Optimizing Input Sequence for CNN-LSTM Multi-Step Load Prediction

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Short-term electricity load forecasting helps sustain grid operations while increasing power generation output and supporting efficient energy distribution. The study examines how different input sequence lengths affect deep learning model performance during multi-step load forecasting. The researchers conducted a study to assess four models which included Gated Recurrent Unit (GRU) and CNN-LSTM and Bidirectional LSTM (BiLSTM) and CNN-RNN through testing on a real-world electricity consumption dataset from Panama which included both hourly and daily forecasting tasks. Tested multiple historical window sizes to study input sequence optimization effects while they used Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) to assess model performance. The results show that CNN-LSTM model delivers better accuracy for daily forecasts while BiLSTM model produces the most precise hourly forecasts. The research shows that using the optimal input sequence length leads to better forecasting accuracy because it helps predict time-based patterns while reducing unnecessary data. The research investigates historical load data together with time-related features but it recognizes that external elements like weather and holidays significantly affect electricity demand which should be examined in upcoming research. The team created a Flask-based web application which allows users to predict and display real-time load data through the most successful model.

Keywords: Short-term load forecasting, CNN-LSTM, GRU, BiLSTM, CNN-RNN, electricity demand, input sequence length, deep learning, web application.

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1. Introduction

Electricity load forecasting has become an instrumental tool in ensuring that there is stability in the grid and balancing of energy supply and demand, as well as optimising resource allocation. Operational Planning, demand-side management, and cost reduction in the electricity market are all especially dependent on short-term load forecasting (typically ranging over a few hours to a few days). When properly forecasted, such predictions enable power suppliers and grid operators to maximize generation plans, minimize operating expenses and eliminate squandering or lack of energy. Nevertheless, electricity demand is always a challenging issue because of non-linearity, dynamism and time-dependence of the load patterns which are affected by time of the day, seasonality, weather as well as the human activity. Conventional forecasting models, such as ARIMA, linear regression and exponential smoothing, non-cyclic statistical models tend to miss these complicated time dependencies. They typically use historical inputs of a fixed length and linear assumptions and are restricted in their multi-step predictions. ML models, including Support Vector Machines and Random Forests, enhance the ability to predict, although they are yet to master the issue of sequential dependencies and changing input settings. Moreover, a large majority of the current systems do not contain user friendly interfaces whereby the accurate forecasting cannot be made available to the non-technical stakeholders.

This project will solve these problems through exploration of how the length of input sequence can affect the precision of short-term multi-step electricity load prediction with sophisticated deep learning architectures. In particular, there are four models, namely, Gated Recurrent Unit (GRU), Convolutional Neural Network with LSTM (CNN-LSTM), Bidirectional LSTM with Dense layers (BiLSTM) and a CNN-RNN hybrid, which were trained and tested on a Panama-based real-world electricity consumption dataset. Hourly and daily forecasts have been taken into account to examine the performance of the model in terms of various granularities. The CNNLSTM was the most accurate at prediction and it can respond to both time and space features of load data used to test the models. In order to enable effective implementation, the chosen CNN-LSTM model was implemented in the form of a Flask-based web-application. The site offers a safe login service and gives the user an opportunity to add dates to the site to get predictions with interactive visuals that allow one to make decisions that will guide them to manage their energy well. This study handles this gap by studying the input sequence length role, and it provides users with a functional forecasting tool, which is scalable, precise, and provides a user-friendly solution to electric load forecasting on a short time frame.

2. Related Work

Deep learning-based hybrid architectures have become the main method for improving STLF prediction accuracy through their recent developments. The hybrid models that combine convolutional neural networks with recurrent architectures for electricity load data analysis achieve high performance because they can handle both spatial and temporal dependencies. The particle swarm optimization method has been used to create a multi-head attention system that enhances feature extraction from load data by combining spatial and temporal representations together with CNN–LSTM networks [1]. The application of hybrid CNN-BiLSTM systems to residential load forecasting showed that bidirectional methods effectively capture how energy consumption changes over time through sequential data analysis [2]. The optimized CNN-LSTM hybrid frameworks have outperformed both CNN and LSTM models in forecasting accuracy because they use Pearson correlation feature selection before training the model [3].

The development of hybrid deep learning architectures combined with transfer learning and sequence-to-sequence modelling approaches has demonstrated their ability to enhance forecasting accuracy for various energy systems. The application of deep transfer learning methods to day-ahead load forecasting proved that pretrained knowledge enhances prediction accuracy for different clients and regions according to [4]. Researchers investigated how dimensional expansion methods combined with convolutional neural networks enable them to extract superior feature representations from high-dimensional electricity load datasets according to their study in [5]. The development of integrated smart-grid information management systems used deep learning-based STLF models to assist decision-making processes and energy management activities according to [6].

Another emerging trend in load forecasting research involves feature decomposition and attention-based hybrid models. Advanced architectures combining decomposition techniques with recurrent neural networks and attention mechanisms have been proposed to capture multi-scale patterns in load data, thereby improving prediction accuracy under complex temporal dynamics [7]. Hybrid networks integrating DenseNet structures, attention mechanisms, and LSTM layers have also been proposed to address challenges related to long-term dependency modelling and feature reuse in smart grid forecasting tasks [8]. Comparative analyses of spatial and recurrent deep learning models have further highlighted the importance of spatio-temporal correlations in improving short-term electricity load prediction performance [9]. In parallel, transformer-based architectures and dynamic graph models have recently emerged as promising alternatives for modelling complex multi-scale temporal dependencies in energy forecasting systems [10].

Residential energy consumption forecasting uses deep hybrid architectures as their prediction method. The system uses Dilated convolutional neural networks together with LSTM autoencoders and attention mechanisms to model nonlinear residential load patterns [11]. The research team combined variational mode decomposition with deep learning frameworks to create a pre-processing solution that handles non-stationarity problems in multi-horizon load forecasting while improving data representation for prediction purposes [12]. Hybrid CNN and stacked BiLSTM architectures have been used successfully in real-world datasets to forecast electricity loads at the city scale which resulted in better prediction outcomes for urban energy systems [13].

The latest research investigates ConvLSTM-3D networks which use fusion-based feature learning methods because they enable three-dimensional spatial-temporal modelling of electricity load data which enhances forecasting systems' ability to identify complex dependencies [14]. The existing surveys of CNN-based hybrid architectures already demonstrate their ability to solve traditional statistical forecasting model problems while the surveys identify present obstacles and future research possibilities for deep learning-based load forecasting systems [15].

3. Proposed Methodology

The suggested system presents a deep learning framework of short-term multi-step electricity load prediction, the aim of which is to know how the length of the input sequence influences the accuracy of the prediction. In contrast to classic statistical models where nonlinear temporal relationships cannot be defined, this design makes use of hybrid neural network models that can model the complex patterns in electricity consumption data. The system is created to be practically implemented as web application using Flask, which gives users the opportunity to communicate with forecasting model.

3.1 System Overview

The framework is broken down into three major sections, which include data pre-processing, model development and evaluation, and web application deployment. The basis of this study is the historical electricity load data of Panama that contains hourly and daily consumption data. The pre-processing of data consists of cleaning up missing or inconsistent data, normalization and conversion into sequences of variable input length appropriate to multi-step forecasting. The system identifies the size of the best sequence to use in order to make correct predictions by evaluating the various input windows.

3.2 Methodology

1. Data Collection and Cleaning: Load data is brought by the official records and trimmed to eliminate anomaly and outliers. Linear interpolation is used to provide missing values so that continuity among time series sequences is guaranteed.
2. Feature Engineering: Hour of day, day of week, and seasonality are also added to represent the editorial changes in electricity demand.
3. Sequence Generation: The clean data is divided into overlapping sequences with varying lengths in order to test the effects of input size on forecasting. Multi-step forecasting is aimed at the short-term hourly and daily predictions.
4. Model Implementation: There are four deep learning architectures that are implemented to compare them:
    - Gated Recurrent Unit (GRU): GRU is effective to address the problems of temporal dependence, as well as to cope with vanishing gradients, which is why it is a good choice when working with sequential load data.
    - CNNLSTM Hybrid: This model consists of convolutional LSTM layers forming hybrid spatial and temporal dependencies. This composite method has shown higher effectiveness in the process of capturing the local and long-term trends in the electricity load.
    - BiLSTM with Dense Layers: Works in both forward and backward directions, enabling the model to learn past and future contexts. Layers of density help to intensify non-linear transformations to predict.
    - CNN + RNN: This is a hybrid architecture that combines CNN with local pattern recognition and simple RNN with local pattern recognition to give a baseline of a hybrid architecture.
5. Model Training and Evaluation: MSE loss is used to train the models and Adam optimizer is used to optimize them. In order to prevent overfitting, cross-validation is used. Multi-step prediction performance metrics are RMSE, MAE and MAPE.
6. Input Length Optimization: The system systematically changes the length of input sequence to find the best window that gives maximum prediction accuracy in hourly and daily forecast.

3.3 Flask-Based Application for System Implementation

The development team created a web-based application through Flask to deliver an easy-to-use interface which solves electricity load forecasting needs. The platform enables users to create secure accounts and access their accounts while entering date information to receive multi-step load forecasts produced by the CNN-LSTM model. The application uses interactive visualizations to show forecasted and actual load values which non-technical stakeholders can easily understand. The application combines all stages of prediction from data preprocessing to model inference to produce dependable results. Its modular design enables future system enhancements which will add new models and external features to create an energy management system that operates effectively in practical environments.

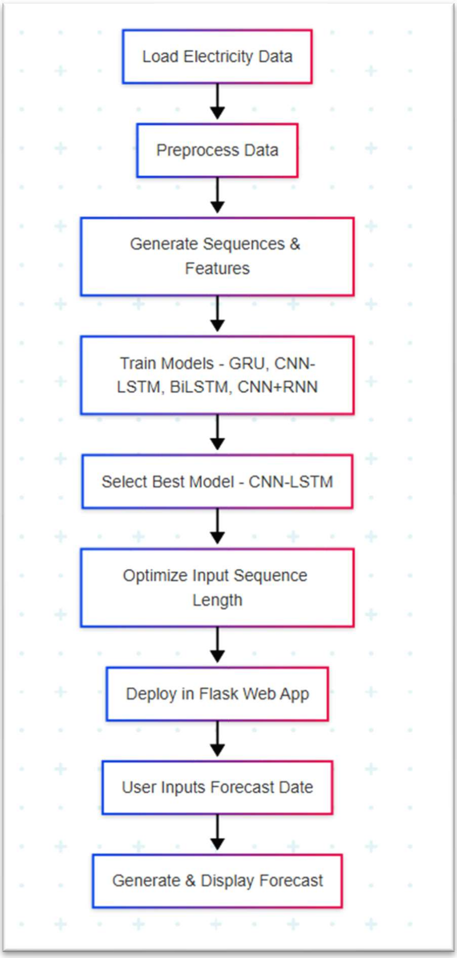

Figure 1 Proposed Methodology flow

4. Architecture Details

4.1 CNN-LSTM Architecture

The hybrid CNN-LSTM model is made up of one-dimensional convolutional layers followed by layers of max-pooling which are used to derive the temporal features. These features are then fed into LSTM layers that are stacked in order to learn the time-dependencies. Finally, the multi-step predictions are made through the fully connected dense layers. This architecture balances the two aspects of recognizing short-term local patterns and modelling the dependencies that last over a long time which is a crucial requirement in load forecasting.

The proposed system offers multiple advantages over traditional forecasting approaches:

- Higher Prediction Accuracy: Utilizing hybrids deep learning models, the system is able to identify complex temporal and spatial dependencies in load data.
- Input Length Analysis: Conducts a thorough evaluation of input sequence lengths systematically to achieve maximum multi-step forecasting performance.
- Multi-step Forecasting: Encompasses both hourly and daily predictions, thus satisfying different operational needs.
- User-centric Interface: User-centric Interface: Forecasting is made available to stakeholders who are less technical through a Flask web application.
- Modularity: The design facilitates easy extension to cover renewable energy data, dynamic retraining, or other deep learning models.

5. Results and Discussion

The section demonstrates the experimental testing process of deep learning models which have been developed for short-term electricity load forecasting. The researchers tested four different architectural models which included GRU CNN-LSTM BiLSTM and CNN-RNN to assess their performance with hourly and daily electricity consumption data. The researchers evaluated model performance through three standard evaluation metrics which included Mean Absolute Error and Mean Squared Error and Root Mean Squared Error.

5.1 Model Performance Comparison

Tables I and II summarize the performance of the evaluated models for hourly and daily forecasting respectively.

Table 1 Performance Comparison for Hourly Load Forecasting

Model	MAE	MSE	RMSE
BiLSTM	12.49	320.82	17.91
CNN-RNN	13.39	370.20	19.24
CNN-LSTM	16.66	533.38	23.10
GRU	17.34	520.36	22.81

Table 2 Performance Comparison for Daily Load Forecasting

Model	MAE	MSE	RMSE
CNN-LSTM	1114.06	2301292.15	1517.00
CNN-RNN	1147.07	2398798.90	1548.81
GRU	1419.31	3210338.77	1791.74
BiLSTM	1439.89	3335320.80	1826.29

Forecasting models show different results because their performance depends on the specific time intervals used for making predictions. The BiLSTM model performed best in hourly forecasting because it achieved the lowest error rates which showed its ability to track brief electricity load changes. The CNN-RNN model achieved good results that were almost equal to the performance of the other system although its error rates were slightly higher. The GRU and CNN-LSTM models showed lower accuracy because they could not predict hourly forecasts correctly.

The CNN-LSTM model achieved the highest performance among all tested systems during daily forecasting. The hybrid structure of CNN and LSTM allows the model to effectively capture both local temporal patterns and long-term dependencies in the electricity consumption data. The CNN-RNN model also showed comparable performance, while GRU and BiLSTM produced higher prediction errors for daily load forecasting.

The results show hybrid deep learning systems which combine convolutional and recurrent components successfully model complex time-based patterns in electricity load data.

5.2 Effect of Input Sequence Length

The researchers tested various historical window sizes to determine how different input sequence lengths affected the ability to forecast results. The researchers conducted tests with three input sequence durations which included 24 hours, 72 hours, and 168 hours across all models.

The results indicate that shorter input sequences, such as 24 hours, are insufficient to capture long-term temporal dependencies, which leads to increased prediction errors. The sequence length needs to be extended to 72 hours, which results in better performance because it enables the system to access more situational details. The optimal results occur when the system uses an input sequence that lasts 168 hours because this duration shows complete weekly usage patterns.

The system tested multiple settings, which showed that 168-hour input sequence length achieved the lowest error rates across essential performance standards. This finding demonstrates that proper sequence selection plays a critical role in enhancing multi-step load forecasting accuracy.

Table 3 Effect of Input Sequence Length on CNN-LSTM Performance

Sequence Length	Performance Trend
24 hours	Higher error due to limited temporal context
72 hours	Improved performance with moderate context capture
168 hours	Lowest error with optimal temporal dependency learning

Figure 2 GRU Model

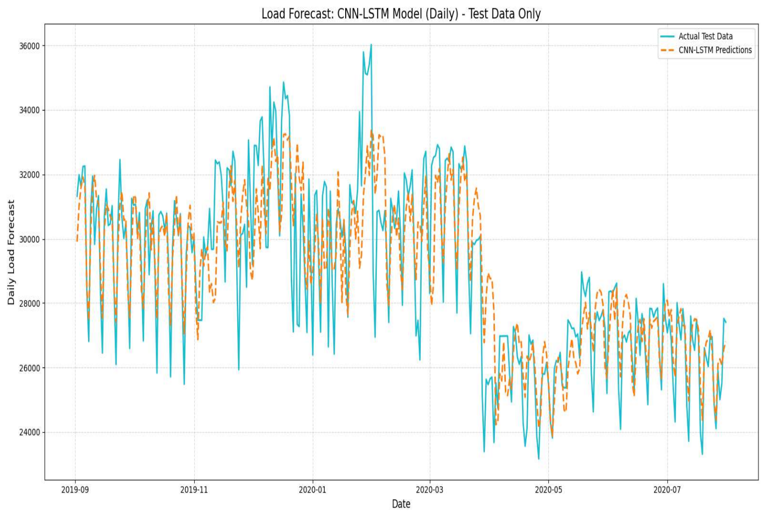

Figure 3 CNN+LSTM Model

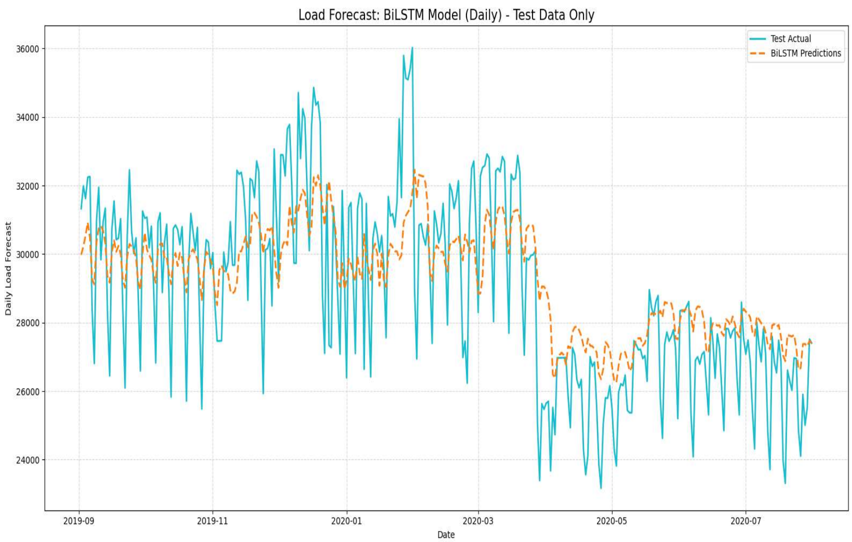

Figure 4 Bi-LSTM Model

Figure 5 CNN-RNN Model

The prediction performance of each model is further illustrated through graphical comparisons between the actual and predicted electricity load values. The forecasting results of the GRU model are shown in Fig. 2, where the predicted load values generally follow the overall trend of the actual electricity consumption data. The model shows minor deviations between actual and predicted values because it lacks the ability to detect sudden changes in demand.

The performance of the CNN-LSTM model is illustrated in Fig. 3. The actual load patterns can be tracked by the predicted load values which the model uses to establish both short-term and long-term patterns. The system experiences only brief interruptions which happen when demand reaches its highest point.

The BiLSTM model forecasting results display their outcomes in Fig. 4. The model succeeds in showing the main electricity demand pattern but it creates a smooth effect on extreme demand peaks. The model generates stable predictions which show a small tendency to underpredict quick demand changes.

The CNN-RNN model predictions appear in Fig. 5. The predicted values in the figure show a close match to the actual load curve throughout most of the time periods. The model shows minor deviations between actual load patterns and predicted values during instant load shifts, which creates chances for improved model development.

The graphical results prove that all four models successfully learn how electricity consumption data behaves over time. The hybrid architectures which combine CNN-LSTM and CNN-RNN systems demonstrate better performance than other systems for handling complicated time-dependent patterns, which makes them ideal for short-term load forecasting in real-world scenarios.

6. Conclusion

Researchers developed a deep learning framework to forecast electricity load for multiple steps within a short timeframe while studying how different input sequence lengths affect their forecast accuracy. Researchers used a real-world electricity consumption dataset from Panama to implement and assess four deep learning models which included GRU and CNN-LSTM and BiLSTM with Dense layers and a CNN-RNN hybrid model for both hourly and daily load forecasting tasks.

The experimental results demonstrate that the CNN-LSTM model consistently outperforms the other architectures in terms of prediction accuracy and stability. The CNN-LSTM architecture uses convolutional layers for local feature extraction and LSTM layers for long-term temporal dependency modeling to capture both electricity demand short-term fluctuations and long-range patterns. The evaluation using performance metrics such as RMSE, MAE, and MAPE shows that this hybrid model produces predictions that closely follow the actual load trends, particularly during normal demand periods.

The study makes an essential contribution through its organized exploration of how various input sequence lengths affect predictive accuracy in forecasting models. The experiments indicate that selecting an appropriate historical window significantly improves prediction accuracy, as it enables the model to learn meaningful temporal patterns without introducing unnecessary noise or redundancy. The findings show that input sequence length optimization functions as a vital element which enhances the dependable performance of multi-step load forecasting models.

The forecasting system implemented their most successful CNN-LSTM model into a Flask-based web application to achieve better practical system performance. The platform provides a secure login interface where users can input specific dates to obtain load forecasts along with interactive visualizations. This implementation connects academic research with actual implementations by providing energy planners and stakeholders with accessible forecasting insights through a user-friendly interface.

7. Future Scope

Future research can improve the electricity load forecasting framework through the inclusion of additional external factors which affect energy consumption patterns. The deep learning models will achieve better predictive performance through the integration of temperature and humidity and weather conditions and public holidays into their input features. The proposed system can also be extended to support medium-term and long-term load forecasting which would benefit strategic energy planning and grid management. Advanced deep learning architectures such as attention-based models and transformer networks and graph neural networks should be studied to detect electricity demand patterns from space and time. The system can be improved through the creation of adaptive or dynamic input sequence selection systems which will identify the best historical window from which to make predictions. The current Flask-based web application can be developed into a scalable cloud-based system which will process data from multiple regions while delivering real-time energy forecasting solutions to utilities and smart grid networks.

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