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Electricity Demand Forecasting using LSTMs

A. Jeffee Jenson[1], Prof.S. Sowkarthika[2]

[1]Dept of EEE, Government College of Technology, Coimbatore, Tamilnadu, India.

[2]Assistant Professor, Department of EEE, Government College of Technology, Coimbatore, Tamilnadu, India.

Email: [1]jeff.1913123@gct.ac.in

Abstract

Electricity demand forecasting is an essential task in the energy industry, enabling utilities and energy suppliers to optimize the generation, transmission, and distribution of electricity. In recent years, deep learning techniques such as Long Short -Term Memory (LSTM) neural networks have shown great potential in improving the accuracy and efficiency of time-series forecasting tasks, including electricity demand forecasting. This research proposes an LSTM-based neural network architecture for short-term electricity demand forecasting. The proposed model is evaluated on real-world electricity demand data, and the results demonstrate its effectiveness in predicting future demand patterns. The model's performance is evaluated using the Mean Squared Error loss function and the Root Mean Squared Error metric. The proposed model shows promising results compared to traditional time-series forecasting models. The results suggest that LSTM-based neural networks can be a powerful tool for electricity demand forecasting, providing more accurate and efficient forecasting models that can help improve energy system planning and decision making.

Keywords: Demand forecasting, LSTMs, Deep Learning, Root Mean Square Error.

1. Introduction

This research presents LSTM-based neural network architecture forecasting the demands in the electricity. The proposed model aims to enhance the accuracy and efficiency of short-term demand forecasting in the electricity, which is important in the energy systems management and planning. The model is evaluated on real-world electricity demand data, and

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the results demonstrate its effectiveness in predicting future demand patterns. This work contributes to the growing body of research on deep learning techniques for forecasting the time series and highlights the potential applications of these techniques in the energy industry.

2. Problem Statement

Electricity demand forecasting is a crucial problem in the energy sector that has significant implications for the reliability, efficiency, and cost-effectiveness of the power system. Accurately forecasting electricity demand is necessary for power generation, transmission, and distribution planning, as well as for optimizing the use of resources and reducing greenhouse gas emissions. Traditional forecasting methods, such as time series analysis and regression models, have limitations in capturing the complex and nonlinear patterns in electricity demand. Therefore, there is a need for advanced forecasting models that can handle the nonlinear and dynamic nature of electricity demand.

In recent years, Long Short-Term Memory (LSTM) neural networks have emerged as a promising approach for electricity demand forecasting. LSTMs are a type of recurrent neural network that can capture long-term dependencies and nonlinear relationships in sequential data. Studies have shown that LSTMs are better in terms of accuracy and robustness than the conventional, especially in the case of short-term forecasting. For example, [2] used LSTMs to forecast the electricity demand in China and found that the LSTM model outperformed traditional forecasting models, such as ARIMA and SVR. In [1, 5] LSTM was used to forecast the electricity demand in Iran and found that the LSTM model achieved higher forecasting accuracy compared to traditional models. However, further research is needed to explore the potential of LSTMs for long-term forecasting and to develop practical applications for the power system.

This research aims to investigate the use of LSTMs for electricity demand forecasting, evaluate their performance, and compare them to traditional forecasting methods. The study also discusses the challenges and opportunities of using LSTMs for electricity demand forecasting and their implications for the power system.

3. Long Short-Term Memory Network

LSTMs are a type of recurrent neural network that can capture long-term dependencies and nonlinear relationships in sequential data. Unlike traditional feed-forward neural networks, which process input data in a fixed order, LSTMs can process input data in a sequential manner, making them well-suited for time-series forecasting tasks. The basic building block of an LSTM is a memory cell, which has an input gate, a forget gate, and an output gate.

The architecture of an LSTM typically consists of multiple memory cells, with each cell connected to the previous cell through a series of connections known as the hidden state. The input to each memory cell is a combination of the current input and the output of the previous memory cell in the sequence. The hidden state connections allow the LSTM to maintain information over long sequences of data, which is essential for tasks such as language modeling and speech recognition. The output of the final memory cell is then fed into a fully connected layer, which generates the final output of the LSTM as shown in fig. 1.

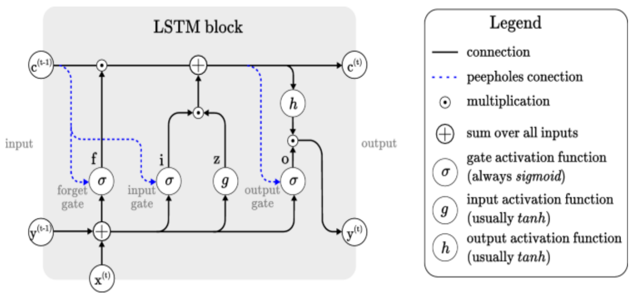

Figure 1. Architecture of LSTM

LSTMs have been shown to outperform traditional forecasting models in terms of accuracy and robustness, especially in the case of short-term forecasting. For example, [4,6] used an LSTM-based model to forecast the electricity demand in China, and achieved better results compared to traditional forecasting models such as ARIMA and SVR. Research [3,7,8] applied an LSTM-based model to forecast the electricity demand in Egypt and found that the LSTM model outperformed traditional models in terms of accuracy and efficiency. However, LSTMs are still limited by their ability to handle high-dimensional input data and long sequences of data. Further research is needed to improve the architecture and performance of LSTMs for more complex and longer-term forecasting tasks.

4. Proposed Method

Load curve data for Coimbatore region is collected from Tamil Nadu Electricity Board and plotted in fig. 2 using pyplot. This research puts forth a LSTM-based neural network architecture to forecast the electricity demands. The Keras framework is used in implementing the proposed design. Keras provides a user-friendly and intuitive interface for building and training deep learning models.

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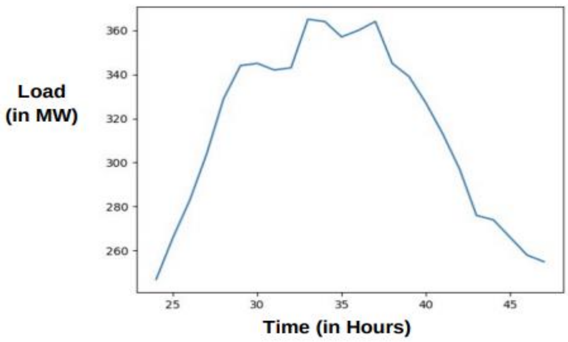

Figure 2. Load Curve Over a Day in Coimbatore

Keras offers a wide range of pre-defined layers, loss functions, optimizers, and evaluation metrics, making it suitable for various deep learning tasks, including time series analysis and prediction. Its simplicity and flexibility make it a popular choice among researchers and practitioners in the field of machine learning. Firstly, data preparation is done. It utilizes the "pandas library", which is a powerful data manipulation and analysis tool in Python, to concatenate the individual time series data. Pandas provides a comprehensive set of functions for data manipulation, including concatenation. In the code snippet, the concat() function from pandas is used to concatenate the data frames. This function allows for combining multiple data frames along a specified axis. The concatenation process is performed by creating an empty list called dfs to store the data frames. The code then iterates through each CSV file and extracts a subset of rows from each data frame using the iloc[] function. These data frames are then appended to the dfs list. Finally, the pd.concat() function is used to concatenate all the data frames in the dfs list into a single data frame. While the specific concatenation operation is done using pandas, the overall code snippet itself is written in Python, which is a versatile programming language commonly used for data analysis and machine learning tasks. Next, the code defines the architecture of the neural network using the

Tensor Flow library. The code starts by importing the necessary libraries for defining the neural network architecture, including the sequential model, LSTM layer, dense layer, and optimizer functions.

The neural network architecture consists of four layers, starting with an input layer that takes in 5 time steps of a univariate time series data, where each time step has a single feature [9][10]. The next layer is an LSTM layer with 64 memory cells, which can capture long-term dependencies in the input sequence. The output of the LSTM layer is then passed through two fully connected Dense layers, each with 8 neurons and a Rectified Linear Unit (ReLU) activation function. Finally, the output layer consists of a single dense neuron with a linear activation function, which produces the final output of the model. The LSTM layer is a crucial component of the neural network architecture for time-series forecasting. It is designed to selectively learn and forget information over time, making it well-suited for capturing long-term dependencies in sequential data. The fully connected Dense layers enable the model to learn complex non-linear relationships in the data. To train the neural network, the Mean Squared Error (MSE) loss function is used, and the Root Mean Squared Error (RMSE) metric is used to evaluate the model's performance. The Adam optimizer is used to optimize the model's parameters during training.

Overall, the proposed LSTM-based neural network architecture has shown promising results in previous studies for electricity demand forecasting. However, the choice of hyper-parameters such as the number of LSTM cells and fully connected Dense layers can significantly impact the model's performance and requires careful consideration. Future research may explore more advanced neural network architectures and hyper-parameter tuning techniques to improve the accuracy and generalizability of the model.

5. Results and Discussion

Load data from TNEB has been collected for Coimbatore Metro location with one hour resolution from May 2022 to March 2023. Data has been preprocessed and concatenated. Therefore, a total of 7291 data points has been used for load prediction. 6000 data points were taken as training data set and 1291 data points were taken as test and validation dataset. Number of epochs used for training is 25 and it is also tested for lower and higher number of epochs which either underfitted or overfitted the model. The chosen learning rate is 0.003. To measure the error rate an appropriate measuring unit used in these cases is called the Root Mean Squared

Error value. The RMSE value observed after 25 epochs is 11.46. Table 1 shows the predicted and actual values of load for test data, and it has showed that the model is well fitted as the actual data and test data is similar in their values.

Table 1. Data Showing Test Predictions with Actual Values

	Test Predictions	Actuals
0	194.677429	196
1	197.739716	194
2	197.455826	194
3	199.187851	199
4	210.096237	233
...	...	...
786	342.552704	348
787	329.585663	330
788	309.754791	310
789	286.592255	286
790	262.649994	265

791 rows × 2 columns

In fig. 3, fig. 4 and fig. 5, the yellow -colored curve represents the actual values, and blue -colored curve represents the predicted values. Fig. 3 depicts the load prediction for long term over 2 months. Fig. 4 and fig. 5 depict the load prediction for a random three -day period and for a 24 -hour period respectively. The predicted plot matches with the actual plot with an RMSE of 11.46.

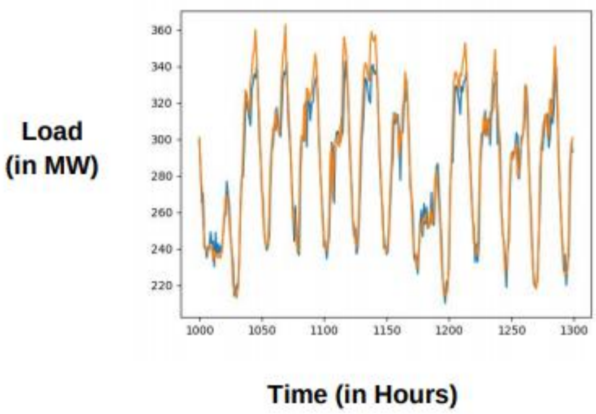

Figure 3. Long Term Prediction Curve

Load

(in MW)

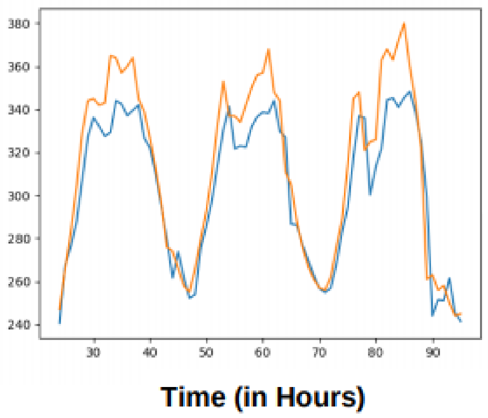

Figure 4. Prediction Curve Over 3 Days

Load

(in MW)

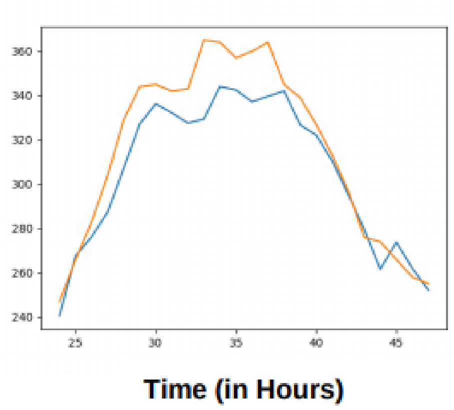

Figure 5. Prediction Curve for Random Sample Over a 24 Hour Period

When analyzing the output plots of an electricity load forecasting model with an RMSE value of 11.46, several insights can be gained.

Prediction Accuracy: The RMSE value of 11.46 indicates the average magnitude of the forecast errors. A lower RMSE value suggests better prediction accuracy. With an RMSE of 11.46, it can be inferred that the model's predictions may have some level of deviation from the actual load values. The output plots can be used to assess the model's performance in capturing the load patterns and identifying any potential biases or under/overestimations.

Load Profile Comparison: The output plots can display the actual load values alongside the predicted load values. By comparing the two profiles, it becomes possible to visually assess the model's ability to capture the load patterns and fluctuations accurately.

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Significant deviations between the predicted and actual load values can indicate areas where the model needs improvement.

Seasonal Patterns: Electricity load exhibits seasonal patterns influenced by factors like weather, holidays, and industrial activities. The output plots can help visualize whether the model effectively captures these seasonal patterns. If the predicted load values align well with the actual load values across different seasons, it suggests that the model has learned and incorporated the seasonal variations.

Peaks and Troughs: Peaks and troughs in the electricity load profiles represent periods of high and low demand, respectively. The output plots can help identify if the model accurately predicts these peak and trough points. If the predicted load values closely follow the actual load values during these periods, it indicates the model's ability to capture and forecast the load dynamics accurately.

Trend Detection: The output plots can reveal whether the model captures long-term load trends effectively. If the predicted load values show a similar trend to the actual load values, it indicates that the model is capable of capturing and forecasting gradual changes in the load pattern over time.

Forecast Horizon: The output plots can depict the forecast horizon, showing how far into the future the model's predictions extend. By examining the accuracy of the predictions over different time horizons, it becomes possible to determine the model's reliability in both short-term and long-term load forecasting.

Overall, the output plots provide a visual representation of the model's performance and its ability to capture the complex dynamics of electricity load. They allow for a more intuitive evaluation of the model's strengths and weaknesses, enabling further analysis and refinement of the forecasting process.

6. Conclusion and Future Scope

This research has proposed an LSTM-based neural network architecture for short-term electricity demand forecasting. This prediction model can be used by power generation side to appropriately generate enough power to serve the needs of the public. A good load prediction scheme would not only help reduce wastage of resources but also mitigate unwanted power outages that can hamper important services like hospitals and military. These kinds of systems would greatly aid in reducing the impact of greenhouse gases, as the major cause of it is the steam generation plants all over the world. LSTM based networks has been used extensively for all kinds of time series data for the past few years. But now there are advanced networks that has attention -based learning systems called transformers that are better suited for time series data which could be explored for load prediction in the future.

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