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ORIGINAL RESEARCH

Daily average load demand forecasting using LSTM model based on historical load trends

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Abstract

Load demand forecasting is very important for the management, designing and analysis of an electrical grid system. Load forecasting has progressively become a crucial component of the energy management system with the growth of the smart micro grid. This study presents a new framework to long term load forecasting in the world of electricity power with the help of historical load trends. The main objective of this research work is estimating monthly electricity demand of an Indian state Chhattisgarh, in terms of per day average load demand using a machine learning model—Long Short-Term Memory (LSTM). This framework considers average of each day load demand for every month of years 2018–2022 and forecasted per day average load demand for each month of the year 2023. Furthermore, the predicting accuracy is evaluated for training and testing phase, in terms of error metrics like Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The MAPE values under the training and testing phase are in the range of 0.010%–0.652% and 0.378%–10.54%, respectively. A comparative study of LSTM model with Artificial Neural Network (ANN) model indicates the proposed LSTM model is more accurate and can be applied for real time load demand forecasting.

1 | INTRODUCTION

1.1 | Motivation and incitement

Power system resilience requires a delicate equilibrium between supply and demand. Maintaining this balance becomes difficult because of population growth and economic expansion, which affects the demand for electrical energy. Additionally, the push for a sustainable grid that integrates renewable energy sources and electric vehicle technology to reduce pollution emissions adds to the existing imbalance. Therefore, accurate demand estimation becomes crucial in improving system reliability, security and mitigating the differences. Load forecasting, an important component of the smart grid, has gained significant attention from researchers. It is categorized into various types based on the forecasting timeframe, including very-short-term load forecasting (VSTLF), short-term load forecasting (STLF), medium-term load forecasting (MTLF), and long-term load forecasting (LTLF). Different forecasting purposes attracted increasing research interest and exploration in load forecasting field. Comprehensive exploration of scientific and technical motivations behind various methodologies for STLF in the energy field suggested a hybrid strategy that associated the strengths of different forecasting approaches [1]. It also provided a promising avenue for further research and development in the field, offering potential improvements to the existing forecasting techniques.

1.2 | Literature review

Research in load forecasting covers a wide range of time horizons, including VSTLF, STLF, MTLF, and LTLF. Electrical load demand forecasting reviews for low and middle income countries across various time horizons indicates the widespread use of time series modelling for long and medium-term forecasts [2]. A review on different LF techniques for MTLF and LTLF, concluded with for future research direction. It also presented various parametric, AI, other mathematical methods of LF for MTLF and LTLF in one place [3]. LSTM-based LF method is proposed for energy integrated system, it involves multi features and meteorological data of dynamic similar day. Construction process of similar day is applied feature engineering techniques GMM (Gaussian Mixture Model) and gray correlation analysis is also applied to select highest correlated days features to calculate weighted for similar day construction, basically adjacent days and similar day features were used to forecast multi loads [4]. VSTLF using hybrid Kalman filter to predict loads in moving window manner, 1 h into 5 min time steps of future is proposed [5]. NN model is trained to predict load and tested on IOS New England data. For data analysis, Kalman filter is applied for low-low frequency, low–high and high frequency component to capture their non-linear relationships between input load component and the output measurement [5]. A short term prediction of heating, cooling and electric load using various methods such as Kalman filters, multivariable phase space restoration and BP neural networks and Elman neural networks are presented [6]. However, these traditional forecasting techniques face challenges to achieve improved performance when dealing with large amounts of data and complex environments. As a result, data-driven approaches have been proposed as alternatives. LSTM and CNN have gained significant popularity, CNN algorithm is applied for feature extraction and abstraction purposes, while LSTM is employed for temporal characteristics within the load data [6, 7]. For STLF, LSTM and CNN based model is combined to design a hybrid neural network, correlation coefficient between load and temporal data is also evaluated [8]. CNN-LSTM-BILSTM attention mechanism based model for short term load prediction is contributed to energy management companies, past 5 day's load data, temperature, cooling load and gas consumptions are taking as input features for proposed model to predict next 1-h load data prediction. Various models—CNN-LSTM, Bi-LSTM, SVR, and LSTM are compared to validate the proposed model with the help of error metrics MAE, RMSE and R^2 values as 4.781, 6.396 and 0.991, respectively [9]. A mid-term load forecasting is performed by using a linear regression parametric load model, the correlation between load data pattern is observed for 24-h (daily) and 52-week (yearly), average power is forecasted on weekly basis for 24-h period with lead-time ranging few weeks to years [10]. Year ahead load forecasting is demonstrated with MAE 3.8% by training and testing the model [10]. An annual peak load forecasting model with particle swarm optimization technique is utilized to reduce any potential errors in the estimated model parameters. The evaluation and comparison of results are carried out using real time data obtained from Kuwaiti and Egyptian networks. A comparative assessment of the proposed method is also presented, in addition the estimated model parameters are employed to forecast the annual peak demands in Kuwait [11].

Two LTLF models (Regression based and ANN-based) on New England market data set is applied and compared on the basis of MAPE%, ANN performed better then regression model, MAPE% is 5.89 for ANN model which is less than 16.45 for regression model [12]. An LF method is introduced Fuzzy-ANN model for residential loads indicates best performance with MAPE of 5.73% [12]. Three methods—Multivariate adaptive regression spline (MARS), Artificial Neural Network (ANN) and Linear Regression (LR) applied on Turkish electricity distribution network for LTLF, these methods presented a relationship between various environmental factors and load demand during training [13]. Two-year data from year 2011 to 2013 for tanning and dataset from year 2013 to 2015 is utilized for testing; by comparison, it is observed that MARS model is most stable and accurate than the other two model, with multiple coefficients of determination (R^2_{adj}) value of 0.907. An overview of existing methods used for long-term hourly electricity demand prediction on a national scale, spanning 10 to 50 years is the presented [13].

The work considered the challenges posed by future energy system characterized by increased integration of renewable energy sources and closer interconnections among the building sector, transportation sector and power sector [14]. It concludes by offering recommendations on key factors to consider when conducting LTLF in a dynamic power system. The concepts behind GRU and LSTM networks is well explained, followed by a detailed discussion on feature engineering, feature selection and model implementation steps. Additionally, a real-life application example involving a large urban grid in West Canada is presented, showcasing the practicality and relevance of the proposed hybrid modelling approach [15]. A method is proposed, based on Recurrent Neural Network (RNN) architecture, specifically with LSTM cells, to forecast electricity load demand with a focus on long-term relationships in time series data [16]. By incorporating LSTM-RNN, the model improved accuracy in load demand forecasting. The model's performance was evaluated using real-time data from the ISO New England electricity market of year 2004 to 2015, for training and validation purposes. The model was then used to make electricity demand predictions for a five-year period (2011 to 2015) on a rolling basis with high accuracy MAPE of 6.54. Machine learning methods have gained attention for their effectiveness in accurate load forecasting and handling stochastic load patterns [16]. A study focuses on LTLF in the New England Network presents numerous commonly used machine ML methods, such as support vector machines, ANN, recurrent neural networks, and others, are evaluated [17]. The results of these methods is compared using the mean MAPE as the evaluation metric. The aim of the study is to identify the most suitable method for long-term LF in the New England Network.

A novel deep neural network framework is proposed, combined the hidden features of CNN and LSTM models, to enhance the accuracy of load forecasting [18]. The performance results demonstrated that the proposed model outperforms the LSTM and CNN models, offering improved and consistent performance in STLF. LF in Renewable energy system, is introduced with improvement in accuracy from 97.7% to 99.5% accuracy by combination simulation of wavelet and fuzzy system [19]. An STLF based on historical data only, first analysed the seasonality and trends of load data then by SAM important input load data information is used in forecasting. The results indicate proposed deep LSTM-CNN model outperforms CNN-GRU-based SAM by 10% in 8 buildings and shows its capability to decrease data contributions along improvement in LF accuracy [20]. The ML model Gaussian Process Regression (GPR) is introduced, to forecast the monthly load demand for Australian and India. Total 12 models with kernel functions are trained and tested with different validation percentages and the best combination of kernel and basic function of GPR model is identified by calculating MAPE values. The forecasting accuracy is validated by comparing it with other two ML methods—NN and Decision tree. By GPR model MAPE value for Australia is 0.15% and for Indian cities—Nasik is 0.002%, for Bhusawal is 0.209%, for Kolhapur is 0.077% and for Aurangabad 0.140% indicates the best model performance [21].

The proposed model for ultra-STLF, improved complete ensemble empirical mode decomposition with adaptive noise ICEEMDAN, CNN, and Bi-LSTM neural networks [22]. ICEEMDAN decomposed the non-stationary load sequence into IMF components, which reduces complexity. The load series are divided into trend, periodic, and random parts, GRG analysis identified the correlated influencing factors for constructing feature sets, then CNN extracted features from historical load data and impact factors, followed by Bi-LSTM for dynamic prediction [22]. The model was validated using user-side load data from a micro-grid community system in China's Sichuan Province. Results indicates, its effectiveness in capturing short-term data dependencies, outperforming SVM and ARIMA models in prediction accuracy and stability. The CNN-Bi-LSTM model reduced MAPE by 3.547% from 4.222%, and RMSE by 0.421 kW from 0.554 kW, which demonstrates high accuracy and stability in load forecasting [22]. The research strengthened power system's flexibility and adaptability by integrating network constraints and uncertainties of renewable energy and load [23]. Results demonstrated the achievement of a more flexible and resilient topology in the DN system. The bi-level expansion planning model, improving the economic efficiency and reliability of distribution networks concentrated on uncertainties related to renewable energy, load demands, and contingency outages affecting critical infrastructure. The Stochastic models were used to represent renewable energy and load fluctuations, employing techniques like LHS for scenario generation and piecewise linearization to handle non-linearity. Uncertainties in pivotal components were considered to enhance distribution network reliability. Multiple cases validated the model's effectiveness in economic analysis and reliability assessment, showing improved performance in both aspects while complying with ESS functionalities [24].

1.3 | Contribution and paper organization

This paper contributes to Load Forecasting (LF) for the Load Dispatch Centre (LDC) for Indian state of Chhattisgarh. The different load forecasting models are selected for different regions due to their demographic, geographic location, population, industrialization, urbanization and many such factors, therefore an analysis of such parameters are essential, before working on any model. This paper distinguishes itself through load pattern analysis to choose a correct model for further load forecasting process and then training-testing of the model by different input features and historical load demand is performed.

The highlights of research work in this paper are as follows:

- Chhattisgarh state historical load demand pattern is analysed for all seasons separately.
- The average daily load demand is calculated for each month (from January to December) for the years 2018 to 2022, by using datasets, recorded at 15-min intervals throughout for each day.
- Datasets are normalized during training and testing, then again convert to actual data range after forecasting, on the basis of maximum and minimum load demand values, by using scale in the range approach.
- The proposed model LSTM is trained and tested on different input features to forecast load demands.
- Error metrics are calculated and analysed for both training and testing phases to indicate the accuracy of model.

Here, a real time filed recorded Load demand from Chhattisgarh State Load dispatch centre has been studied. The latest deep learning technique known as LSTM based load forecasting scheme has been designed considering latest load patterns from year 2018–2023. In the proposed study, the main objective has been made to forecast the load demand for future coming months of a year. Thus, this is the main contribution of the proposed method. Also, the accuracy of the proposed methos surpasses that of other works, as demonstrated in Table 4 in the revised paper. This forecasting method has been implemented for the first time for Chhattisgarh state load dispatch centre, India. Additionally, based on load pattern analysis, this study provides forecasted values for the maximum and minimum average demand for each month, which is very useful for the demand side management of the load dispatch centre. Consequently, the contributions of this research significantly aid in seasonal peak load forecasting, monthly load demand forecasting, and day-ahead load demand forecasting which are very important for operation planning the load dispatch centres.

The structure of this paper is as follows: Section 2 includes load demand pattern analysis of Chhattisgarh (CG) load data, Section 3 describes the proposed model—LSTM, Section 4 is proposed methodology, Section 5 is model result, Section 6 is discussion and comparative assessment, and Section 7 concludes the research.

2 | LOAD DEMAND PATTERN ANALYSIS

The load demand of a country is directly affected by the weather conditions. Variations in meteorological factors directly impact the electrical load requirements. The Indian Meteorological Department classifies the climate of India into four distinct seasons: winter, summer, rainy, and autumn shown in Figure 1. CG is a state in India that experiences the different seasonal patterns and their impact on load demand can be seen in Figure 2. It displays the daily (per day) average load demand for each season in the year of 2022. Specifically, the load pattern for the winter season in December indicates a daily average load

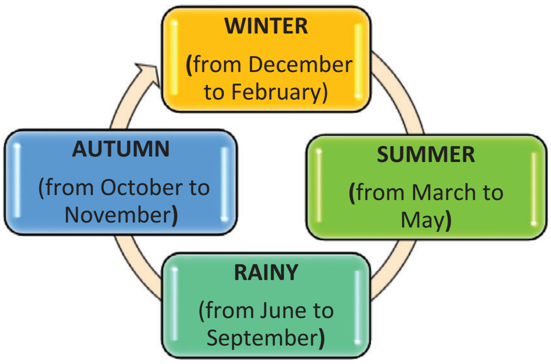


FIGURE 1 Four seasons in India.

range of approximately 3800 to 4165 MW. Whereas, the load range is higher for the summer season in March, varying from approximately 4200 to 4900 MW due to significant temperature fluctuations. Similarly, the average load demand decreases from the rainy season to the autumn season, which can be observed by comparing the load patterns in June and October months.

Analysing the load patterns of the CG state facilitates the prediction of the average load demand for the year 2023.This research paper focuses on observing the per day average load demand for a span of five years (2018–2022) to predict the load demand for the months of year, 2023. The findings indicate a consistent increase in load demand each year, due to population growth and climate change.

3 | PROPOSED MODEL—LSTM

Long short-term memory (LSTM) network is a part of deep learning field. The LSTM networks are an extension of Recurrent Neural Networks (RNN) specially developed to overcome the vanishing gradient problem and capture long term dependency in sequential data. The RNN fails in storing data for long period of time hence it is not capable to handle long term dependency. Now the LSTM is introduced by the design without altering training model as vanishing gradient problem is removed completely. Figure 3 shows the architecture of LSTM network, where is hidden state (new), $h_{t\text{-}1}$ is hidden state (previous), C_t is new cell state, $C_{t\text{-}1}$ is previous cell state, and X_t is input data. This model also helpful in handling continuous value and noise. LSTMs offer several advantages over hidden Markov models (HMMs), eliminating the need to maintain a predetermined set of states. Unlike HMMs, which have a fixed number of states, LSTMs are equipped with a wide range of adjustable parameters, including learning rates, input biases, and output biases. These parameters provide flexibility and control during the learning process, enabling the network to adapt and improve its performance. Consequently, LSTMs offer a more powerful and flexible framework for modelling sequential data compared to the constraints imposed by HMMs.

The LSTM model is made up of three gates—input, forgetting and output gates with unit storage [25]. For t time step, the LSTM process can be explained as [25]:

$$\left.\begin{aligned} i_t &= sig\,(Wi\ \cdot [h_{t-1}, x_t] + bi) \\ f_t &= sig\left(W_f \cdot \left[h_{t-1}, x_t\right] + bf\right) \\ o_t &= sig\left(W_o \cdot \left[h_{t-1}, x_t\right] + bo\right) \\ \overline{C_t} &= \tanh\left(W_c \cdot \left[h_{t-1}, x_t\right] + bc\right) \\ C_t &= f_t * C_{t-1} + it * \overline{C_t}] \\ h_t &= o_t * tanh\,(C_t) \end{aligned}\right\} \tag{1}$$

where i_t is input gate, f_t is forget gate, o_t is output gate, $\overline{C_t}$ and C_t is cell state, h_t is hidden state, Wi, Wf, Wo, Wc are weight matrices, bibfbobc are bias terms, sig is sigma the sigmoid activation function, and tanh is the hyperbolic tangent activation function [25].

4 | PROPOSED METHODOLOGY

This paper utilizes Chhattisgarh state, average load demand dataset for a span of five years (2018–2022), to forecast the average load demand of the year 2023 and the LSTM model is applied for this purpose.

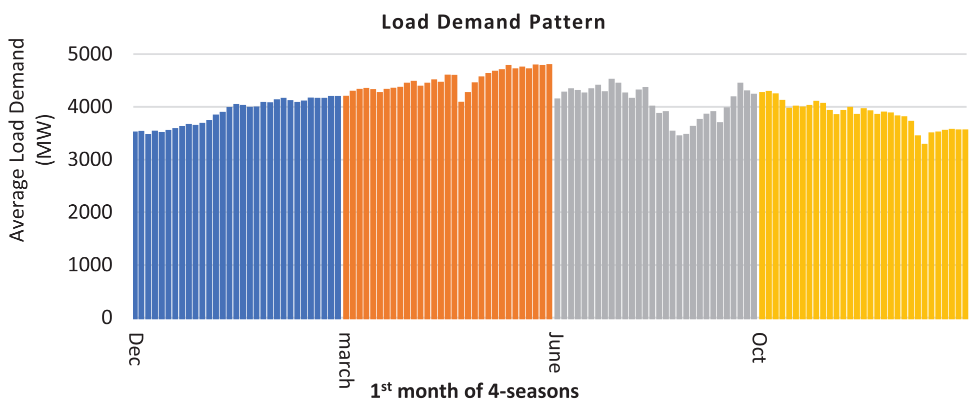


FIGURE 2 Per-day average load demand pattern of 1st months of 4 seasons (Winter—December, Summer—March, Rainy—June, Autumn—October).

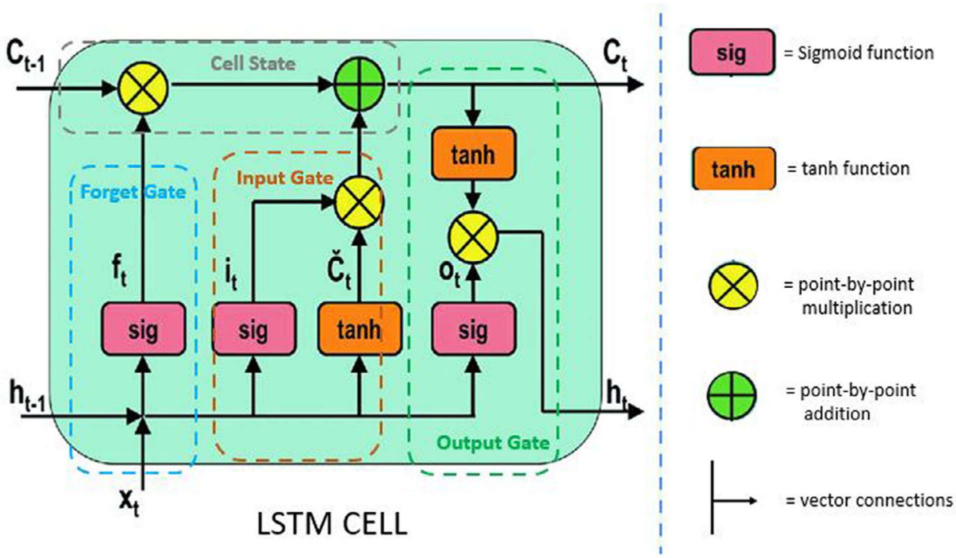


FIGURE 3 LSTM architecture.

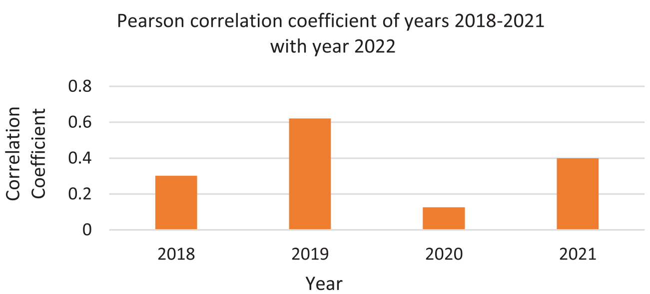


FIGURE 4 Pearson correlation coefficient of years 2018–2021 with year 2022.

- Data collection: The historical yearly load data is collected from Chhattisgarh LDC.
- Data preprocessing: In this stage, data is processed before applying to the algorithm. Feature engineering have been applied to the raw historical data to remove outliers, finding duplicate data and updating missing data.
- Feature selection: The correlation between the historical load demand data set plays a crucial role in the load forecasting process. Pearson's correlation coefficient for years 2018–2021 with year 2022 is illustrated in Figure 4. This correlation simplifies the process of selecting features for the forecast. It indicates the Pearson's correlation coefficient between the load demand of 2018, 2019, 2020, and 2021 with 2022. The highest correlation coefficient depicted in Figure 4 is 0.621 for the year 2019, whereas the lowest correlation is observed in the year 2020 due to the disruptive impact of the COVID pandemic in India. Hence, these four years of data used for model training to predict the load demand for year 2022.
- Data scaling/data normalization: it is also an important part, scales the data in the range 0 to 1 by using linear scaling approach [26].

The formula for linear scaling is as follow [26]:

$$z = \frac{(x - \min(x))}{(\max(x) - \min(x)) * 100} \tag{2}$$

Here, z is normalized value and x is original data set value, $\min(x)$ is minimum value of x dataset, $\max(x)$ is maximum value of x dataset.

- The five years CG historical average load demand data is normalized by using (2).
- The training and testing data sets are divided and the proposed LSTM model is applied to observe the forecasting performance.

Figure 5 represents the flowchart of the proposed methodology for the training and testing phases of the algorithm. Initially, the model is trained by initializing the parameters to obtain the optimal parameter settings for the LSTM model. The trained model is then tested with the data to forecast the results. If the obtained results are not satisfactory, the model parameters are adjusted, and the simulation is repeated to find the optimal parameter values. This iterative process helps refine the model until satisfactory results are achieved.

To assess the accuracy and effectiveness of the prediction models, it is common to use various statistical performance metrics. These metrics play a crucial role in evaluating the quality of the forecasts by comparing them to the actual values [26].

The following metrics frequently employed for this purpose are:

1. Mean absolute error (MAE): The absolute differences between the forecast values and the actual values is called MAE, it provides a measure of the average magnitude of the errors without considering their direction.

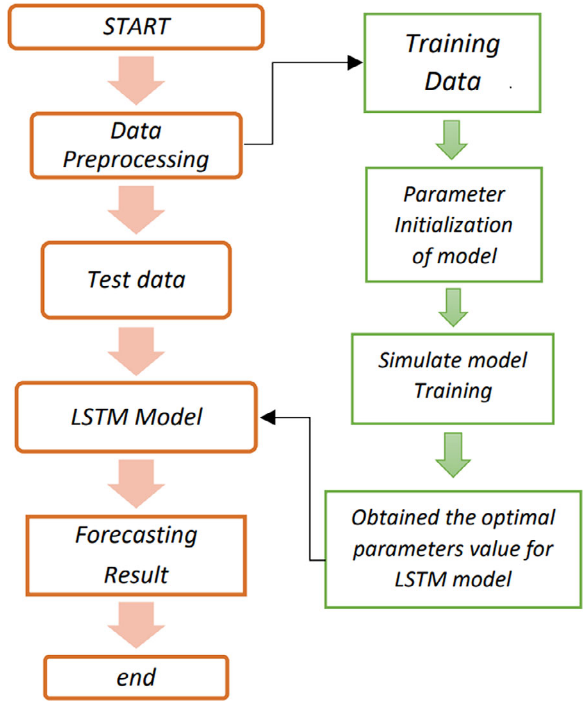


FIGURE 5 Flowchart of the proposed methodology.

TABLE 1 Error statistics.

Parameter	Formula
MAE	$\frac{\sum_{i=1}^{n}\lvert x_i - y_i\rvert}{n}$
MAPE	$\frac{\sum_{i=1}^{n}\lvert y_i - x_i\rvert}{n} * 100$

2. Mean absolute percentage error (MAPE): It measures the average percentage difference between the forecast values and the actual values. It is useful when the magnitude of the errors relative to the actual values is important.

The error metrics can be calculated by using the formula shown in Table 1. By calculating and analysing these metrics, the accuracy and effectiveness of the prediction models can be evaluated, providing insights into the performance of the network. In Table 1, y represents the forecasted load demand, x represents the original load demand, and n represent the total number of time steps. Once the training phase is completed, the same algorithm is applied for testing the data and forecasting the results.

5 | PROPOSED LSTM-BASED LOAD FORECASTING MODEL RESULTS

The LSTM model undergoes training and testing using the load demand dataset of CG for LTLF. The data is obtained from the Chhattisgarh Electricity Board (Chhattisgarh LDC). Initially, all the raw data is processed, normalized, and organized to represent the per day average load demand for each month from the years 2018 to 2022. For testing the model and forecasting the average load demand, the load data from January 2023 to June 2023 is also arranged in a similar manner. This arrangement enables the model to forecast the average load demand for the period from July 2023 to December 2023.

Training phase: The training of the LSTM model is conducted using load data spanning five years (2018–2022). The training phase is divided on a monthly basis from January to December month of the years 2018–2022. Each month consists of samples of per day load demand data, resulting in a total of 365 days of load demand data for each year. During the training phase, the input is the average load demand from the years 2018 and 2019, and the predicted output is the load demand for the year 2022. The error is evaluated by comparing the actual load demand with the forecasted load demand for each month of the year 2022. The training continues until satisfactory results are achieved, utilizing optimal parameters for the LSTM model. Once the training phase obtained satisfactory results, the testing phase can be executed to forecast the average load demand for the year 2023. Figure 6 illustrates the training results for the initial three months of the year 2022, displaying the error values between the actual and forecasted load demand. The overlapped pattern of the actual and forecasted load demand can be observed in Figure 6a–c, indicating the accuracy of the training phase. Similarly, Figure 6d–f depicts the error ranges for the months of January 2022, February 2022 and March 2022, respectively.

The Figure 7 shows similar training results for the last three months of the year 2022, specifically for October, November and December. Figure 7g–i presents the actual and forecasted load demand, while Figure 7j–l indicates the error ranges for the months of October 2022, November 2022, and December 2022, respectively.

Testing phase: For the testing of the LSTM model and forecasting average load demand from July 2023 to December 2023, load data from the year 2019 to 2022, as well as January 2023 to June 2023, is used. By analysing the load patterns of CG state, it is marked that the load demand increases with each passing year. The LSTM model predicts the average load demand for July 2023 to December 2023. Additionally, on the basis of load pattern analysis, approximate values for the maximum and minimum average demand for each month are also provided to de-normalized the forecasted load demands.

Figure 8 represents the load demand forecasting result for the year 2022 during the training phase of the LSTM model. The overlapping of the actual load demand and forecasted load demand demonstrates the high accuracy in the training phase. Table 2 represents the MAE and MAPE values for the training data on a monthly basis while forecasting the average load demand for the year 2022. The monthly training results for the year 2022, as shown in Table 2, demonstrate the accuracy of the load demand forecasting. The MAPE range being less than 10% signifies highly accurate forecasting, while the MAE less than 47 MW represents an acceptable level of average absolute error. Based on the training results obtained from the LSTM model, it can be concluded that the forecasting model utilized in this

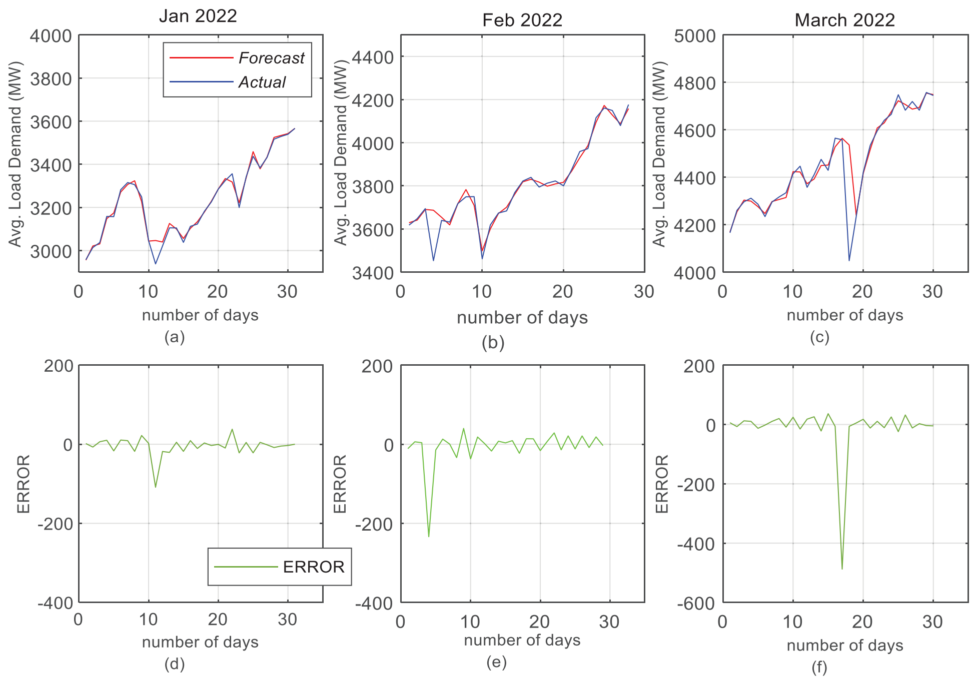


FIGURE 6 (a–c) The actual versus forecasted average load demand of training phase, (d–f) error range for months January 2022, February 2022 and March 2022, respectively.

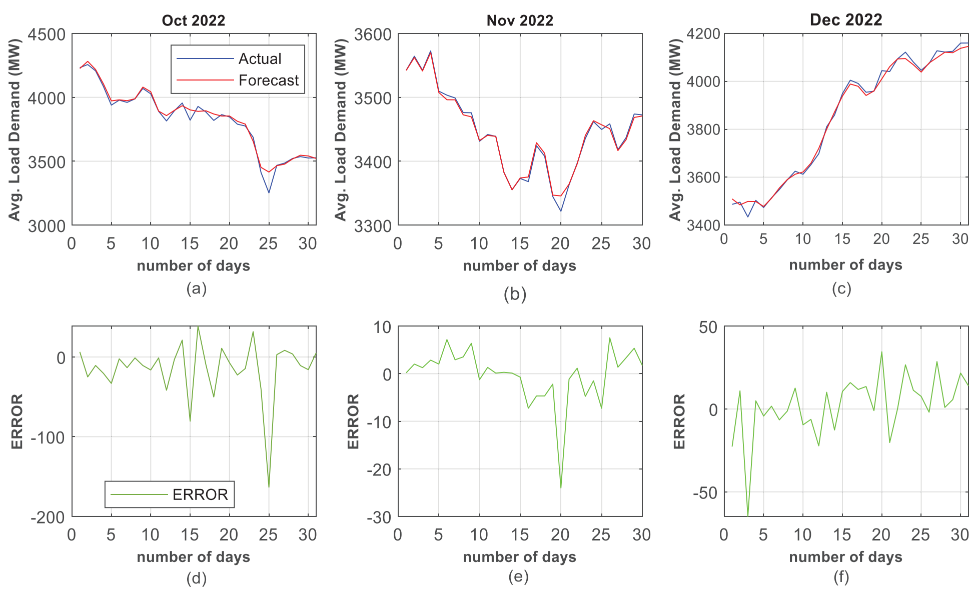


FIGURE 7 (a–c) The actual versus forecasted average load demand of training phase, (d–f) error range for months October 2022, November 2022 and December 2022, respectively.

paper closely approximates the accurate forecast of the average load demand for Chhattisgarh state of India. Table 3 represents MAE and MAPE values for testing phase, on monthly basis similar to Table 2, for forecasting average load demand in the year 2023.

Another test results of the proposed model for months January 2023 and March 2023 forecasted and actual load demand are exemplified in Figure 9a,b. These datasets are different from the training phase, and furthermore from the Figure 9, it is clear that the forecasted load demand follows the actual load demand pattern in a reasoned way and provides the test results which are useful for the power engineers handling the demand management side in a load dispatch centre.

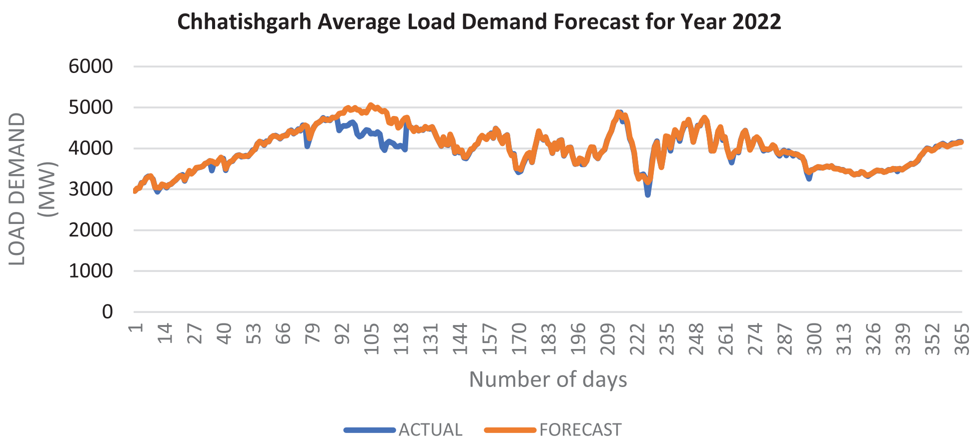


FIGURE 8 Average load demand forecasting result during training with actual load demand for the year 2022.

TABLE 2 Monthly error metrics for the year 2022.

Month	MAE (in MW)	MAPE
Jan	13.534	0.177
Feb	23.16	0.209
March	29.748	0.32
April	12.515	0.512
May	11.124	0.218
June	18.136	0.241
July	11.051	0.189
Aug	46.319	0.652
Sep	15.879	0.166
Oct	23.34	0.429
Nov	3.675	0.010
Dec	13.457	0.041

The difference between the actual and forecasted values is calculated as the error metrics, which can be observed in Table 3. Additionally, Figure 10 also represents the future per day average load variation for the months of July 2023 to December 2023. This provides a visual representation of the forecasted average load demand for the upcoming time interval. Table 3 represents the MAPE range for the testing phase of Year 2023. The majority of the MAPE values being less than 10% indicates good forecasting accuracy. The moderate correlation can be attributed to the fact that various environmental conditions change on a daily basis, leading to fluctuations in the load range each year, which tends to increase error. The MAE values fall within a good range, further indicating accurate forecasting performance.

TABLE 3 Monthly error metrics for the year 2023.

Month	MAE (in MW)	MAPE
Jan	127.018	0.378
Feb	190.184	0.619
March	372.706	2.452
April	464.297	9.180
May	328.798	4.615
June	518.207	10.542

6 | DISCUSSION AND COMPARATIVE ASSESSMENT

A comparative analysis of the proposed work with other existing works [27–30] is carried out in this section and represented in detail in Table 4. A combined random forest model is pre-

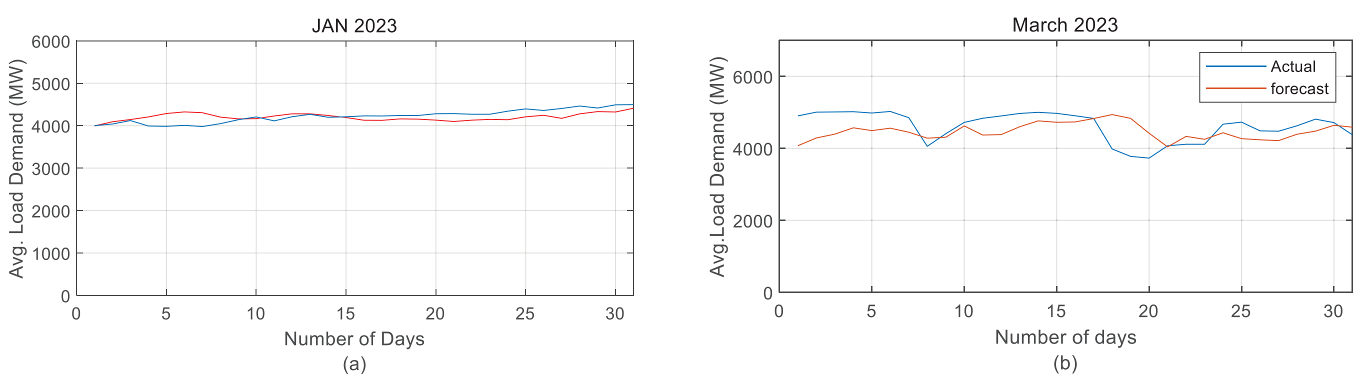


FIGURE 9 (a,b) Actual versus forecasted average load demand of month January 2023 and March 2023 respectively in testing phase.

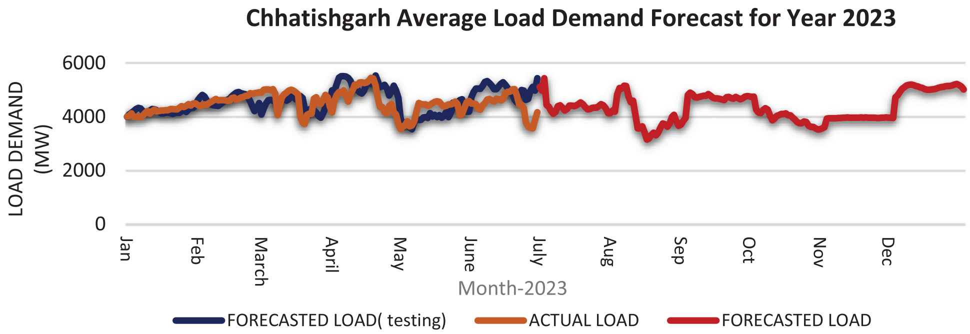
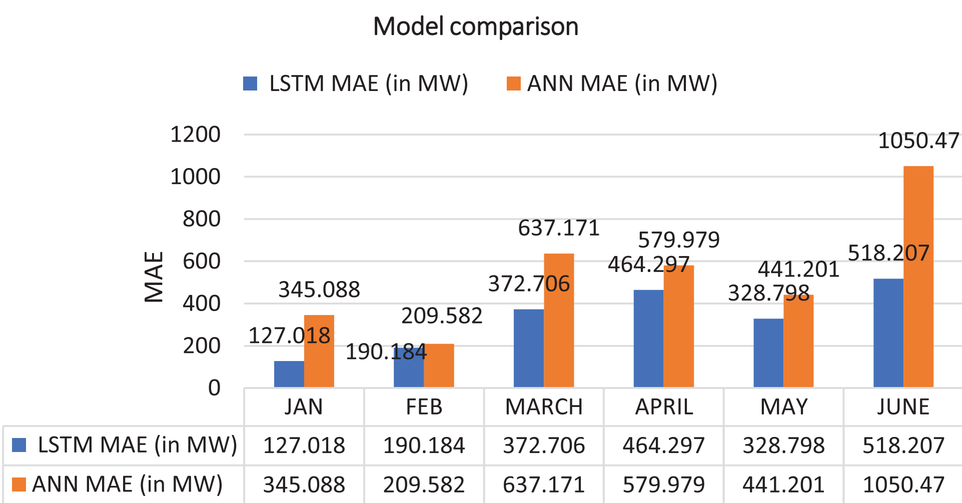


FIGURE 10 Average load demand forecasting result during testing for the year 2023.

TABLE 4 Comparative analysis of model on the basis of results and algorithm.

Ref.	Algorithm	Data set	Result
[27]	Combined Multivariate Random Forest and Random Forest model	STLF for 15 buildings at 24 hr prediction time for each building	MAPE = 11.7-28.6%
[28]	Hybrid CNN-LSTM	Short term individual household load forecasting SGSC project initiated by the Australian Government	MAPE = 40.38%
[29]	A multi-step deep learning CNN-LSTM model	Italy-North Area data set (from 1 January 2015 to 31 December 2017) to forecast next 24 hr	MAE = 692.1446MW
[30]	STLF based on LSTM model	12 months data at every 24hr is recorded and trained to forecast next 30 days	MAPE = 9.75 %
Proposed Model	LSTM based daily average load demand forecast	Five years (2018-2022) Chhattisgarh average load data is used to forecast next year 2023 average load demand	Monthly, for Jan- June 2023, MAE in MW is 127.018-518.207 and MAPE are % 0.378-10.542

sented for 15 buildings to forecast load at 24 prediction time for each building and MAE and MAPE values are calculated for each buildings at each time step [27]. Numerous studies have explored CNN-LSTM, multi-step CNN-LSTM, and LSTM models [27–30] across different regional datasets and time zones. When comparing these findings with the proposed model, it indicates the accuracy of this proposed work. Specifically, the MAPE and MAE values of the LSTM model for daily load demand forecasting are lower than those achieved by other models [27–30]. The research work represents a LSTM model forecasting accuracy, measured through monthly MAE and MAPE values from January 2023 to June 2023. The MAE varies between 127.018 MW (minimum) and 518.207 MW (maximum). The effectiveness of the proposed model is compared with deep learning model, that is, ANN using the same dataset as used by the proposed LTM-based model and depicted in Figure 11. To validate the proposed work results, the same dataset is applied on ANN model and their forecasting result



	JAN	FEB	MARCH	APRIL	MAY	JUNE
LSTM MAE (in MW)	127.018	190.184	372.706	464.297	328.798	518.207
ANN MAE (in MW)	345.088	209.582	637.171	579.979	441.201	1050.47

FIGURE 11 LSTM model and ANN model comparison based on MAE values.

based on MAE values are compared and shown in Figure 11 for the period of Jan to June 2023. It is clear from Figure 11, the LSTM based model provides the prediction of load demand with least MAE and MAPE as compared with ANN and other existing methods in literature as illustrated in Table 4. Figure 11 indicates proposed model LSTM, is more accurate than the ANN model, because the MAE values of the proposed LSTM model is lesser than that of ANN model.

7 | CONCLUSION

This paper presents an LSTM-based model for per day average load demand forecasting using historical load demand patterns. The real time field historical load data of Chhattisgarh State of India located in central Asia Continent spanning from the year 2018 to June 2023 is utilized in this study. The LSTM model is trained using data from year 2018 to 2022, and testing is conducted using data from year 2019 to June 2023. By analysing the historical load data, assumptions can be made regarding the maximum and minimum average load demand values for each day of the month for the next year. During training, the model MAE ranges between 3.675 MW to 46.319 MW and while MAPE is 0.010%–0.652%. Similarly, during testing January 2023 to June 2023 MAE is in between 127.018 to 518.207 MW and MAPE is between 0.378% to 10.542%. The results support the accuracy of the proposed model. The primary challenge in the proposed model lies in mitigating over-fitting and under-fitting issues, attributed to the LSTM model's numerous parameters and computational complexity, which can make training and optimization challenging. Future endeavours could focus on employing this proposed model with feature decomposition methods or optimization techniques to enhance the model's performance, smoothing its operation, and improve overall accuracy.

Nomenclature

$\boldsymbol{i_t}$	Input gate
$\boldsymbol{f_t}$	Forget gate
o_t	Output gate
a^t	Input Modulation gate
c_t	Storage cell state
$\boldsymbol{sig}$	Sigmoid function
tanh	Hyperbolic tangent function
$\boldsymbol{W}*,$	Weight matrices
$b*$	Bias vector
h_t	New hidden state
$h_{t\text{-}1}$	Previous hidden state
C_t	New cell state
$C_{t\text{-}1}$	Previous cell state
X_t	Input

AUTHOR CONTRIBUTIONS

Rashmi Bareth: Resources; software; writing—original draft. Anamika Yadav: Conceptualization; software; supervision; writing—review and editing. Shubhrata Gupta: Visualization; supervision; writing—review and editing. Mohammad Pazoki: Validation; visualization; writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Author's do not have permission to share the Research data as per Non-Disclosure Agreement signed.

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