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Driving efficiency and sustainability: deep learning-based load forecasting at the substation level

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Abstract

This paper presents an investigation into the effectiveness of Long Short-Term Memory (LSTM) neural networks for forecasting electrical load at a substation level. Electrical load forecasting is a challenging task due to the stochastic nature of time series data, which creates noise and reduces prediction accuracy. To address this issue, we propose a deep learning model based on LSTM recurrent neural networks, which we evaluate using a publicly available 30-minute dataset of real power measurements from individual zone substations in the Ausgrid3 supply area. Our proposed LSTM model with 2 hidden layers and 50 neurons outperforms alternative configurations, achieving a mean absolute error (MAE) of 0.0050 in short-term load forecasting tasks for substations. The findings suggest that the proposed LSTM model is a promising tool for accurate electrical load forecasting, which can be applied to other substations worldwide to improve energy efficiency and reduce the risk of power outages. This paper contributes to the ongoing discussion surrounding the development of reliable forecasting models for electrical load, providing valuable insights for researchers and industry professionals alike.

Keywords: electrical load forecasting, long short-term memory (LSTM), recurrent neural networks, deep learning, substation, energy efficiency.
JEL classification: Q40, Q49, C53.

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Impulsando la eficiencia y la sostenibilidad: previsión de carga basada en aprendizaje profundo a nivel de subestación

Resumen

Este artículo presenta una investigación sobre la eficacia de las redes neuronales de memoria a corto plazo (LSTM) para predecir la carga eléctrica a nivel de subestación. La predicción de la carga eléctrica es una tarea difícil debido a la naturaleza estocástica de los datos de series temporales, que crea ruido y reduce la precisión de la predicción. Para abordar este problema, proponemos un modelo de aprendizaje profundo basado en redes neuronales recurrentes LSTM, que evaluamos utilizando un conjunto de datos de 30 minutos disponible públicamente de mediciones de potencia real de subestaciones de zonas individuales en el área de suministro Ausgrid3. Nuestro modelo LSTM propuesto con 2 capas ocultas y 50 neuronas supera a las configuraciones alternativas, logrando un error medio absoluto (MAE) de 0,0050 en tareas de previsión de carga a corto plazo para subestaciones. Los resultados sugieren que el modelo LSTM propuesto es una herramienta prometedora para la previsión precisa de la carga eléctrica, que puede aplicarse a otras subestaciones de todo el mundo para mejorar la eficiencia energética y reducir el riesgo de cortes de suministro. Este artículo contribuye al debate en curso sobre el desarrollo de modelos fiables de previsión de la carga eléctrica, proporcionando información valiosa tanto para investigadores como para profesionales del sector.

Palabras clave: previsión de carga eléctrica, memoria a largo plazo (LSTM), redes neuronales recurrentes, aprendizaje profundo, subestación, eficiencia energética.
Clasificación JEL: Q40, Q49, C53.

1. Introduction

Load forecasting plays a crucial role in the efficient operation and planning of the electricity system. Accurate forecasts of electricity demand are essential for utilities to effectively manage their generation, transmission, and distribution resources, and ensure reliable and cost-effective power supply.

Load forecasting enables utilities to make informed decisions regarding capacity expansion, load balancing, and demand response programs.

According to a study by (Yaoyao, Jingling, Xueli, Chaojin, & Jian, 2022), load forecasting has become increasingly important in the electricity industry. The authors emphasize that accurate load forecasts are vital for optimizing resource allocation, improving energy efficiency, and enhancing grid stability. Moreover, load forecasting has gained even more significance with the emergence of smart grid technologies, as it enables utilities to effectively integrate renewable energy sources, electric vehicles, and demand-side management strategies.

This research aims to contribute to the field of load forecasting by proposing an integrated framework that utilizes Long Short-Term Memory (LSTM) neural networks. LSTM networks have shown promising results in capturing the complex temporal dependencies and non-linear patterns present in load data, making them well-suited for accurate load forecasting. The proposed framework will be tested using publicly available data from the Newcastle CBD substation in the Ausgrid network.

The structure of this research is as follows: In Section I, we provide an overview of the importance of load forecasting in the electricity system, highlighting its role in resource optimization and grid stability. Section II presents the methodology and framework, detailing the architecture and training process of the LSTM neural network for load forecasting. Section III describes the experimental setup, including the dataset used and the evaluation metrics employed. The results of the load forecasting experiments are presented and discussed in Section IV. Finally, Section V concludes the research, summarizing the findings, discussing their implications, and suggesting potential avenues for future research in this field.

Through this research, we aim to demonstrate the effectiveness of LSTM neural networks in load forecasting and contribute to the development of accurate and reliable methods for load forecasting in the electricity system.

2. An overview of the importance of load forecasting in the electricity system

2.1 Introduction to Load Forecasting

Load forecasting plays a pivotal role in the electricity system by enabling utilities to effectively manage their resources, balance supply and demand, and ensure reliable power supply. Accurate load forecasts are crucial for optimizing resource allocation, enhancing grid stability, and supporting decision-making processes in the energy industry (ABDULLAH, y otros, 2020) With the rapid advancements in technology and the increasing integration of renewable energy sources, electric vehicles, and demand-side management, load forecasting has gained even greater significance in recent years.

Traditionally, load forecasting relied on statistical techniques such as time series analysis and regression models. However, these methods often struggle to capture the complex temporal dependencies and non-linear patterns present in load data, leading to suboptimal accuracy. The emergence of deep learning techniques, specifically Long Short-Term Memory (LSTM) neural networks, has revolutionized load forecasting by effectively capturing long-term dependencies and modeling intricate relationships within the data (Cai, Yuan, Tianqi, & Zhixiang, 2021). LSTM networks have demonstrated remarkable success in various domains, including speech recognition, natural language processing, and, more recently, load forecasting.

Accurate load forecasting is paramount for utilities to make informed decisions regarding capacity planning, load balancing, and demand response programs. Underestimating or overestimating electricity demand can have substantial economic and operational consequences, such as excessive costs for infrastructure investments or insufficient power supply during peak periods. Consequently, accurate load forecasts enable utilities to optimize their operations, reduce costs, and enhance energy efficiency.

By providing a comprehensive overview of load forecasting's significance, the limitations of traditional techniques, and the emergence of LSTM neural networks, this research aims to contribute to the ongoing discussion on accurate load forecasting. The subsequent sections will delve into the methodology, experimental setup, and results, showcasing the proposed integrated load forecasting framework based on LSTM neural networks and its effectiveness in improving load forecasting accuracy.

I.2 Review of literature

Load forecasting techniques and methodologies have evolved significantly over the years, driven by the need for accurate predictions in the electricity industry. This section provides a comprehensive review of relevant literature on load forecasting, exploring both traditional statistical methods and the emergence of deep learning techniques, particularly Long Short-Term Memory (LSTM) neural networks.

Traditional statistical methods, such as time series analysis and regression models, have long been employed for load forecasting. These methods rely on historical load data, weather variables, and other relevant factors to predict future electricity demand. However, traditional methods often struggle to capture the complex non-linear relationships and non-stationary nature of load data, resulting in suboptimal forecasting accuracy (Pełka, 2023). Additionally, these methods may not effectively handle the temporal dependencies present in the data.

In recent years, deep learning techniques, particularly LSTM neural networks, have gained attention for their ability to capture temporal dependencies and model complex relationships within time series data. LSTM networks are a type of recurrent neural network (RNN) that have shown remarkable success in various domains, including load forecasting. By utilizing memory cells and gating mechanisms, LSTM networks can effectively capture long-term dependencies and handle the challenges posed by non-linear load data.

(Nada, Hamid, & Ismael, 2023) highlight the effectiveness of LSTM neural networks in load forecasting. Their study proposes an integrated framework that combines LSTM networks with probabilistic load curves to improve forecasting accuracy. The results demonstrate that the proposed framework outperforms traditional statistical methods, showcasing the power of deep learning techniques in load forecasting.

The literature on load forecasting also explores other aspects, such as feature selection, model evaluation metrics, and ensemble methods. Feature selection techniques help identify the most relevant predictors that contribute to accurate load forecasts. Model evaluation metrics, such as mean absolute error (MAE) and root mean square error (RMSE), assess the performance of forecasting models. Ensemble methods, such as combining multiple models or incorporating external data sources, aim to further enhance forecasting accuracy.

I.3 Importance of accurate load forecasting

Accurate load forecasting is of paramount importance in the electricity industry, as it has far-reaching implications for utilities and the overall electricity system. This section highlights the significance of accurate load forecasting, discussing its implications on resource optimization, grid stability, and cost-effective power supply.

Resource optimization is a critical aspect of the electricity system, and accurate load forecasting plays a pivotal role in this process. By predicting future electricity demand with precision, utilities can optimize the allocation of generation, transmission, and distribution resources. This enables utilities to make informed decisions regarding capacity expansion, ensuring that the infrastructure meets the projected demand while avoiding unnecessary investments in excess capacity (Mir, y otros, 2020). Accurate load forecasting also aids in load balancing, enabling utilities to efficiently manage supply and demand and avoid potential grid congestion or overloads.

Grid stability is another crucial consideration in the electricity system, and load forecasting contributes significantly to maintaining a stable grid. Reliable load forecasts allow grid operators to anticipate and respond to fluctuations in demand, ensuring that generation resources are dispatched efficiently to meet the load requirements. This helps prevent issues such as voltage instability, frequency deviations, and power quality problems. Moreover, load forecasting supports the integration of renewable energy sources by providing valuable insights into their intermittent nature, allowing for effective grid management and enhanced system reliability.

Cost-effective power supply is a key objective for utilities, and accurate load forecasting plays a vital role in achieving this goal. By accurately predicting electricity demand, utilities can optimize their resource planning and procurement strategies, minimizing excess generation capacity or the need for expensive last-minute power purchases. This leads to cost savings, which can be passed on to consumers, ultimately resulting in more affordable electricity prices (Alhmoud, Abu, Al-Zoubi, & Aljarah, 2021). Accurate load forecasts also facilitate the implementation of demand response programs, enabling utilities to incentivize consumers to adjust their electricity consumption patterns during peak demand periods. This demand-side management helps reduce strain on the grid, lowers the overall cost of power supply, and promotes energy efficiency.

The study by (Ashraful & Saifur, 2022) emphasizes the importance of accurate load forecasting in resource optimization, grid stability, and cost-effective power supply. Their integrated framework, combining LSTM neural networks with probabilistic load curves, demonstrates the potential to enhance load forecasting accuracy and improve the overall performance of the electricity system.

By recognizing a comprehensive overview of load forecasting, the existing literature on load forecasting techniques and methodologies and the significance of accurate load forecasting, this research aims to contribute to the advancement of load forecasting methodologies. The subsequent sections will introduce the proposed integrated load forecasting framework based on LSTM neural networks, addressing the limitations of traditional methods and aiming to improve forecasting accuracy. The research will present the experimental setup, analyze the results, and discuss the implications and potential applications of the proposed framework in the electricity industry.

3. Load forecasting framework based on LSTM neural networks

This section outlines the plan for presenting the load forecasting framework based on Long Short-Term Memory (LSTM) neural networks. The framework aims to improve load forecasting accuracy and address the limitations of traditional methods.

3.1 Load forecasting framework based on LSTM

Load forecasting plays a critical role in the electricity industry, enabling utilities to effectively plan, operate, and optimize their resources. Traditional statistical methods have been widely used for load forecasting, but they often struggle to capture the complex dynamics and temporal dependencies present in load data. To address these limitations, this research proposes a load forecasting framework based on Long Short-Term Memory (LSTM) neural networks.

LSTM neural networks, a type of recurrent neural network (RNN), have gained prominence in various domains for their ability to capture long-term dependencies and handle sequential data. Unlike traditional statistical models, LSTM networks utilize memory cells and gating mechanisms to retain and selectively forget information over extended time intervals. This allows them to effectively capture complex patterns and relationships in time series data, making them well-suited for load forecasting tasks.

The mathematical development of the LSTM model involves understanding the components and computations involved in the network. The LSTM architecture consists of memory cells, input gates, forget gates, and output gates. These components work together to process sequential data and learn meaningful representations. The memory cells store information over time, while the input, forget, and output gates regulate the flow of information into, out of, and within the memory cells.

The LSTM model can be mathematically represented as follows:

$$f_t = \delta_g(W_f.[h_{t-1}, x_t] + b_f)$$
$$i_t = \delta_g(W_i.[h_{t-1}, x_t] + b_i)$$
$$o_t = \delta_g(W_o.[h_{t-1}, x_t] + b_o)$$
$$c_t = f_t * c_{t-1} + i_t * \delta_c(W_c.[h_{t-1}, x_t] + b_c)$$
$$h_t = o_t * \delta_h(c_t)$$

Where:

f_t is the forget gate activation at time step t.
i_t is the input gate activation at time step t.
o_t is the output gate activation at time step t.
c_t is the cell state at time step t.
h_t is the hidden state at time step t.
x_t is the input at time step t.
W_f, W_i, W_o, W_c are the weight matrices.
b_f, b_i, b_o, b_c are the bias vectors.
δ_g represents the sigmoid activation function.
δ_c and δ_h represent the hyperbolic tangent activation function.

The LSTM model learns the parameters (W_f, W_i, W_o, W_c, b_f, b_i, b_o, b_c) through a process called backpropagation, minimizing the difference between the predicted and actual load values during training (Hochreiter & Schmidhuber, 1997).

This research builds upon the foundations of LSTM neural networks and their application to load forecasting. By leveraging the power of LSTM models, this framework aims to improve the accuracy and reliability of load forecasting, enabling utilities to make more informed decisions regarding resource allocation and grid management.

3.2 Methodology

The proposed load forecasting framework based on LSTM neural networks requires a well-defined methodology to effectively capture and predict the complex patterns in load data. This section presents the methodology used in this research, encompassing data preprocessing, LSTM model architecture, and training/validation strategies.

Data Preprocessing: The first step in the methodology involves data preprocessing to ensure the quality and suitability of the input data for the LSTM model. The load data is cleaned, removing any outliers or missing values that could potentially affect the model's performance. Additionally, normalization techniques are applied to scale the data within a specific range, facilitating the convergence and stability of the LSTM model during training. Feature selection is also conducted to identify the relevant input variables that have the most significant impact on load forecasting accuracy.

LSTM Model Architecture: The architecture of the LSTM model is a crucial aspect of the load forecasting framework. This research utilizes a multi-layer LSTM network, allowing for the extraction of hierarchical representations of the input data. The number of LSTM layers, hidden units, and other architectural hyperparameters are carefully chosen based on empirical analysis and model performance evaluation. The model's architecture is designed to strike a balance between complexity and efficiency, ensuring optimal forecasting accuracy.

Training and Validation Strategies: To train and validate the LSTM model, appropriate strategies are employed to ensure robust performance. The dataset is divided into training and validation sets, with a suitable temporal split to capture the temporal dependencies in the load data accurately. The training set is used to optimize the model's parameters, while the validation set is utilized to assess the model's generalization ability and prevent overfitting. Cross-validation techniques may also be employed to further evaluate the model's performance and robustness.

The methodology presented in this research follows a systematic approach to preprocess the data, design the LSTM model architecture, and establish effective training and validation strategies. By employing this methodology, the proposed load forecasting framework based on LSTM neural networks aims to enhance the accuracy and reliability of load forecasting, enabling utilities to make informed decisions for resource planning and grid management.

3.3. Experimental setup

The experimental setup section describes the dataset used for the implementation of the load forecasting framework and provides details on the Newcastle substation, the source of the data. It also explains the reformatting of the dataset to adhere to a consistent data format and the rationale behind selecting a three-year time frame for analysis.

Dataset description the load forecasting framework was implemented and evaluated using a dataset of real power load. The dataset comprises 30-minute metered real power data for Newcastle substations in the Ausgrid supply area. The data spans from january 1st, 2014, to December 31st, 2016, divided into annual sets. The dataset was sourced directly from the original Ausgrid zone substation dataset. However, to ensure consistency across distribution businesses like the TransGrid network, the data was reformatted to adhere to the NEAR-WESCML data format for zone substation data.

Newcastle Substation and Ausgrid Network The Newcastle substation, located in New South Wales (NSW), Australia, is a significant infrastructure component of the Ausgrid network. Ausgrid is responsible for supplying electricity to homes and businesses in Seahampton, Rhondda, Holmesville, Barnsley, Killingworth, Teralba, West Wallsend, and surrounding areas. As a distribution business, Ausgrid operates alongside other entities like Endeavour Energy and Essential Energy to deliver electricity to over 3 million residential and commercial customers throughout NSW and the Australian Capital Territory (ACT).

Reformatting and Data Consistency To ensure consistency and facilitate seamless integration into the load forecasting framework, the original Ausgrid zone substation dataset was reformatted to adhere to the NEAR-WESCML data format for zone substation data. This consistent data format allows for a standardized view of zone substation data across distribution businesses such as the TransGrid network. The reformatting process ensures that the load data is compatible with the forecasting framework and can be effectively utilized for training and prediction tasks.

Selection of a Three-Year Time Frame The decision to limit the dataset to a three-year time frame, covering the period from 2014 to 2016, was based on the need to maintain data stationarity for improved training and prediction. By focusing on a relatively shorter time span, the dataset can capture the low-demand trends associated with organic growth, which are closely linked to economic development, as measured by the gross domestic product (GDP). By keeping the dataset as stationary as possible, the load forecasting framework can achieve better training performance and more accurate predictions.

By utilizing the real power load dataset from the Newcastle substation in the Ausgrid supply area, this research aims to evaluate the effectiveness of the load forecasting framework based on LSTM neural networks. The selected dataset and its reformatting process ensure compatibility and consistency, enabling accurate and reliable load forecasting analysis.

3.4. Data preparation

Data preparation is a crucial step in developing LSTM models for sequence prediction problems. While the process is similar to developing recurrent neural networks (RNNs), there are important differences to consider. One key aspect is scaling the data to ensure effective learning and convergence of the network.

Scaling the data is particularly important when dealing with unscaled data that has a wide range of values. Without proper scaling, large inputs can slow down the learning process, impede convergence, and hinder the network's ability to learn the problem effectively. Two common scaling techniques are normalization and standardization, with this paper focusing on normalization.

Normalization involves rescaling the data from its original range to a range between 0 and 1. It requires knowledge of, or accurate estimation of, the minimum and maximum observable values. Estimating these values can be challenging if the time series exhibits an upward or downward trend. In Python, the Scikit-learn library provides the MinMaxScaler function to perform normalization. The process involves fitting the scaler with available training data to estimate the minimum and maximum values, and then transforming and normalizing the data accordingly.

Another scaling technique is standardization, which rescales the distribution of values so that the mean becomes 0 and the standard deviation becomes 1. This technique is useful when input values have different scales and can be necessary for certain machine learning algorithms. However, standardization assumes that the observations follow a Gaussian distribution with a well-behaved mean and standard deviation. If this assumption is not met, the results may not be reliable. To standardize the data, the mean and standard deviation of the observable values must be known or accurately estimated.

In deep learning libraries, such as LSTM, the input sequence is expected to have a consistent length for all features. This means that the input data must be reshaped into a three-dimensional form, consisting of samples (typically the number of rows in the dataset), time steps (past observations of a feature), and features (columns of the dataset).

By appropriately scaling the data and ensuring a consistent input sequence representation, the LSTM model can effectively learn from the dataset and make accurate load forecasting predictions.

4. Case study

In this research, a comprehensive case study was conducted to investigate the effectiveness of the proposed LSTM load forecasting model. The study utilized a dataset of real power load spanning a three-year period, specifically from January 1st, 2014, to December 31st, 2016, in the Ausgrid supply area. The dataset consisted of 30-minute metered real power data from Newcastle substations.

To prepare the dataset for the LSTM model, several steps were taken. Firstly, the 30-minute interval data was converted into an hourly interval to align with the forecasting horizon of predicting load in the hours ahead. This conversion resulted in a sample of 26 280 data points.

Next, the dataset was divided into a training set and a test set. The training set comprised the first 98% of the data, representing approximately 1 075 days, while the remaining 2% (approximately 20 days) was reserved for the test set. This division ensured that the model was trained on a significant portion of historical data while maintaining a separate set for unbiased evaluation.

To optimize the performance of the deep neural models, hyperparameter tuning was conducted. Initially, the tuning process was performed on a single machine, considering one configuration at a time. Various configurations with different combinations of hidden layer units and epochs were evaluated. The mean absolute error (MAE), mean squared error (MSE), mean absolute percentage error (MAPE), and validation MAE were calculated as evaluation metrics for each configuration.

To facilitate the hyperparameter tuning process and expedite computation, the configurations were trained in parallel on individual nodes using Spark, a powerful distributed computing framework. This approach allowed for faster exploration of different hyperparameter combinations and facilitated the identification of the best set of hyperparameters for training the LSTM model.

The selected LSTM model architecture, as summarized in table 1, consisted of two LSTM layers and two dense layers with 50 neurons. The total number of trainable parameters was 33.201. The configuration with these specifications demonstrated the best performance in terms of MAE on the training set.

Table 1
Sequential LSTM model summary with 50 neurons

Layer (type)	Output shape	Param #
Lstm (LSTM)	(None, 24.50)	10.400
Lstm_1 (LSTM)	(None, 50)	20.200
Dense (Dense)	(None, 50)	2.550
Dense_1 (Dense)	(None, 1)	51
Total params		33.201
Trainable params		33.201
Non-trainable params		0

Source: own elaboration in Python with data from Ausgrid.

Table 2
Errors for various configurations of LSTM Network model on the training set

Configuration	Hidden layers	Units	Epochs	MAE	MSE	MAPE	Val MAE
1	2	128	135	0.0051	7.2928e-05	2.5534	0.0116
2	2	50	193	0.0050	6.2276e-05	2.4550	0.0121
3	2	30	186	0.0051	7.1659e-05	2.6321	0.0113
4	2	20	184	0.0055	7.9212e-05	2.7540	0.114

Source: own elaboration in Python with data from Ausgrid.

Table 2 presents the errors obtained for various configurations of the LSTM Network model on the training set. Each configuration differed in the number of hidden layers, units, and epochs. The mean absolute error (MAE), mean squared error (MSE), mean absolute percentage error (MAPE), and validation MAE were computed as evaluation metrics.

Configuration 2, with 2 hidden layers, 50 units, and 193 epochs, achieved the lowest MAE of 0.0050 and MSE of 6.2276e-05, indicating its superior performance in capturing the load patterns. Additionally, the MAPE value of 2.4550 highlights the accuracy of the model's load predictions.

The evaluation of different configurations on the training set allowed for the selection of an optimal configuration that demonstrated the best performance in terms of error metrics. This configuration will be evaluated on the test set.

The performance of the chosen LSTM configuration was further evaluated on the test set, as depicted in table 3. The results showcased the model's ability to provide accurate load forecasts with low error rates. The MAE, MSE, MAPE, and validation MAE values obtained from the test set confirmed the effectiveness of the LSTM network architecture.

Table 3
Errors of LSTM Network model on the test set

Configuration	Hidden layers	Units	Epochs	MAE	MSE	MAPE	Val MAE
2	2	50	155	0.0051	7.2928e-05	2.4934	0.0112

Source: own elaboration in Python with data from Ausgrid.

The table presents the performance metrics of the LSTM Network model on the test set. The selected configuration had two hidden layers with 50 units and was trained for 155 epochs. The model achieved an MAE of 0.0051, indicating a low average absolute error in load forecasting. The MSE value of 7.2928e-05 reflects the mean squared error of the model's predictions. The MAPE, which represents the average percentage deviation of the forecasts from the actual values, was calculated as 2.4934. Additionally, the validation MAE, denoting the mean absolute error on the validation set, was obtained as 0.0112.

These results demonstrate the effectiveness of the LSTM network architecture in accurately predicting the load for future hours based on the historical data from the previous 24 hours. The low error ratios obtained highlight the model's capability to provide reliable load forecasts, indicating its potential for application in the electricity system's load management and planning.

In conclusion, the case study conducted on the LSTM load forecasting model using real power load data from Newcastle substations demonstrated its ability to effectively predict load demand. The hyperparameter tuning process, parallel training using Spark, and careful selection of the LSTM configuration yielded promising results. The findings indicate that the LSTM model can be a valuable tool in enhancing the accuracy and efficiency of load forecasting in the electricity system.

5. Conclusion

In conclusion, this research focused on developing an integrated load forecasting framework with a specific concentration on the substation level. The LSTM model was employed to analyze the Newcastle CBD substation system's load data over a three-year period. The purpose was to predict the next hours' load in the substation and automate the forecasting process. The results demonstrated the effectiveness of the LSTM model in accurately predicting the real power demand, with a mean absolute error (MAE) of 0.0050.

The study highlighted the significance of load forecasting in the energy sector, particularly with the growing importance of smart grid technologies and their applications in demand-side management, electric vehicles, and distributed energy resources. By utilizing advanced forecasting techniques, such as LSTM, utilities can optimize their planning, operations, and maintenance processes, leading to more efficient resource allocation.

The research also emphasized the importance of data preparation, including scaling techniques such as normalization, to enhance the performance of deep neural models like LSTM. The data used in the study was sourced from the Ausgrid zone substation dataset, and appropriate scaling methods were applied to ensure accurate predictions.

Based on the findings, it is recommended that utilities and energy companies adopt LSTM-based load forecasting frameworks at the substation level to improve their operational efficiency. The integration of advanced machine learning techniques into the forecasting process can provide valuable insights for decision-making, allowing for better load management, grid stability, and resource optimization.

Furthermore, future research directions could explore the application of LSTM models in other substation areas or different geographical regions to validate the framework's effectiveness across diverse contexts. Additionally, incorporating other factors such as weather conditions, customer behavior patterns, and market dynamics could further enhance the accuracy and robustness of load forecasting models.

Overall, this research contributes to the field of load forecasting by presenting a comprehensive framework and demonstrating the capabilities of LSTM models in substation-level load prediction. By embracing advanced forecasting techniques and leveraging the power of data analytics, the energy industry can achieve greater operational efficiency, sustainability, and reliability in meeting the ever-growing demands of modern electricity systems.

References

Abdullah, A. M.; S. MD.; M. Naeem; S. H. MD.; R. D. Debopriya, & H. Eklas (2020). A Comprehensive Review of the Load Forecasting Techniques Using Single and Hybrid Predictive Models. *IEEE Access*, 8, 134911-134939. doi:10.1109/ACCESS.2020.3010702.

Alhmoud, L.; K. R. Abu; A. Al-Zoubi, & I. A. Aljarah (2021). Real-Time Electrical Load Forecasting in Jordan Using an Enhanced Evolutionary Feedforward Neural Network. *Sensors (Basel)*, 21(10:6240). doi:doi: 10.3390/s21186240.

Ashraful, H., & R. Saifur (2022). Short-term electrical load forecasting through heuristic configuration of regularized deep neural network. *Applied Soft Computing,* 122, 1568-4946. doi:https://doi.org/10.1016/j.asoc.2022.108877.

Cai, C.; T. Yuan; Z. Tianqi, & D. Zhixiang (2021). Short-Term Load Forecasting Based on Deep Learning Bidirectional LSTM Neural Network. *Applied Sciences,* 11(17). doi:https://doi.org/10.3390/app11178129.

Hochreiter, S., & J. Schmidhuber (1997). Long Short-Term Memory. *MIT Press*, 9(8). doi:10.1162/neco.1997.9.8.1735.

Mir, A. A.; A. Mohammed; U. Kafait; A. K. Zafar; L. Yuehong, & I. Muhammad, (2020). A Review of Electricity Demand Forecasting in Low and Middle Income Countries: The Demand Determinants and Horizons. *Sustainability* , 12(15:5931). doi:https://doi.org/10.3390/su12155931.

Nada, M.; Hamid, O., & J. Ismael (2023). Short-term electric load forecasting using an EMD-BI-LSTM approach for smart grid energy management system. *Energy and Buildings*, 288. doi:doi.org/10.1016/j.enbuild.2023.113022.

Pełka, P. (2023). Analysis and Forecasting of Monthly Electricity Demand Time Series Using Pattern-Based Statistical Methods. *Energies,* 16(2). doi:https://doi.org/10.3390/en16020827.

Yaoyao, H.; X. Jingling; A. Xueli; C. Chaojin, & X. Jian (2022). Short-term power load probability density forecasting based on GLRQ-Stacking ensemble learning method. *International Journal of Electrical Power & Energy Systems*, 142. doi:https://doi.org/10.1016/j.ijepes.2022.108243