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Modelling and Distribution of Electricity Load Forecasting in Nigeria Power System (Olu-Ode Community)

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Abstract: ***To plan for energy generation to fulfill customer demand as the population grows, load forecasting is often used to anticipate and predict a region's power demand growth. A power load To sell, plan, and purchase energy for power systems, forecasting might be employed. From electrical energy production through distribution, it is highly helpful. Power system forecasting may be broadly categorized into three classes: An hour to a week is considered short-term electric load forecasting, a week (7 days) to a year is considered medium-term electric load forecasting, and a year and beyond is considered long-term electric load forecasting. In emerging nations where the energy demand is erratic due to fast economic expansion and a rise in the rate of rural-urban migration, accurate load forecasting may aid in creating a strategy. Various load forecasting techniques, including expert systems, fuzzy logic, regression techniques, and artificial neural networks (ANN), were researched. However, current methods may only sometimes provide more accuracy in predicting short-term stress. To address this issue, a novel strategy for anticipating short-term load is put forward in this study. Long short-term memory (LSTM) and convolutional neural networks are included in the created approach. The technique is used to anticipate the short-term electrical demand for the power system in Nigeria. Additionally, the usefulness of the proposed method is confirmed by comparing the forecasting errors of the suggested method with those of other existing methods like the long short-term memory network, the radial basis function network, and the extreme gradient boosting algorithm. It is discovered that the suggested technique produces better short-term load forecasting precision and accuracy.***

Keywords: Regression, Forecasting, Load, Demand, Power, Electric, Generation

I. INTRODUCTION

Electric load forecasting is necessary for today's economic development of a nation. Accurate prediction of electric future load needs will assist in determining and calculating roughly the energy required to prepare for power production (Idowu, 2019).

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Demand energy forecasting is determining the amount of electric energy required by a certain region utilizing historical data on energy use in that place and other pertinent factors like temperature, weather prediction, and population, among others. The challenge with demand forecasting is figuring out what will be required in future demand, mostly by extrapolating historical consumption and other variables that may impact how much energy a region consumes at a certain time (Adepoju et al.,2021). Given that electric power cannot be stored later using current technology and infrastructure, it is essential to comprehend how electric load demand will behave. Energy forecasting is the first step in developing an electric utility since new utility stations are required. Any utility's planning and operation are only possible with accurate models for estimating electric demand.

Due to the wide variations in modes, the rate of energy needed from one site, and the increasing growth rate of load demand, forecasting is exceedingly difficult in emerging nations. Electric load forecasting is crucial for energy providers, financial institutions, and other players in producing, transmitting, and distributing electric energy (Feinberg and Dora, 2020). a power load In the power system, forecasting is utilized for electric energy sales, planning, and purchases. Since electric energy cannot be stored effectively, it is very important in the power sector. It has a significant economic benefit as it aids the power-producing and distribution company in estimating the quantity of power required to be created and provided to a certain geographic region. It is an important tool for utility while making decisions and planning. Additionally, it is used in the system's overall planning.

Accurate load forecasting is useful for creating development plans and energy supply policies, particularly in emerging countries where unpredictable energy demand results from rapid population expansion and rural-urban mobility. Electric load forecasting has other benefits: • Effective investment and network preparedness • Improved and heuristic risk management • Decreased costs.

The projected amount (peak, integral, and hourly load) and the predicted time may be used to categorize forecasting. It may be divided into three types based on the predicted time. As follows:

• Forecasting short-term load: This typically covers an hour to a week. It helps estimate the load flows and make wise judgments to avoid overloading. It is used for contingency analysis, input to load flow, control, and power scheduling.

• the forecasting of mid-term load, which typically ranges from a week to a year;

• Forecasting of long-term electrical demand starts one year out. Forecasting long-term electric demand is used to check the power system's capability.

The kind of place, historical demand load data, the time factor, socioeconomic contexts (festivals and working days), weather data, and special times like Christmas or Ramadan are only a few variables that affect forecasting (Ibitoye & Adenikinju, 2017). The abovementioned criteria will determine the quantity of energy a region needs at any time. Making resolutions requires much forecasting. Its purpose is to reduce the risk associated with decision-making and unplanned expenses. As operations under circumstances of short-term part maintenance service, daily, hourly, and weekly load scheduling of generating stations, secure operation of power systems, and economic (Gangshem, 2018), information derived from short-term electric load forecasting is crucial to power supply systems.

The following contributions are what this study hopes to contribute in that regard.

• A hybrid technique is suggested for predicting short-term electricity demand. To consider the benefits of both methodologies, the methodology is built on the merging of CNN and LSTM networks.

• Nigeria Power System (NPS) load forecasting for the day ahead and the weak ahead is done using the defined approach. Note that at the moment, BPS mostly relies on anecdotal information for short-term load projection. As a result, there may be a significant mismatch between real and anticipated demand, which presents extra difficulties for network operators.

II. LITERATURE REVIEW

Precise electrical load forecasts greatly benefit power production, transmission, distribution planning, and operations. Accurate load forecasting is crucial for the unit commitment and scheduling of the power plants (Yu, Niu., Tang, and Wu, 2019). In addition, it is impossible to calculate operating expenses without a reliable load forecast. There are typically three main types of load forecasting. There are three types of load forecasting: short-term, which looks ahead a few hours to a few weeks; intermediate, which looks ahead a week to a year; and long-term, which looks ahead more than a year (Jacob., Neves. and Greetham, 2020). Short-term load forecasting is used to anticipate the load for the next day, which is crucial for the operation and management of power systems.

Several methods are described in the literature for making short-term load forecasts (STLF). Traditional methods, on the one hand, and methods based on artificial intelligence, on the other, may be used to accomplish the same goals. Statistical techniques are often employed in conventional procedures (Christiaanse 2021). Among them are ARIMA (C.-M. Lee and methods), exponential smoothing (Christiaanse 2021), and multiple linear regression (Charytoniuk, Chen, and Van Olinda 2018). Remember that the methods mentioned above may not always provide desirable results in STLF owing to the nonlinear aspects of time series unilabiate load data. Lee, C.-M., and Taylor, J.-W.

Machine learning-based solutions have been developed and used widely in STLF to address this concern (Hong, Pinson, Wang, & Yang, 2020). The clustering technique is one example of these A. Jain and B. Satish, a support vector machine (SVR; Chen, Xu, Chu, Li, Bao, and Wang, 2017), a fuzzy logic framework (evil and unkaş, 2019), an artificial neural network (ANN; Salhay, Bishat, Banda.E., and Huang, 2021), a radial basis functional network (RBFN; W.-Y. Chang), and a hybrid approach. Several recent studies support this idea (Ekonomou, Christodoulou, and Mladenov 2016), (Motepe, Hasan, and Stopforth 2016). Electric load forecasting using a kernel-based SVR model has been published (Che and Wang, 2014). The proposed model offers a fresh means of deciding on the SVR model's kernel function. The operational effectiveness of the network is evaluated concerning the actual power grids in Australia and California. Hourly load forecasting using fuzzy logic has been described in (Ganguly, Kalam, and Zayegh 2017) (Che and Wang 2014). Large-scale power system data covering a year's use has been used for load forecasting. The suggested solution uses fuzzy rules to combine time, day (weekend or weekday), and historical load data. This study analyzes data from major manufacturing facilities over a year to predict the daily load curve. An efficient technique for forecasting near-term load demand is presented in (Ekonomou, Christodoulou, and Mladenov, 2016), using ANN techniques bolstered by a wavelet de-noising algorithm. The suggested method's results demonstrate that it significantly improves prediction accuracy. Due to its ability to handle complex nonlinear patterns, deep learning algorithms have garnered much interest recently (Bouktif, Fiaz, Ouni, and Serhani, 2018; Merkel, Povinelli, and Brown, 2018). Wind power forecasting (WPF) utilizing a machine learning-based method is described six months in advance (Ahmadi, Nabipour, Mohammadi-Ivatloo, and Piran 2020). Decision trees, bagging trees, random forests, boosting (AdaBoost), gradient boosts, and extreme gradient boosts (XGBoost) are only a few of the tree-based methods used in WPF model training. The suggested framework has shown to be very effective and efficient in predicting wind power at the Ghadamgah wind farm. Because of its superior learning capability to capture the non-stationary load data pattern, recurrent neural network (RNN) is also used for STLF. For improved root mean square error (RMSE) performance, see (Shi, Xu, and Li 2018), which implements an RNN approach for domestic load forecasting. In (Wei. 2017), we are introduced to an up-to-date RNN-based load forecasting strategy that considers looking forward one step. Both low-power and high-power regions benefit from the suggested method's satisfactory performance. In addition, its regional changes are the smallest compared to competing models. An RNN's prediction accuracy may suffer from vanishing and ballooning gradient problems. Since there is no vanishing gradient issue with a gated recurrent unit network (GRUN) (Kuan, Yan, Xin, Yan, and Xiangkun 2017), it has seen widespread application in recent years. A GRUN-based method is presented for STLF using many sources of information (Wang, Liu, Bao, & Zhang, 2018). This network surpasses state-of-the-art approaches because it produces the lowest MAPE.

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The gradient vanishing issue has also been addressed using long short-term memory (LSTM) in New York (Muzaffar and Afshari, 2018). For more complicated time series load data with long-term dependencies, (Hossain & Mahmood, 2020) creates an efficient technique using LSTM networks to provide accurate forecasts. The suggested method outperforms the state-of-the-art. Due to its superior capacity to capture the trend of load data, the convolutional neural network (CNN) has widely used load prediction alongside the abovementioned methods (Rafi and Nahid-Al-Masood, 2020). A CNN-based model for load forecasting is presented and compared to other types of artificial neural networks (Amarasinghe, Marino, & Manic, 2018). According to the findings, using a CNN-based technique improves STLF accuracy. Furthermore, time-dependent convolutional neural networks (TD-CNNs) and cycle-based long short-term memory (C-LSTM) networks have been deployed in the STLF domain to enhance forecasting accuracy (Han, Peng, Li, Yong, and Shu 2019). After extracting considerable and complex features from the electric load sequences, the prediction ability is greatly enhanced by the multistep STLF approach presented in (Deng, Wang, Xu, Xu, Liu, and Zhu 2019), which is based on time-cognition CNN (TCMS-CNN). It produces accurate results in probabilistic forecasting, allowing robust simplification in the energy market's bidding and spot price computation processes. By combining the strengths of the modified grasshopper optimization algorithm (MGOA) and the locally weighted support vector regression (LWSVR), (Elattar, Sabiha, Abd-Elhady, and Taha 2020) provide a powerful hybrid approach for STLF in smart cities. To achieve these goals of consistent performance and improved accuracy, LWSVR is used here. Additionally, MGOA is applied after adjustments to conventional GOA. After that, the act of the developed LWSVR-MGOA is evaluated using different real-world datasets. Given the above discussion, both LSTM and CNN can provide satisfactory results in short-term load forecasting (Alhussein, Aurangzeb, and Haider, 2020). Therefore, it is logical to anticipate that integration of CNN, and LSTM will further reduce the forecasting error. Based on the recent works, it is found that existing STLF approaches may not always be suitable due to abrupt changes in load demand. Also, in Nigeria's power system, no fruitful method is yet implemented for forecasting short-term load. Therefore, further research is still required to mitigate the current challenges and limitations of the existing techniques. Authors Z. Deng, B. Wang, C. Liu, and Z. Zhu only consider individual household load forecasting of a Smart Grid Smart City (SGSC) project. In contrast, the proposed algorithm of this paper can forecast the load of an entire power system of a country in different time horizon

A. Electric Load Forecasting Method

Electric load forecasting is difficult due to the variety of associated electric loads. Electric load forecasting uses a variety of techniques. Common categories include statistical approaches and expert systems. The following sections elaborate on the many approaches that may be taken:

a. Simple Statistical Method

Statistical techniques often need a mathematical model depicting load as functions of some variables, including consumer class, weather, and time. Multiplicative and additive models are two major classes of this kind (George and Burton, 2019). The predicted load is the sum of numerous variables and computations. This method's simplicity and effectiveness stem from the fact that it uses a small number of variables. It's also the simplest to calculate, albeit its lack of precision is a drawback. It applies to all forms of forecasting.

b. Regression Methods

Typically, the link between energy usage and other characteristics like time of day, consumer type, and weather is modeled using regression techniques (Hafiz et al., 2020). Regression analysis employs the least-squares approach of linear regression to fit a line across a collection of observations. Load forecasting on a short time scale uses this method often.

B. Expert Systems

Artificial intelligence "expert systems" automate prediction tasks that would otherwise need human intervention by codifying the rules and metrics used by human experts in the topic of interest. As more data becomes accessible, the program can reason, execute, and provide an explanation. To wit: (Amit & Satish, 2018).

C. Fuzzy Logic

The standard Boolean logic used in digital circuit design is summarised by fuzzy logic. Inputs in fuzzy logic are associated with certain quality intervals. It enables inferring outcomes from ambiguous inputs reasonably. The core of its operation is the mapping of inputs to outputs. In addition, this technique used the average or steady-state component. However, the load is computed based on the components' constantly shifting weighted grouping (Amit and Satish, 2018).

D. Support Vector Machines

A new and effective method for dealing with regression and classification issues is the support vector machine (SVM). In other words, they do a nonlinear data mapping into a higher dimensional space. Then, in this new space, support vector machines employ simple linear functions to define verdict bounds. Optimization lies at the heart of Support Vector Regression. When pitted against the regressive approach, the support vector technique comes out on top (Weichang, 2019). Choosing a suitable kernel for the support vector machine is a new challenge that may rival the difficulty of deciding on a structure. It will be used for load forecasting shortly.

E. Artificial Neural Network

Part of AI, this model of the central nervous system, runs without a hitch. Building machines with components that act like biological neurons is an effort to create machines with similar capabilities to the human brain. A neural network consists of linked neural computing fundamentals that can respond to incoming inputs and adapt to and learn from their surroundings. It can be taught to tackle complex issues that would stump even today's most advanced supercomputers. After being taught, a neural network may accurately anticipate future outcomes.

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Table 1: Representation of Variables of the Neural Network Equation

Parameter	Definition
L.W.	Layer Weight
I.W.	Input Weight
F	Network function
P	Input
B	Network bias

F. Training, Network Parameters, and Error Correction

In terms of learning methods, backpropagation is the most ubiquitous. The correction period and the prior value of the weights combine to skew the weights. It's a kind of error correction that may be used to fine-tune the link strengths between concealed layers. The restitution criterion is stated in the form of the learning legislation. In essence, it's a "steepest dive" procedure. In ANN writing, the step size (in this case, 1.000) is referred to as the learning rate, which is required for the gradient descent method. Since the learning rate determines the magnitude of weight change, it is crucial for backpropagation in learning algorithms (Uduehi, 2019).

III. METHODOLOGY

It's good knowledge that the deepest dive faces difficulties, including poor efficiency and sluggish convergence due to its lack of resilience. The pace of learning is also taken into account. Slower learning occurs at lower learning rates, whereas network oscillation in the weight space is possible at higher rates. To calculate the error at a node h in the hidden layer using backpropagation, you must first find the error at every other node in the network that is connected to h by an incoming association from h.

$$\delta_n = w_1\delta_1 + w_2\delta_2 + w_3\delta_3 + ... + w_n\delta_n \tag{3.2}$$

Where δ_n is the error between the actual value and the output from node h.

w_n is the weight of the connection to node n

δ_h is the error of the hidden layer node (Jaap,2019)

So the Weight Change = some constants × input activation x error

Output node, the error is given as:

Error = (target activation - output activation) × (1 - output activation) x output activation

In the hidden node, the error is given as

Error = weighted sum of to-node errors × (1 - hidden activation) x hidden activation (Uduehi, 2019).

A. Proposed Methodology

The steps of the proposed methodology are briefly described as follows.

Step 1: Data Framing

In this stage, historical load data from a specific area are gathered, and null values are verified. The missing data must be modified to match the load pattern trend in earlier records. As a result, a dataset of extremely high quality may be generated, and the forecasting performance is little affected. A load dataset must be split into training and test sets to evaluate the suggested model. The collected data are divided into several standard weeks. The model that can forecast power usage for the next week and month may be effectively defined by reformatting this data frame.

Step 2: Constructing Multistep Time Series

The suggested model requires translating the electric load information into [sample, time steps, and attributes]. Seven-time steps with a single feature represent the complete daily power use of seven days in the first sample. This pattern does not have enough information for the network to be taught. To provide more training data, the issue must be modified such that it predicts the next seven days given the prior seven days, independent of the typical week. The dataset must first be flattened before eight-time series sequences may be generated. The dataset must then be partitioned into overlapping windows and iterated over the time steps before going along a single step and anticipating the following seven days. However, the test data from the data set is constant for every occurrence.

Step 3: Building Forecasting Model

The encoder-decoder CNN-LSTM model must be used, which primarily handles the one-dimensional data in the three-dimensional pattern. The suggested model's CNN block is defined by two convolutional layers, with convolution performed with the aid of a kernel filter. The first convolution layer reads the input series, which projects its sequences onto the feature windows. The purpose of the second convolution layer is to enhance the characteristics of the first layer. Each convolutional layer in the suggested model has 64 feature maps, and the kernel filter has three steps. The values obtained after two convolutions in the convolution layers are typically obtained using a maximum pooling layer. It's used to make the input features simpler. The maximum pooling operation in the suggested model must be carried out using just one-fourth of the data from the original sequence. The output of this operation is then flattened into a lengthy vector, which is utilized as the input for the LSTM unit's decoding operation, followed by a dense layer. This layer provides the output. The developed load forecasting model is shown in Fig.

Step 4: Training The Proposed Model

The proposed CNN-LSTM architecture is built using Keras, an open-source neural network library written in Python. Afterward, the model must be tested with different unseen data sets to check its general applicability and enhance performance. In the proposed framework, the network is trained with the following hyperparameters

- Type of convolution: One dimensional
- No of filter: 64 with kernel size 3
- Activation: Rectified linear unit (RELU) for CNN, LSTM, and Dense layer
- Optimizer: Adam
- No. Of hidden layer: 200 for LSTM
- No. Of training iterations (epochs): 20
- Batch size: 16

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IV. RESULT AND DISCUSSION

A. How to use Artificial Neural Networks in Forecasting Loads

The following steps must be taken when using an artificial neural network:

- Idea

A better understanding of what the network is expected to give must be well cleared.

- Information

The information required for the predictions must be decided.

- Data Collection

The information required must be obtained from the available source.

- Building a Network

When building a neural network, the number of input and output neurons must be specified.

- Training the Network

The actual load generated is used as input load to train the network, which takes in each input and makes a guess as to the output.

- Testing the Network

It is important to test a network on data it has never seen.

- Run The Network

Entering new input into the network and gathering usable results.

B. Forecasting Outcomes

The trained suggested CNN-LSTM and LSTM models can forecast load at half-hourly intervals across various time horizons, including 24 hours, one week, and one month. There are 105168 data points in the time series load data from January 2014 to December 2019; each point contains half-hourly data. It is broken down into 260 samples, 8 features, and 7-time steps to generate extra data for the network's training.

The first five years of load data (i.e., from January 2014 to December 2018) are chosen to train the suggested technique. However, the test method uses the 2019 dataset (i.e., January 2019 through December 2019). The results of BPS forecasting using the proposed method are shown in Figs. 6 to 1. Additionally, loads are forecasted using the LSTM model for comparison's sake. Figures 1 to 6 clearly show that the CNN-LSTM and LSTM models can forecast the real load demand pattern. In contrast to the LSTM approach, CNN-LSTM forecasting results accurately predict real load patterns.

C. Evaluation Metrics

The suggested technique is tested by comparing its error metrics (also known as evaluation metrics) to those of the LSTM, RBFN, and XGBoost methods. To do this, three different error measures include Mean Average Error (MAE), Root Mean Squared Error (RMSE), and Mean.

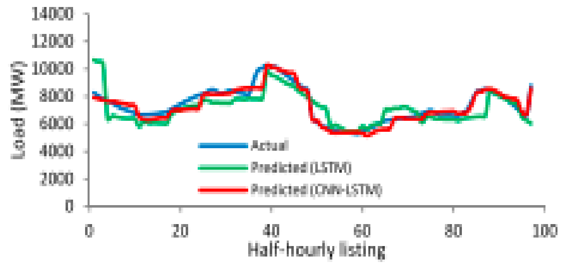

Figure 1. Comparison of Load Forecasting Results of BPS using Different Networks for 11-12 March 2022

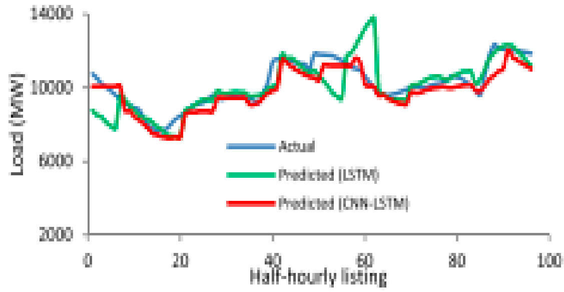

Figure 2. Comparison of Load Forecasting Results of BPS using Different Networks for 07-08 July 2022

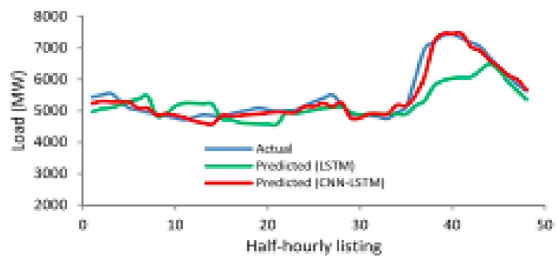

Figure 3. Comparison of Load Forecasting Results of BPS using Different Networks for April 01, 2022

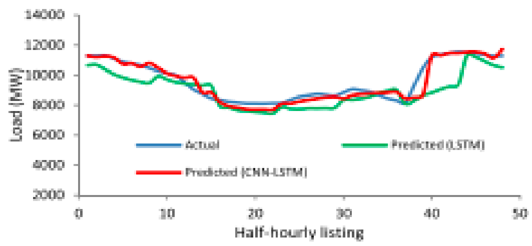

Figure 4. Comparison of Load Forecasting Results of BPS using Different Networks for July 15, 2022

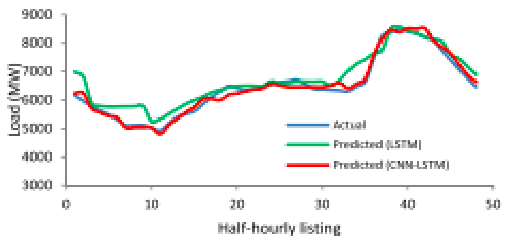

Figure 5. Comparison of Load Forecasting Results of Bps using Different Networks for September 07, 2022

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Absolute Percentage Error (MAPE) is taken into account. Better forecasting is indicated by the relatively lower values of these metrics. The mathematical expressions of the above error metrics are given as follows

$$MAE - \frac{1}{N}\sum_{L-1}^{N} |(F_L - Y_L)| \tag{9}$$

$$MAPE = \frac{\sum_{L=1}^{N} |\frac{(F_L - Y_L)}{Y_L}}{N} \times 100 \tag{10}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{L=1}^{N}(F_L - Y_L)^2} \tag{11}$$

Where N is the number of data points in the forecasted load, F.L. denotes the magnitude of the forecasted load, and Y.L. stands for actual load at any instant. In addition, another indicator named coefficient of determination (R 2) is considered for performance comparison. It can be calculated as follows.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(F_L - Y_L)^2}{\sum_{i-1}^{N}(F_L - A_L)^2} \tag{12}$$

Where AL indicates the mean value of the observations, higher forecasting accuracy is obtained when the value of R 2 is closer to 1.

D. Weekly Comparison of Evaluation Metrics

Table 2 compares the proposed CNN-LSTM, LSTM, RBFN, and XGBoost algorithms weekly for MAE, RMSE, MAPE, and R 2. For instance, the LSTM network offers an RMSE of 803.53 for the predicted data in Januarys 01–07, 2019, whereas the suggested

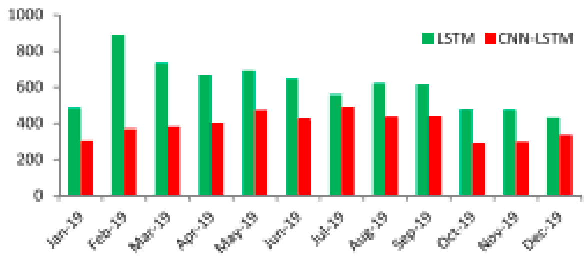

Figure 6. Comparison of MAE Obtained from LSTM and Proposed CNN-LSTM for 30 Days Prediction

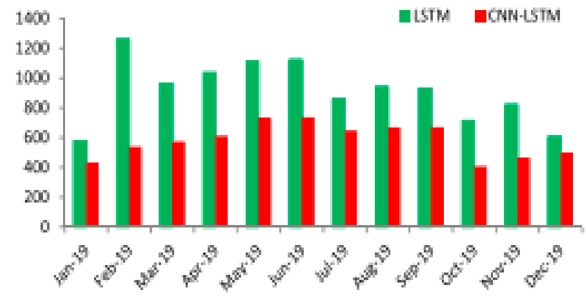

Figure 7. Comparison of RMSE Obtained from LSTM and Proposed CNN-LSTM for 30 Days' Prediction

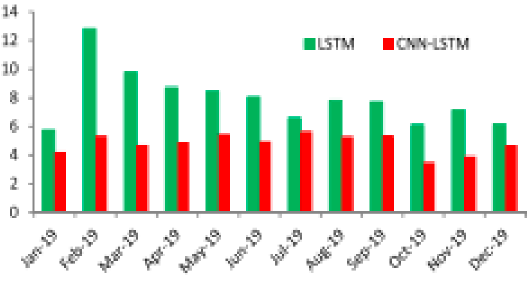

Figure 8. Comparison of MAPE Obtained from LSTM and Proposed CNN-LSTM for 30 Days' Prediction

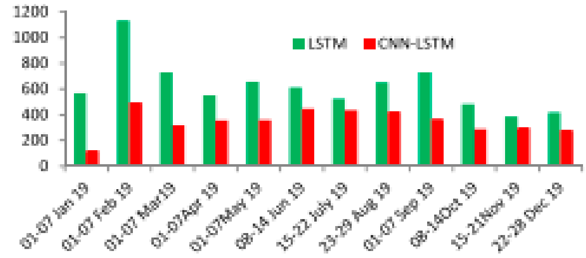

Figure 9. Comparison of MAE Obtained from LSTM and Proposed CNN-LSTM for 07 Days' Prediction

The RMSE provided by CNN-LSTM is 331.91. Similarly, the suggested approach provides reduced RMSE from October 8–14, 2019. Other weeks have likewise shown a similar pattern. Compared to the LSTM network, the suggested technique offers, on average, 271, 400.77, and 3.63% fewer MAE, RMSE, and MAPE. Figures 8 through Figure 11 show the changes in all measures.

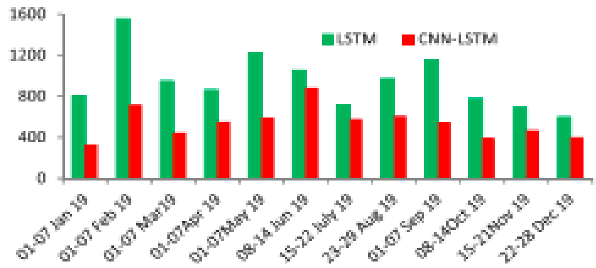

Figure 10. Comparison of RMSE Obtained from LSTM and Proposed CNN-LSTM for 07 Days' Prediction

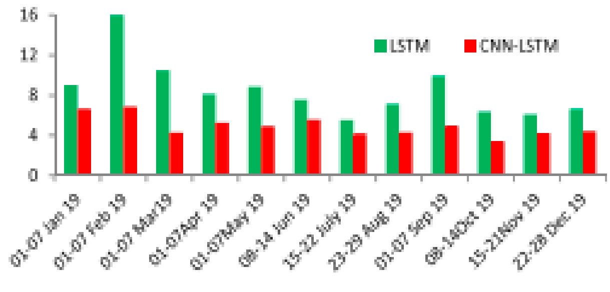

Figure 11. Comparison of MAPE Obtained from LSTM and Proposed CNN-LSTM for 07 Days' Prediction

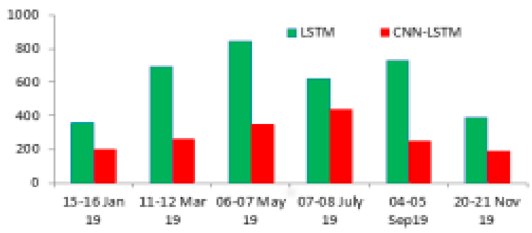

Figure 12. Comparison of MAE Obtained from LSTM and Proposed CNN-LSTM for 02 Days

E. 48 Hours Comparison of Evaluation Metrics

The 48-hour comparison of MAE, RMSE, MAPE, and R 2 for the proposed CNN-LSTM, LSTM, RBFN, and XGBoost algorithms is shown in Table 3. For instance, the suggested CNN-LSTM network delivers an RMSE of 290.17 with the anticipated data for 15–16 January 2022, while the LSTM network offers an RMSE of 503.85. Similarly, the suggested approach provides reduced MAPE on September 04–05, 2022. Other predicting findings also show a similar tendency. The suggested technique, on average, offers LSTM network 324.22, 529.96, and 4.37% fewer MAE, RMSE, and MAPE, respectively. In Figures 13 to 15, the improvements of all indicators are shown.

F. Comparison of Evaluation Matrices for 24 Hours

Daily comparison of the CNN-LSTM, LSTM, RBFN, and XGBoost algorithm network's projected MAE, RMSE, MAPE, and R2 metrics.

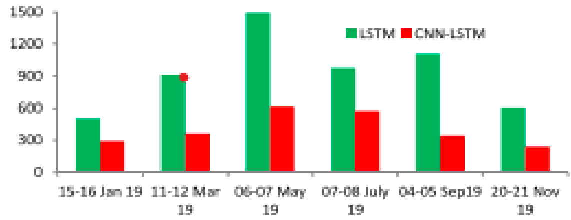

Figure 13. Comparison of RMSE Obtained from LSTM and Proposed CNN-LSTM for 02 Days

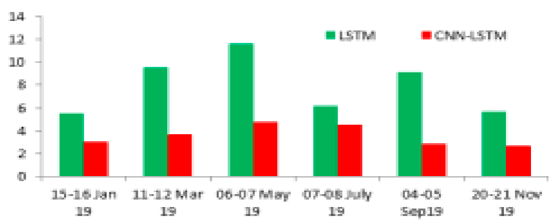

Figure 14. Comparison of MAPE obtained from LSTM and proposed CNN-LSTM for 02 days

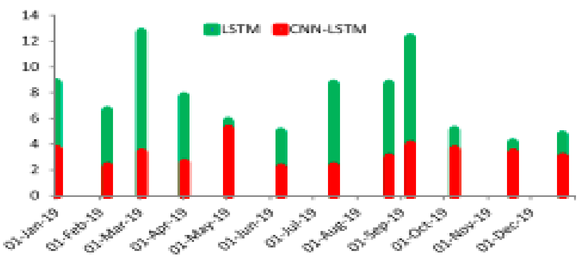

Figure 15. Comparison of MAE Obtained from LSTM and Proposed CNN-LSTM for 24 Hours

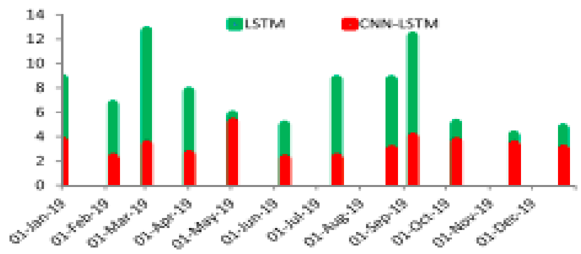

Figure 16. Comparison of RMSE Obtained from LSTM and Proposed CNN-LSTM for 24 Hours

With the forecasted data on January 01, 2022, the LSTM network provides an RMSE of 652.79, whereas the proposed CNN-LSTM offers an RMSE of 249.90. Similarly, the suggested approach provides reduced RMSE on September 7, 2022.

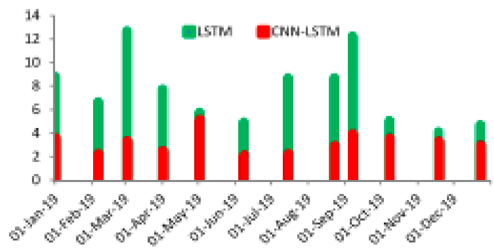

Figure 17. Comparison of MAPE Obtained from LSTM and Proposed CNN-LSTM for 24 Hours

A similar trend is also observed in other cases. On average, the suggested technique delivers 324.7693, 434.4985, and 4.3275% fewer MAE, RMSE, and MAPE correspondingly than the LSTM network. The results are graphically shown in Fig. 15 to Fig. 17

V. CONCLUSION AND RECOMMENDATION

Electric utility planning starts with an estimate of the load the company will give its customers. Precise load forecasting models are essential for any utility to plan and run efficiently. The forecasting of the load has been done using the techniques mentioned above. These strategies' benefits and drawbacks are described. The forecasting of electric loads in the power system's generation, transmission, and distribution may be done using any of the approaches outlined above. The dataset is performed following the numerous segments to guarantee stability and efficacy. The constructed network's resilience and wide applicability are also examined. Simulations show that, compared to the LSTM, RBFN, and XGboost models, the suggested CNN-LSTM model has the lowest MAE, RMSE, and MAPE values. Additionally, CNN-LSTM had the greatest R 2 values among the four models. The CNN-LSTM algorithm outperforms LSTM, RBFN, and XGBoost algorithms in every validation condition. The suggested CNN-LSTM model can handle the long sequence time series electric load data and estimate the future load demand over a significant length of time, as can be shown in conclusion. Using the GRU-integrated CNN network, a framework for very accurate load forecasting may be created in future work.

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Availability of Data and Material	In this research work authors used publicly available data across Ecommerce websites.
Authors Contributions	All authors having equal participation in the article.

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