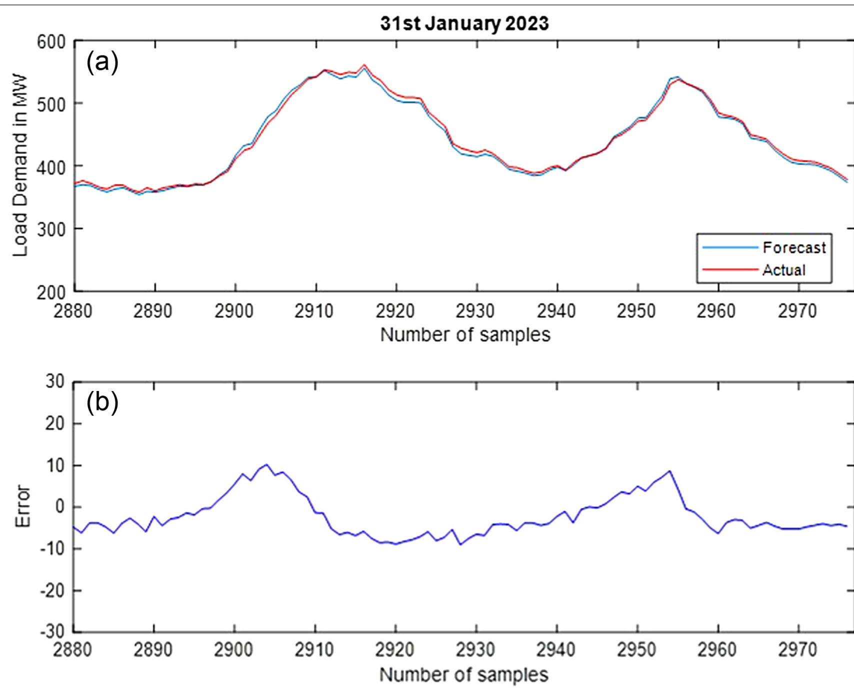

Fig. 18. On 31st January 2023. (a) Actual and predicted load. (b) Error.

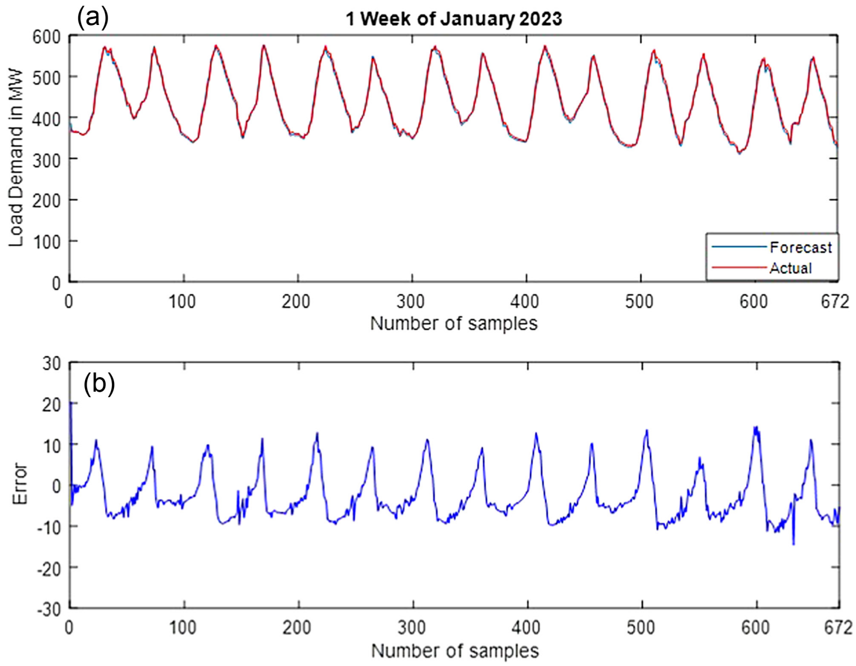

Fig. 19. During first week of January 2023. (a) Actual and predicted load. (b) Error.

using LSTM is 0.2134%, which is least in comparison with earlier reported schemes. Furthermore, numerical results confirm that the LSTM has better performance in comparison to the GPR and the ANN in terms of load forecasting accuracy. These findings show the efficacy of the proposed LSTM model for predicting future load patterns. The future scope of this paper involves long-term load forecasting, extending up to a year ahead. Additionally, it aims to explore forecasting methods based on historical load data, considering the impact of holidays on load patterns, conducting seasonal and trend analyses of load data, and identifying other meteorological factors closely associated with load demand. Furthermore, the study intends to develop alternative artificial intelligence-based algorithms to enhance forecasting accuracy. The dependency on meteorological data can occasionally restrict the forecasting horizon due to data availability constraints. Moreover, increasing the number of features increases the complexity of the model, thereby prolonging simulation time. Therefore, future works could focus on reducing this complexity while adding the number of input features. Additionally, efforts can be made to mitigate the dependency on meteorological datasets.

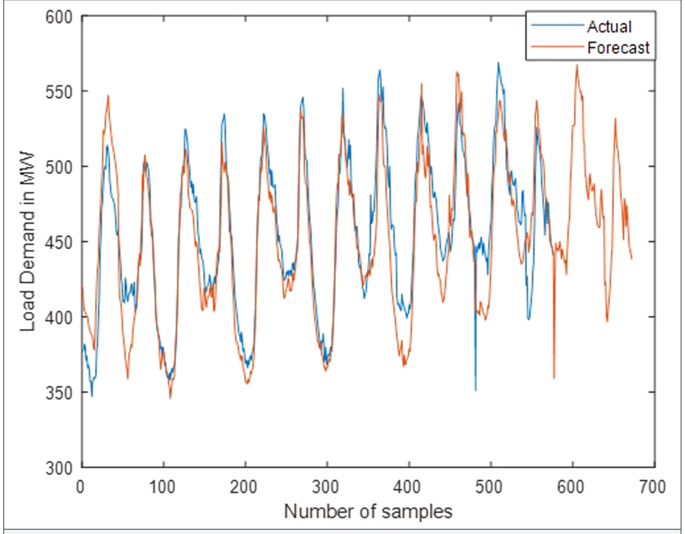

Fig. 20. Actual and forecasted plot of 22nd March 2023.

TABLE 2. EVALUATION METRICS

Model Name	MAE MW	MAPE %	RMSE MW
Exponential GPR	22.0412	0.6201	1.1880
Squared exponential GPR	19.9441	0.4987	1.0846
Rational quadratic GPR	21.3106	0.5803	1.3139
Matern 5/2 GPR	20.9792	0.6008	1.5033
ANN	11.1976	0.2567	0.3877
LSTM	5.9443	0.2134	2.8743

TABLE 3. R^2 VALUE OF DIFFERENT MODELS

Model Name	R^2
GPR	0.853
ANN	0.949
LSTM	0.959

TABLE 4. COMPARISON AMONG DIFFERENT MODELS

Comparison Parameters	Scheme	Dataset Location	Training Dataset and Validation / Testing Dataset	Input Parameters	Evaluation Matric
[4]	Effective RNN (GRU)-based Short Term Load Forecasting (Germany)	European Network of Transmission System Operators	Training: 01-01-2015 to 31-12-2019, Validation: 01-01-2020 to 31-12-2020, Testing: 01-01-2021 to 15-07-2022	Hour, Day, Month, Year, Day of year, Week of year, Quarter, Rolling moving average, Rolling standard deviation, Exponential weighted moving average, Exponentially weighted moving variance, Exponentially weighted moving standard deviation, Seasonal component, Trend and Residual component	MAE: 5.9615 RMSE: 8.1331
[14]	Short-Term Load Forecasting using an ensemble model of extreme learning machine	Australian National Electricity Market (NEM)	Training: 2009 Testing: 2010	24 hourly loads of day k-1, Daily temperature vector of the day k-1, Daily forecasted temperature inputs of the day k, Day type index of the day k-1, and day k-2.	MAE: 171.7 MAPE: 1.82
[15]	A Hybrid Model for Daily Electricity Peak Load Forecasting	Electricity Generating Authority of Thailand	Training: 2016-2018 Validation: 7 days before forecasting date (22 to 28-Feb-2018) Testing: forecasting date (1-March-2018)	Date, Historical daily peak load, day of the week, lagged daily peak to moving average weekly and monthly index, and moving average	MAE: 14 MAPE:4.894 RMSE: 159.3
[17]	Short term load forecasting using Hybrid prophet-LSTM model optimized by BPNN	Belgium based Elia Grid data	Training: January 2014– December 2019 Validation/ Testing Dataset January 2020–September 2021	Historical electrical load	MAE: 46.05 MAPE: 0.49 RMSE: 35.79
[18]	STLF based on LSTM and RNN Deep Neural Network	-	24 and 168 hours forward records for day and week ahead prediction	Historical electrical load, dry bulb temperature, wet bulb temperature, dew point, and humidity	MAPE: 1.01%
[19]	STLF CNN-LSTM model	-	Training May 29, 2021, to May 29, 2022 Testing: for 12 days starting from May 30, 2021	Historical electrical load	MAPE: 3.5%
[20]	Ultra STLF based on CEEMDAN-SE-LSTM model	Changsha, China	Training dataset: May 13, 2014, to May 13, 2017 and Testing for several hours	Historical electrical load, meteorological and holiday factors	MAE:47.490 MAPE:1.64 % RMSE:62.102
Proposed Model	Load Forecasting model using LSTM for Indian State	Odisha State Load Dispatch Center India	Training: 01-01-2022 to 31-12-2022 Validation/Testing Dataset 01-01-2023 to 31-01-2023 and 22nd March 2023.	Temperature, Relative Humidity, Dew Point, Wet Bulb, and Wind speed, load	MAE: 5.9443 MAPE: 0.2134 RMSE: 2.8743

Availability of Data and Materials: The data that support the findings of this study are available on request from the corresponding author.

Peer-review: Externally peer-reviewed.

Author Contributions: Concept – A.Y.; Design – R.B., M.K.; Supervision – A.Y., M.P.; Resources – R.B., M.K.; Materials – R.B., M.K.; Data Collection and/or Processing – A.Y., M.P.; Analysis and/or Interpretation – A.Y., R.B.; Literature Search – M. K.; Writing – R.B., M.K.; Critical Review – A.Y., M.P.

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Rashmi Bareth received her BE degree in electrical and electronics engineering from O.P. Jindal University, CG, India, in 2016, and her MTech degree in electrical power and energy systems from Bhilai Institute of Technology, Chhattisgarh, India, in 2021. She is currently a PhD research scholar in the Electrical Engineering Department at NIT Raipur, CG. Her research focuses on load forecasting.

Matushree Kochar received her BE degree in electrical and electronics engineering from Chouksey Engineering College, CG, India, in 2020. She completed her MTech degree in power systems and control at NIT Raipur, India, in 2023. Her master's thesis focused on load forecasting.

Dr. Anamika Yadav completed her BE degree in electrical engineering in 2002 from RGPV Bhopal and MTech degree in integrated power systems in 2006 from VNIT Nagpur. She obtained a PhD degree in –Electrical Engineering with NIT Raipur as a research center from CSVTU Bhilai CG in 2010. She worked as a –graduate engineer trainee at BALCO Korba, CG, from Dec 2002 to Aug 2003 and as an assistant engineer at Chhattisgarh State Power Generation Company Ltd., Raipur, from 2004 to 2009. She joined the National Institute of Technology Raipur as an assistant professor in the Department of Electrical Engineering in March 2009, and presently, she has been working as Head and Professor since November 2023. She served as Associate Dean (R&C) from July 2018 to Jan 2023. She has supervised 8 PhD theses and 26 master's dissertations. She has successfully executed five sponsored research projects, and two projects are ongoing. She has published two Indian patents. She is a senior member of IEEE and serves as Vice Chair of the IEEE Power Electronics Society Chapter MP Section. She has also been working as Editor of IEEE Transactions on Power Delivery since Oct 2021. She has been enlisted in the Top 2% Scientist list released by Stanford University for three consecutive years from 2021 to 2023. She received the Institution of Engineers India "Young Engineers Award" 2015–2016 and the Chhattisgarh "Young Engineers Award" 2016. Her research interests include power system protection, load forecasting, artificial intelligence applications to power systems, power electronics, HVDC, microgrids, and FACTS compensated transmission lines.

Dr. Mohammad Pazoki received the BSc, MSc, and PhD degrees in electrical engineering from Semnan University, Semnan, Iran, in 2008, 2010, and 2014, respectively. During 2013–2014, he was a Visiting Scholar with The University of Auckland, Auckland, New Zealand. He joined Damghan University as an assistant professor in the School of Engineering in February 2015, and presently, he has been working as an associate professor since February 2021. His research interests include power system protection, FACTS devices, pattern recognition application to power systems, and power quality monitoring.