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Research Article

Electrical Energy Demand Forecasting using Time Series in LSTM and CNN-LSTM Models in Deep Learning Applications

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ABSTRACT

Introduction: Forecasting electrical energy demand is crucial for predicting future energy consumption patterns, which aids in effective energy management and distribution. Various forecasting methods have been developed, yet this study explores univariate time series analysis using Bidirectional Long Short-Term Memory (BiLSTM) and a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) model. These deep learning techniques are designed to capture both temporal dependencies and spatial patterns, improving predictive performance in energy forecasting.

Objectives: This study aims to evaluate the forecasting performance of deep learning models in univariate time series energy demand prediction. Specifically, it seeks to:

1. Implement and compare the forecasting performance of Bidirectional LSTM and hybrid CNN-LSTM models using a publicly available dataset from Transmission Service Operators (TSO).
2. Preprocess the dataset using appropriate data preparation techniques, such as normalization, handling missing values, and feature selection, before training the models.
3. Assess predictive accuracy by evaluating both models using key performance metrics, including Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and R-Squared (R^2).

Methods: The dataset used in this study was obtained from a public portal for Transmission Service Operators (TSO). Before training, the data underwent preprocessing techniques such as normalization, handling missing values, and feature selection to improve model performance. Two deep learning models—BiLSTM and CNN-LSTM—were implemented and trained on the dataset. The performance of each model was evaluated using four key metrics: **Mean Absolute Error (MAE)** – measures the average magnitude of errors, **Mean Absolute Percentage Error (MAPE)** – represents error as a percentage of actual values, **Root Mean Squared Error (RMSE)** – penalizes larger errors more heavily than MAE, **R-Squared (R^2)** – indicates how well predictions align with actual data.

Results: Experimental findings reveal that the hybrid CNN-LSTM model outperformed the BiLSTM model across all evaluation metrics. The CNN-LSTM model achieved a lower MAE of **499.08** compared to **780.56** in BiLSTM, a lower MAPE of **1.80%** versus **2.52%**, and a reduced RMSE of **671.37** compared to **1,042.20**. Additionally, the CNN-LSTM model obtained a slightly higher **R^2 score of 0.97** compared to **0.94** in BiLSTM, indicating a better fit for the data.

Conclusion: The results demonstrate that integrating CNN with LSTM significantly improves predictive accuracy in univariate time series energy demand forecasting. The CNN component enhances feature extraction, allowing the LSTM layers to capture complex temporal dependencies more effectively. Consequently, the hybrid CNN-LSTM model emerges as a more robust approach compared to BiLSTM alone, making it a valuable tool for accurate energy demand forecasting. Further research can explore additional deep learning architectures or hybrid models to optimize forecasting performance further.

Keywords: Hybrid CNN-LSTM, LSTM, Time Series Analysis, Energy Forecasting, Deep Learning

INTRODUCTION

Accurate forecasting of electrical energy demand is essential for ensuring the stability and efficiency of power systems. An overestimation of demand can lead to unnecessary energy production, increasing operational expenses, while an underestimation may cause supply shortages and potential power outages (Kumar & Janghel, 2022). To tackle these issues, researchers have developed advanced predictive models utilizing deep learning techniques, including Long Short-Term Memory (LSTM) networks and hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) architectures (Chung & Jang, 2022).

LSTM networks, a specialized type of recurrent neural network, are well-suited for capturing long-term dependencies in time-series data, making them highly effective in modeling energy consumption trends. The hybrid CNN-LSTM model combines convolutional layers, which extract spatial patterns, with LSTM layers that recognize temporal dependencies, resulting in improved forecasting accuracy for intricate energy usage patterns (Zhao & Zhang, 2023).

This study utilizes a dataset from the European Network of Transmission System Operators for Electricity (ENTSO-E), which provides extensive records of electricity generation, consumption, and cross-border transactions. The dataset contains hourly, monthly, and yearly aggregated consumption data by country, accessible through ENTSO-E's Power Statistics platform (ENTSO-E, n.d.). By employing univariate time series forecasting, this research seeks to enhance energy demand predictions using LSTM and hybrid CNN-LSTM models, ultimately improving the accuracy of demand forecasting and contributing to more effective energy management and operational planning.

Despite advancements in deep learning-based forecasting, further research is necessary to refine LSTM and hybrid CNN-LSTM models for univariate time series energy demand forecasting. Addressing these limitations can lead to more accurate predictions, supporting improved energy distribution, cost efficiency, and overall system reliability.

OBJECTIVES

The general objective of this study is to develop and evaluate deep learning models for forecasting electrical energy demand using univariate time series analysis.

Specific objectives:

1. To implement and compare the forecasting performance of Bidirectional LSTM and hybrid CNN-LSTM models using a publicly available Transmission Service Operators (TSO) dataset;
2. To preprocess the dataset using appropriate data preparation techniques before training the models; and
3. To assess the predictive accuracy of both models using key performance metrics, including Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and R-Squared (R^2).

METHODS

The hardware specifications used in this study are summarized in **Table 2**. These components were selected to provide adequate processing power, memory, and storage for running simulations and executing programs.

Table 2. Computer Hardware Specification

Hardware Components	Specification
CPU	Intel Core i7-8700 CPU @ 3.20Ghz
Memory	16GB RAM
Storage	1 TB HDD
GPU	6GB NVDDIA GTX 1660

B. Software

The software environment for this study consisted of various tools and platforms that facilitated programming, data analysis, and simulation. **Table 3** lists the software used, along with their respective licenses. The execution of python script also requires different deep learning libraries such as pandas, scikit-learn and tensoflow.

Table 3. List of Software

Name	License
Anaconda Navigator	Open-Source
Spyder	Open-Source
Jupyter Notebook	Open-Source
Python Programming Language	Open-Source

Implementation Flow

The implementation process follows a structured pipeline to ensure effective **data preparation, model development, and performance evaluation**. The key stages are shown in Figure 2 below also known as the implementation flow diagram.

Fig. 2. Implementation Flow Diagram

1. Data Gathering

The dataset, obtained from a Transmission System Operator (TSO) portal, covers a four-year period from 2015 to 2018, with hourly recorded measurements (Roy, Ishmam, & Taher, 2021). It encompasses data on electricity generation from various energy sources, including fossil fuels, renewable energy, and nuclear power. Additionally, it provides insights into power consumption by comparing projected electricity demand with actual usage. The dataset also includes electricity pricing details, reflecting hourly market price variations. Due to its high-resolution time-series format, this dataset is valuable for trend analysis and serves as a strong foundation for predictive modeling. Figure 2 presents a visualization of electrical energy consumption.

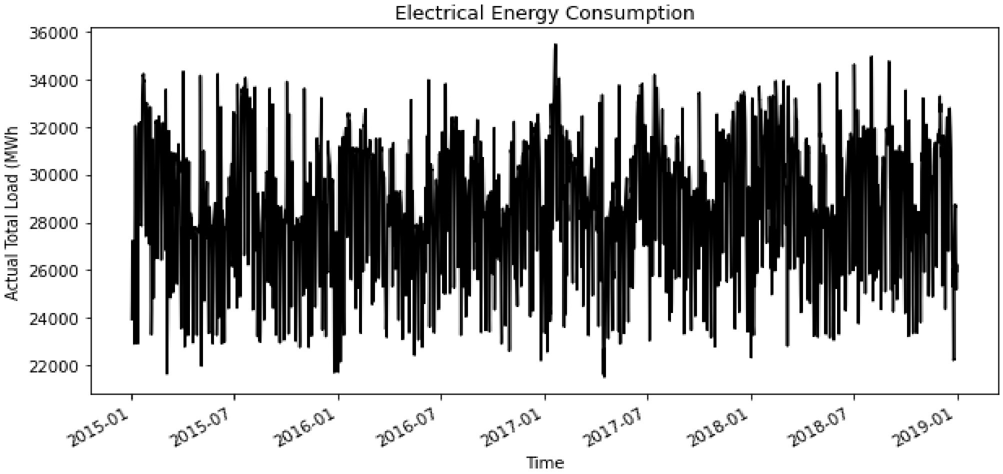

Fig 2. Dataset visualization

2. Data Preprocessing

The dataset was cleaned by removing unnecessary parameters, retaining only time and total load columns. The dataset was loaded from a CSV file using the pandas library, with the first column serving as the target variable. Any missing values were removed to ensure data integrity. To facilitate efficient model training, the data was normalized using MinMaxScaler, which scales values between 0 and 1, preventing large variations from affecting model performance.

The time-series data was transformed into sequences through a custom function that creates input-output pairs based on a predefined sequence length. The dataset is then split into training and testing sets, with 80% allocated for training and the remaining 20% for testing. The preprocessed data is then utilized in training Bidirectional LSTM and hybrid CNN-LSTM models for forecasting.

3. Model Selection & Hyperparameter Tuning

In this study, two deep learning models, Bidirectional Long Short-Term Memory (BiLSTM) and a hybrid Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM), were implemented for time-series forecasting. Both models were configured with carefully selected hyperparameters to produce best predictive performance. The BiLSTM model utilized two bidirectional LSTM layers, each with 64 units and ReLU activation. The first LSTM layer returned sequences to preserve temporal dependencies, while the second layer incorporated L2 regularization (0.001) to prevent overfitting. A dropout rate of 0.2 was applied after the LSTM and dense layers to further enhance generalization. The fully connected layer comprised 32 neurons with ReLU activation, followed by a final output layer with a single neuron for prediction. The Adam optimizer, with a learning rate of 0.0005, was Training was conducted for 30 epochs with a batch size of 32, and early stopping was implemented, monitoring validation loss with a patience level of 20 to prevent unnecessary overfitting.

Similarly, the hybrid CNN-LSTM model was designed with an initial convolutional layer consisting of 64 filters, a kernel size of 3, and ReLU activation to extract spatial features. This was followed by a max pooling layer with a pool size of 2 and batch normalization to stabilize training. The extracted features were then passed through two stacked LSTM layers, each with 64 units and L2 regularization (0.001). Dropout layers with a rate of 0.2 were applied after the LSTM and dense layers to prevent overfitting. A fully connected layer with 32 neurons and ReLU activation was included before the final output layer. Like the BiLSTM model, this architecture was trained using the Adam optimizer with a 0.0005 learning rate and an MSE loss function. The training process followed the same setup of 30 epochs, a batch size of 32, and early stopping with a patience value of 20.

4. Evaluation Metrics

The evaluation of model performance in this study was conducted using four key metrics: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). The formula are:

$\text{MAE} = (1/n) \sum |y_i - \hat{y}_i|$
$\text{MAPE} = (100/n) \sum |(y_i - \hat{y}_i) / y_i|$
$\text{RMSE} = \text{sqrt}((1/n) \sum (y_i - \hat{y}_i)^2)$
$R^2 = 1 - (\sum (y_i - \hat{y}_i)^2 / \sum (y_i - \bar{y})^2)$

Where:
- y_i = actual value
- $\hat{y}_i$ = predicted value
- $\bar{y}$ = mean of actual values
- n = number of data points

RESULTS

A. Training and Validation Loss

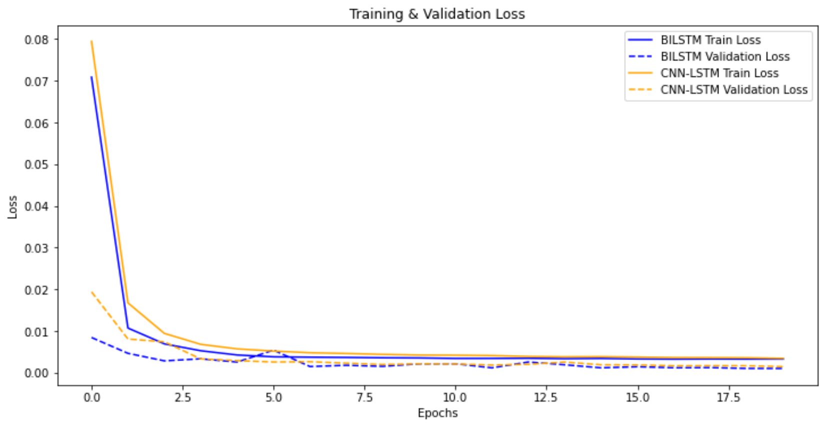

Fig 3. Training and validation loss of LSTM and hybrid CNN-LSTM

B. Evaluation

Table 4. Comparison of the models based on the metrics used

Model	Mean Absolute Error (MAE)	Mean Absolute Percentage Error (MAPE)	Root Mean Squared Error (RMSE)	R-Squared (R2)
BidirectionalLSTM	780.56	2.52	1042.20	.94
hybrid CNN-LSTM	499.08	1.80	671.37	.97

C. Prediction

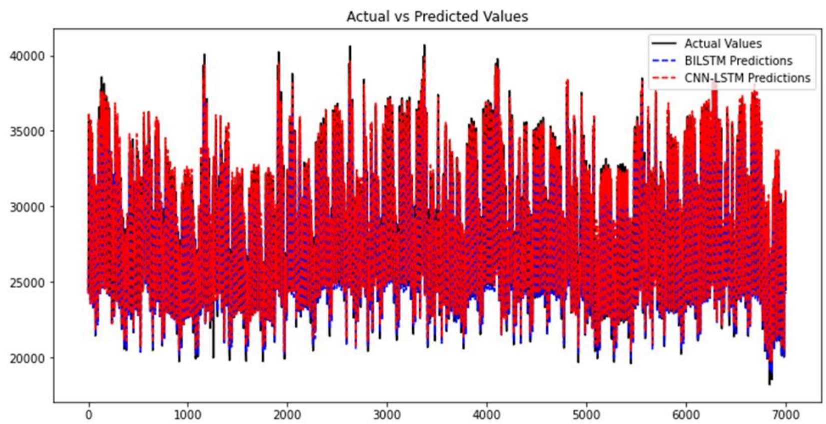

Fig 4. Predicted Graph

DISCUSSION

Illustrated in Figure 3 is the training and validation loss of the Bidirectional LSTM (BiLSTM) and CNN-LSTM models over 30 epochs. Both models demonstrate a rapid decrease in loss during the initial epochs, indicating efficient learning of the data's underlying patterns. As training progresses, the loss values stabilize, suggesting that both models reach convergence effectively.

While Bidirectional LSTM maintains a slightly lower validation loss, CNN-LSTM (represented by the orange lines) exhibits a competitive performance with a smooth and consistent loss path. The CNN-LSTM model benefits from its ability to extract spatial features using convolutional layers before passing the information to LSTM layers for sequential learning.

Furthermore, CNN-LSTM shows a stable training process, as indicated by the absence of significant fluctuations in loss. This stability suggests that the model is learning efficiently without major risks of overfitting or underfitting. While the BiLSTM model slightly outperforms in validation loss, CNN-LSTM remains a strong contender due to its computational efficiency and ability to capture spatial-temporal relationships.

The results presented in **Table 4** between the comparison of the Bidirectional LSTM and hybrid CNN-LSTM models based on evaluation metrics reveals that the hybrid CNN-LSTM outperforms the Bidirectional LSTM in forecasting accuracy. The hybrid CNN-LSTM achieves a lower Mean Absolute Error (MAE) of 499.08 compared to 780.56 for the Bidirectional LSTM, indicating that the hybrid CNN-LSTM has a smaller average difference between predicted and actual values. Similarly, the Mean Absolute Percentage Error (MAPE) is lower for the hybrid CNN-LSTM at 1.80%, compared to 2.52% for the Bidirectional LSTM, signifying a more accurate percentage-based deviation. Additionally, the Root Mean Squared Error (RMSE) for the hybrid CNN-LSTM is significantly lower at 671.37 compared to 1042.20 for the Bidirectional LSTM, suggesting that the hybrid model has better predictive performance with fewer large errors. Lastly, the R-squared (R^2) value of the hybrid CNN-LSTM (0.97) is higher than that of the Bidirectional LSTM (0.94), demonstrating that it explains more variance in the data and provides better model fit.

Figure 4 presented a comparative analysis of actual values and predictions generated by Bidirectional LSTM (BiLSTM) and hybrid CNN-LSTM models for time-series forecasting. The actual observed values are represented by a black line, while the predictions from the BiLSTM model are depicted with a blue dashed line, and the CNN-LSTM predictions are shown using a red dashed line.

Both models effectively capture the overall trend of the dataset, as evidenced by their ability to follow the fluctuations and patterns in the actual values. The predictions exhibit a similar structure to the actual data, indicating that both models have learned the temporal dependencies within the dataset.

However, hybrid CNN-LSTM model appears to provide predictions that are more closely aligned with the actual values compared to the BiLSTM model. The BiLSTM predictions display slightly more deviations, showing struggle to capture extreme fluctuations effectively. The graph demonstrates that both models are capable of time-series forecasting, but the CNN-LSTM model appears to be more effective in aligning with actual values. The integration of convolutional layers within the LSTM framework enhances feature extraction, leading to improved prediction accuracy.

CONCLUSION

This study evaluated the performance of Bidirectional LSTM and hybrid CNN-LSTM models for time series forecasting. The results indicate that the hybrid CNN-LSTM model is more effective than the Bidirectional LSTM in terms of accuracy and error reduction. The hybrid model exhibited lower error rates and a higher R^2 value, confirming its ability to better capture patterns in the data. These results highlight the advantages of combining convolutional and recurrent neural networks for time-series forecasting, particularly in applications requiring high accuracy and strong predictions.

RECOMMENDATION

Based on the findings, it is recommended that future research explore additional enhancements to the hybrid CNN-LSTM model, such as hyperparameter tuning or transformer-based architectures, to further improve predictive performance.

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