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Multi-Horizon Short-Term Smart Grid Load Forecasting Using LSTM Networks for Real-Time Optimisation

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Abstract

Accurate short-term forecasting of electricity demand is essential for real-time smart grid optimisation and efficient energy management. This paper presents a multivariate Long Short-Term Memory (LSTM) neural network framework for short-term multi-horizon electrical load forecasting using historical smart grid operational data, historical load measurements, renewable energy variables, and environmental factors used as explanatory features for load forecasting. A comprehensive data processing pipeline is developed, incorporating time-series feature engineering, cyclical temporal encoding, chronological data partitioning, and standardisation to ensure robust model training without information leakage. Sliding-window sequence generation is employed to transform time-series data into a supervised learning format suitable for deep learning architectures. The proposed stacked LSTM model is trained to forecast short-term load dynamics at a 15-minute temporal resolution using historical energy and environmental data. The forecasting framework is evaluated using multiple performance metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Experimental results demonstrate that the LSTM model effectively captures temporal dependencies and seasonal patterns in energy consumption, achieving high forecasting accuracy suitable for real-time decision support. The forecasting framework developed in this study serves as the predictive component of a broader smart grid optimisation system. The generated forecasts will be integrated with a multi-objective optimisation framework in subsequent work to enable real-time energy management under uncertainty and improve operational efficiency in modern smart grid environments.

Keywords

Smart Grid Forecasting, LSTM Networks, Short-Term Load Forecasting, Multi-Horizon Load Forecasting, Multivariate Time-Series Forecasting, Real-Time Energy Management

1. Introduction

The rapid evolution of modern power systems toward smart grid architectures has introduced significant operational challenges due to the increasing penetration of renewable energy resources, distributed generation, and highly dynamic demand patterns. Accurate short-term forecasting of electricity demand has therefore become a critical component of smart grid management systems. Reliable forecasts enable grid operators to perform efficient energy dispatch, maintain system stability, and support real-time optimisation strategies for energy management that balance multiple operational objectives such as cost, reliability, and environmental impact [1].

Traditional power systems relied primarily on deterministic load prediction techniques based on statistical models such as autoregressive integrated moving average (ARIMA) and linear regression methods. While these approaches have demonstrated acceptable performance in relatively stable grid environments, they often struggle to capture the nonlinear and highly dynamic characteristics of modern energy systems. A conceptual representation of a smart grid architecture, illustrating the interaction between generation, distribution, consumers, and control systems, is presented in **Figure 1**.

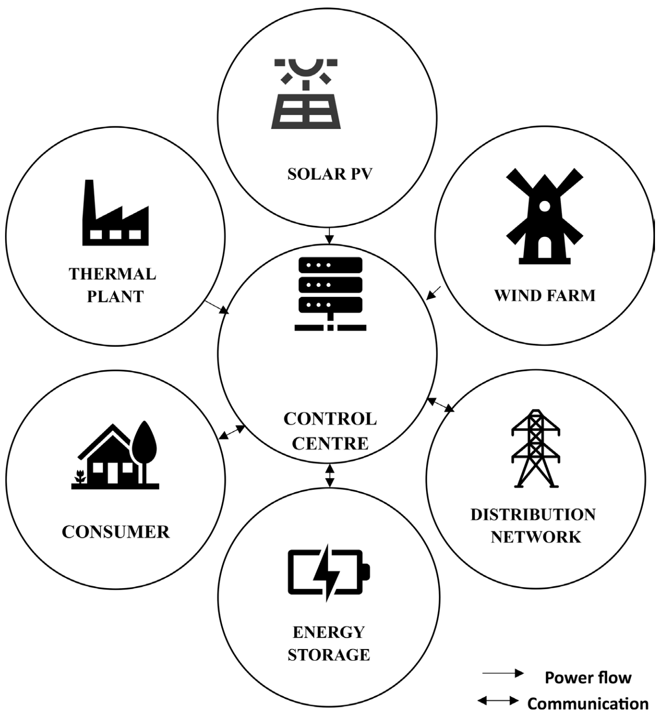

Figure 1. Conceptual smart grid architecture illustrating the integration of renewable generation, communication systems, consumers, and an intelligent energy management component.

The integration of renewable energy sources such as solar and wind introduces significant variability and uncertainty into the grid, making accurate forecasting more challenging. Consequently, advanced machine learning and deep learning techniques have increasingly been adopted to improve forecasting accuracy in smart grid applications [2].

Among these techniques, recurrent neural networks (RNNs), and particularly Long Short-Term Memory (LSTM) networks, have shown strong capabilities in modelling temporal dependencies in time-series data. LSTM networks address the limitations of traditional RNNs by incorporating memory cells and gating mechanisms that enable them to capture both short- and long-term temporal dependencies. These properties make LSTM architectures particularly suitable for forecasting applications in energy systems where consumption and generation patterns exhibit daily, weekly, and seasonal periodicities [3].

Recent studies have applied LSTM networks to short-term load forecasting, renewable generation prediction, and energy demand modelling. Despite these promising results, several challenges remain in developing robust forecasting frameworks for smart grid applications. First, many existing approaches rely on limited feature engineering and do not fully exploit multivariate relationships between load, renewable generation, and environmental factors. Second, data preprocessing pipelines are often insufficiently described, making reproducibility difficult. Third, forecasting frameworks are often evaluated only at a single prediction horizon, whereas practical smart grid operations require reliable forecasts across multiple time horizons [4].

To address these challenges, this paper proposes a multivariate LSTM-based forecasting framework for short-term multi-horizon electrical load forecasting. The proposed approach incorporates a comprehensive data preprocessing pipeline including cyclical temporal feature encoding, chronological data partitioning, and standardisation procedures that prevent information leakage during model training. Sliding-window sequence generation is used to transform time-series data into a supervised learning format suitable for deep learning models. A stacked LSTM architecture is then trained to capture temporal dependencies and nonlinear relationships between load, renewable generation, and environmental variables.

The forecasting model is evaluated using multiple prediction horizons corresponding to 15-minute, 1-hour, and 24-hour ahead forecasts. Performance is assessed using widely adopted forecasting metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Experimental results demonstrate that the proposed LSTM framework successfully captures underlying temporal dynamics and produces accurate short-term forecasts suitable for real-time decision support.

Unlike many existing forecasting studies that evaluate models only as standalone predictive tools, the framework proposed in this work explicitly positions the forecasting model as a predictive input layer for real-time smart grid optimisation systems. By integrating multi-horizon forecasting with a structured preprocessing pipeline and deep learning architecture, the proposed approach establishes a direct link between machine learning-based prediction and optimisation-driven energy management. The predicted electrical load outputs generated by the model will serve as inputs to a multi-objective optimisation system aimed at improving real-time energy management under uncertainty. The overall forecasting architecture and its interaction with the optimisation framework developed in subsequent work are illustrated in Figure 2. This forecasting layer, therefore, represents a critical step toward the development of an integrated smart grid control architecture.

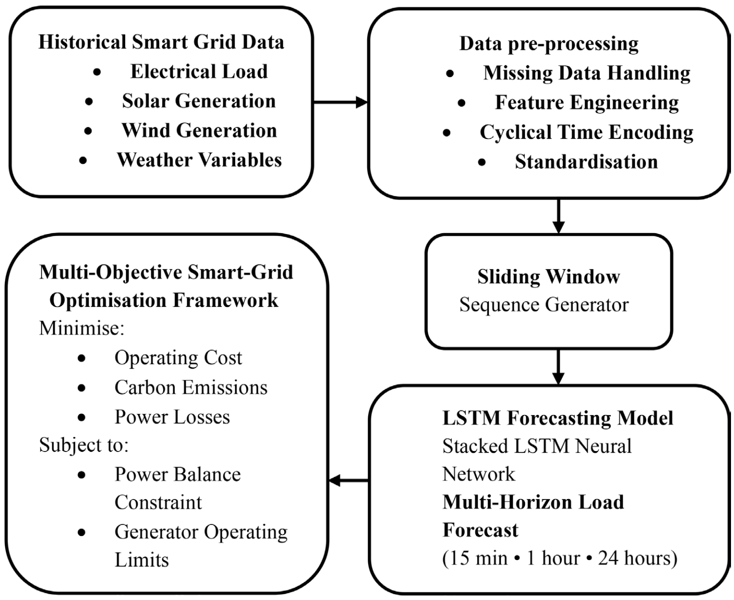

Figure 2. The overall forecasting architecture and interaction with the optimisation framework were developed in subsequent work.

The main contributions of this paper are summarised as follows:

1) A multivariate LSTM-based framework for short-term multi-horizon electrical load forecasting in smart grid environments.

2) A reproducible preprocessing pipeline incorporating cyclical temporal feature encoding, chronological dataset partitioning, and standardisation procedures to prevent information leakage during model training.

3) A sliding-window sequence generation approach for transforming multivariate smart grid time-series data into supervised learning sequences suitable for deep learning forecasting models.

4) A multi-horizon forecasting evaluation framework covering 15-minute, 1-hour, and 24-hour ahead electrical load prediction intervals.

5) A forecasting architecture designed to function as the predictive input layer for future real-time smart grid optimisation and energy management systems.

The remainder of this paper is organised as follows. Section 2 reviews related work on machine learning approaches for energy forecasting. Section 3 presents the proposed forecasting framework, including data preprocessing, sequence generation, and model architecture. Section 4 describes the experimental setup and evaluation methodology. Section 5 presents and discusses the forecasting results across different prediction horizons. Finally, Section 6 concludes the paper and outlines future work related to the integration of the forecasting module with multi-objective smart grid optimisation.

2. Related Work

Accurate forecasting of electricity demand and renewable energy generation has received significant attention in the context of smart grid operation and intelligent energy management systems [5]. Reliable forecasting enables system operators to anticipate future system states, improve energy scheduling, and enhance operational reliability [6]. Forecasting approaches used in the literature can generally be classified into three main categories: traditional statistical models, machine learning methods, and deep learning techniques. Each category provides different modelling capabilities depending on the complexity of the data and the forecasting horizon [7].

2.1. Traditional Statistical Forecasting Methods

Early studies in short-term load forecasting relied primarily on statistical time-series models such as autoregressive (AR), autoregressive moving average (ARMA), and autoregressive integrated moving average (ARIMA) techniques. These models have been widely applied due to their mathematical simplicity, interpretability, and ability to model linear temporal dependencies within electricity demand data [8].

Several studies have demonstrated that ARIMA-based models can produce acceptable forecasting performance in relatively stable power systems where load patterns exhibit consistent daily and weekly trends [1] [2] [7] [9]. However, these approaches rely on linear assumptions and therefore struggle to represent nonlinear relationships and complex temporal dependencies present in modern smart grid environments.

With the increasing integration of renewable energy resources such as solar and wind power, electricity demand patterns have become more dynamic and uncertain. Renewable generation is strongly influenced by environmental factors, including temperature, solar irradiance, and wind speed, which introduce stochastic variability into power system operation. Consequently, forecasting models based solely on linear statistical assumptions often fail to capture these nonlinear dynamics effectively [10]. This limitation has motivated the exploration of more advanced forecasting techniques capable of modelling nonlinear relationships and complex interactions between system variables.

2.2. Machine Learning Approaches for Energy Forecasting

Machine learning techniques have been widely applied to energy forecasting problems due to their ability to capture nonlinear relationships within complex datasets in order to address the limitations of traditional statistical models. Algorithms such as support vector machines (SVM), decision trees, random forests, and artificial neural networks (ANN) have demonstrated improved predictive performance by capturing nonlinear relationships between multiple input variables [11].

Unlike conventional statistical methods, machine learning approaches allow the integration of diverse explanatory features, including historical load measurements, meteorological variables, and temporal indicators. This multivariate modelling capability enables forecasting models to capture interactions between weather conditions and electricity demand patterns.

Random forest models, in particular, have gained popularity due to their robustness, ability to handle high-dimensional datasets, and resistance to overfitting. Several studies have shown that ensemble learning techniques such as random forests outperform traditional regression models in short-term load forecasting tasks [6].

Despite these advantages, many machine learning approaches treat time-series observations as independent samples and therefore do not explicitly model sequential temporal dependencies. As a result, these methods may fail to capture long-term temporal patterns inherent in electricity demand and renewable generation data.

2.3. Deep Learning for Time-Series Forecasting

Deep learning techniques have recently emerged as powerful tools for modelling complex sequential data. Among these techniques, recurrent neural networks (RNNs) are specifically designed to capture temporal dependencies in time-series datasets. However, conventional RNN architectures suffer from the vanishing gradient problem, which limits their ability to learn long-term relationships across extended sequences [12].

Long Short-Term Memory (LSTM) networks were introduced to overcome this limitation by incorporating memory cells and gating mechanisms that regulate the flow of information through the network [10] [13]. These mechanisms allow LSTM models to selectively retain relevant historical information while discarding irrelevant signals, enabling the network to learn both short-term and long-term temporal dependencies effectively.

Due to these characteristics, LSTM networks have been widely adopted for energy forecasting applications, including short-term load forecasting, renewable generation prediction, and electricity price forecasting. Several studies have demonstrated that LSTM-based forecasting models outperform traditional statistical and machine learning approaches when applied to complex energy datasets [1] [10]-[12].

In particular, multivariate LSTM models that incorporate environmental variables such as temperature, humidity, and wind speed have been shown to achieve improved predictive accuracy because they capture interactions between environmental conditions and electricity demand patterns [14]. Nevertheless, many existing studies evaluate forecasting models for a single prediction horizon and often provide limited detail regarding preprocessing pipelines required for reproducible time-series modelling.

2.4. Forecasting for Smart Grid Optimisation

Forecasting models play a critical role in enabling intelligent decision-making within smart grids. Accurate predictions of electricity demand and renewable generation allow system operators to anticipate future system states and perform proactive energy management decisions, including generation scheduling, storage management, and network control [15] [16].

In recent years, several studies have explored the integration of forecasting models with optimisation frameworks for smart grid operation. These frameworks commonly employ multi-objective optimisation techniques to simultaneously minimise operational costs, reduce carbon emissions, and maintain system reliability [17].

However, many optimisation-based energy management studies rely on simplified forecasting assumptions or externally generated prediction inputs [18]. As a result, the potential advantages of advanced forecasting techniques such as deep learning models are not fully integrated into optimisation-based smart grid decision-making systems [19] [20].

2.5. Comparative Analysis of Forecasting Methods

Table 1 summarises the key characteristics of commonly used forecasting techniques reported in the literature.

Table 1. Comparison of forecasting approaches in smart grid applications.

Method	Key Characteristics	Advantages	Limitations
ARIMA	Linear statistical time-series model	Simple, interpretable, and effective for stationary data	Limited ability to model nonlinear relationships
SVM	Kernel-based machine learning model	Handles nonlinear relationships	Limited scalability for large datasets
Random Forest	Ensemble learning method	Robust, handles high-dimensional data	Does not explicitly model temporal sequences
ANN	Feedforward neural networks	Captures nonlinear relationships	Limited temporal memory
LSTM	Recurrent neural network with memory cells	Captures long-term temporal dependencies, suitable for time-series forecasting	Higher computational complexity

The comparison highlights that LSTM networks provide strong modelling capabilities for sequential energy data due to their ability to learn long-term temporal dependencies.

2.6. Research Gap

Although deep learning models such as LSTM have demonstrated strong forecasting capabilities, several research gaps remain in the existing literature.

First, many studies provide limited transparency regarding the preprocessing pipeline required for effective time-series modelling, including feature engineering, temporal encoding, and appropriate dataset partitioning strategies. Second, forecasting models are often evaluated only at a single prediction horizon, whereas practical smart grid operations require reliable forecasts across multiple operational timescales. Third, relatively few studies explicitly design forecasting frameworks as predictive components within larger smart grid optimisation systems.

2.7. Contribution of This Work

To address these limitations, this paper proposes a multivariate LSTM-based forecasting framework designed to support real-time smart grid optimisation systems. The proposed framework incorporates a complete preprocessing pipeline including cyclical temporal feature encoding, chronological dataset partitioning, and data standardisation procedures that prevent information leakage during model training.

The forecasting model is evaluated across multiple prediction horizons, including 15-minute, 1-hour, and 24-hour forecasts, in order to assess its performance under different operational scenarios. By explicitly positioning the forecasting architecture as a predictive input layer for optimisation, this study establishes a direct link between machine learning-based forecasting and smart grid decision-support systems.

The forecasting architecture developed in this study, therefore, functions as the predictive module within a broader multi-objective smart grid optimisation framework that will be presented in subsequent work.

3. Forecasting Framework Methodology

This section presents the proposed forecasting framework used to predict short-term electrical load demand. The methodology consists of five main stages: data generation and preparation, temporal feature engineering, data preprocessing and scaling, sequence generation for supervised learning, and LSTM-based forecasting model development. The forecasting framework follows a structured pipeline consisting of dataset preparation, feature engineering, sequence generation, and deep learning model training. The overall forecasting pipeline is illustrated conceptually in Figure 3.

3.1. Dataset Generation and Structure

To evaluate the proposed forecasting framework, a multivariate time-series dataset was constructed to simulate typical smart grid operational conditions. The dataset represents electrical load demand together with renewable generation and environmental variables used as explanatory features. The generated dataset includes the following variables:

- Electrical load demand
- Solar power generation
- Wind power generation
- Ambient temperature
- Relative humidity

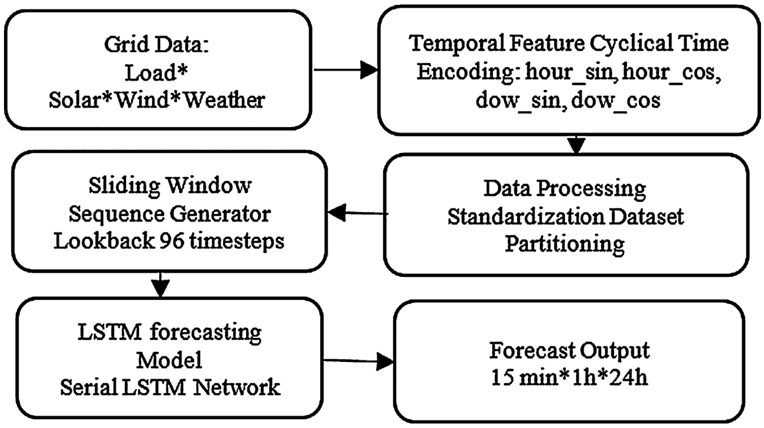

Figure 3. Overview of the proposed LSTM-based forecasting pipeline for smart grid prediction.

These variables represent key factors that influence electricity demand and renewable generation behaviour within modern smart grids.

To simulate realistic energy system dynamics, periodic components were incorporated into the dataset to represent daily and weekly operational cycles commonly observed in electricity consumption patterns. Random stochastic noise was also introduced to emulate the natural variability present in real-world energy systems. The synthetic dataset was generated to represent two years of smart grid operation at a 15-minute temporal resolution, resulting in 70,080 observations. Electrical load demand was modelled using daily and weekly periodic components combined with additive Gaussian noise. Solar and wind generation profiles were generated using cyclical functions with stochastic perturbations, while temperature and humidity variables incorporated seasonal variations. A fixed random seed of 42 was applied during dataset generation to ensure reproducibility of all forecasting experiments.

The resulting dataset provides a controlled experimental environment for evaluating the performance of the proposed forecasting framework while preserving key temporal characteristics of power system operation. The use of a synthetic dataset in this study is intentional, as it enables systematic validation of the forecasting methodology under known conditions, ensures reproducibility of results, and allows isolation of model behaviour without the influence of incomplete, noisy, or proprietary real-world data. However, it is acknowledged that this approach may limit direct real-world generalisability, and future work will therefore focus on validating the proposed framework using real-world smart grid datasets under uncertain operating conditions.

3.2. Temporal Feature Engineering

Time-series forecasting models benefit significantly from explicit temporal information. In this work, cyclical temporal features were introduced to represent repeating patterns within daily and weekly cycles.

Instead of directly using raw time indices, sinusoidal encoding was employed to represent temporal features in a continuous cyclic form. This approach prevents discontinuities that occur when time variables wrap around their boundaries (for example, hour 23 transitioning to hour 0).

The cyclic encoding for hourly and weekly patterns was computed using sine and cosine transformations:

$$hour_{sin} = \sin\left(\frac{2\pi \cdot hour}{24}\right) \tag{3.1}$$

$$hour_{cos} = \cos\left(\frac{2\pi \cdot hour}{24}\right) \tag{3.2}$$

$$dow_{sin} = \sin\left(\frac{2\pi \cdot dayofweek}{7}\right) \tag{3.3}$$

$$dow_{cos} = \cos\left(\frac{2\pi \cdot dayofweek}{7}\right) \tag{3.4}$$

These encoded features allow the neural network to capture periodic temporal relationships effectively while preserving continuity across cyclic boundaries, as shown in Figure 4. This illustrates how time is mapped onto a continuous circular space.

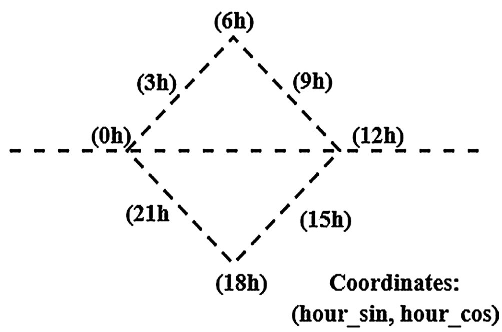

Figure 4. Illustration of cyclical time encoding using sine and cosine transformations. The hour of the day is mapped onto continuous coordinates (hour_sin, hour_cos), preserving the cyclical relationship between adjacent time periods for LSTM input representation.

Cyclical encoding prevents artificial discontinuities in temporal features and allows the neural network to recognise periodic patterns in energy consumption behaviour.

3.3. Dataset Partitioning and Scaling

To ensure unbiased evaluation of the forecasting model, the dataset was divided into three chronological subsets:

- Training set (70%)—used to train the neural network
- Validation set (15%)—used to tune model performance and apply early stopping
- Test set (15%)—used for final model evaluation

Chronological splitting was applied instead of random sampling in order to preserve the temporal ordering of the data and avoid information leakage from future observations.

Prior to model training, all input variables were standardised using the StandardScaler technique. Standardisation transforms each feature according to:

$$z = \frac{x - \mu}{\sigma} \tag{3.5}$$

where:

- x is the original feature value
- μ is the mean of the training dataset
- σ is the standard deviation of the training dataset

Scaling parameters were calculated using only the training data and subsequently applied to validation and test datasets to prevent data leakage.

3.4. Sliding Window Sequence Generation

Deep learning models such as LSTM require sequential input structures rather than flat tabular data. Therefore, a sliding window approach was used to convert the time-series dataset into supervised learning sequences.

Each training sample consists of a fixed historical observation window used to predict a future value.

Let:

- L denote the lookback window length
- H denote the forecasting horizon

For each time step t, the model receives an input sequence:

$$X_t = \left[x_{t-L}, x_{t-L+1}, \cdots, x_{t-1} \right] \tag{3.6}$$

and predicts the target value:

$$y_t = x_{t+H} \tag{3.7}$$

Time-Series Data

In this study, solar generation, wind generation, temperature, and humidity variables were incorporated exclusively as historical input features within the lookback window. Future values of these variables were not assumed to be available during forecasting. The LSTM model, therefore, generated future electrical load forecasts solely from historical multivariate observations.

The sliding window mechanism converts sequential time-series observations into input-output training samples suitable for supervised learning, as illustrated in Figure 5.

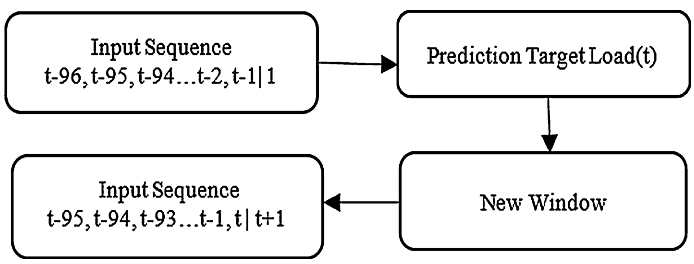

Figure 5. Sliding-window sequence generation for multi-horizon load forecasting. Each prediction is generated from a fixed-length input sequence, after which the window advances by one time step to create the next training sample.

In this study, the lookback window was set to 96 time steps, corresponding to 24 hours of historical data at 15-minute resolution.

Three forecasting horizons were evaluated:

- 15 minutes ahead (H = 1)
- 1 hour ahead (H = 4)
- 24 hours ahead (H = 96)

This multi-horizon evaluation enables assessment of the forecasting model under different operational planning scenarios.

3.5. LSTM Forecasting Model

The forecasting model is based on a stacked Long Short-Term Memory (LSTM) neural network, which is well-suited for modelling temporal dependencies in sequential data.

LSTM networks extend traditional recurrent neural networks by introducing memory cells and gating mechanisms that regulate the flow of information through the network. These mechanisms allow the network to retain relevant historical information while discarding irrelevant signals.

The proposed architecture consists of two stacked LSTM layers followed by a dense output layer (Figure 6). The selected architecture was informed by common practices in short-term load forecasting literature and preliminary experimentation. The 96-step lookback window corresponds to 24 hours of historical observations at 15-minute resolution, enabling the model to capture complete daily demand cycles. Two stacked LSTM layers with 64 hidden units were selected to balance forecasting capability and computational efficiency. A dropout rate of 0.2 was employed to reduce overfitting and improve model generalisation.

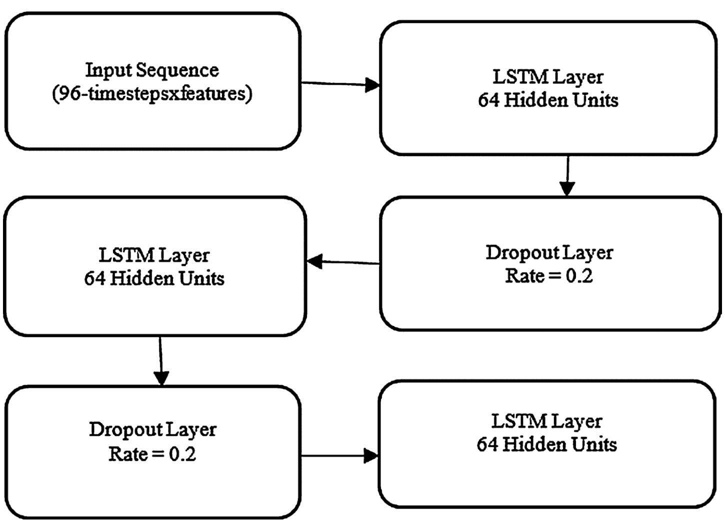

Figure 6. Proposed a two-layer LSTM network architecture used for multi-horizon electrical load forecasting. The network comprises two LSTM layers with 64 hidden units, each followed by a dropout layer (rate = 0.2), before generating the final load forecast through a dense output layer.

The network architecture is defined as follows:

1) Input layer representing the historical sequence window
2) First LSTM layer with 64 hidden units
3) Dropout layer to reduce overfitting
4) Second LSTM layer with 64 hidden units
5) Dropout layer
6) Dense output layer producing the final forecast value

The stacked architecture enables the network to learn hierarchical temporal representations, allowing it to capture both short-term fluctuations and longer-term temporal dependencies within the load profile.

3.6. Model Training Procedure

The LSTM model was trained using the Adam optimisation algorithm, which is widely used for deep learning applications due to its adaptive learning rate capabilities.

The objective function used during training was Mean Squared Error (MSE), defined as:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2 \tag{3.8}$$

where:

y_i is the true value

$\hat{y}_i$ is the predicted value

To prevent overfitting, an early stopping mechanism was implemented. Training was terminated when validation loss failed to improve for five consecutive epochs, and the model weights corresponding to the lowest validation error were restored.

3.7. Forecast Evaluation Metrics

The performance of the forecasting model was evaluated using three commonly used metrics in energy forecasting studies:

Mean Absolute Error (MAE)

$$\text{MAE} = \frac{1}{N}\sum\left|y_i - \hat{y}_i\right| \tag{3.9}$$

Root Mean Square Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum\left(y_i - \hat{y}_i\right)^2} \tag{3.10}$$

Mean Absolute Percentage Error (MAPE)

$$\text{MAPE} = \frac{100}{N}\sum\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{3.11}$$

These metrics provide complementary perspectives on forecasting accuracy and allow consistent comparison across different prediction horizons.

It is important to note that this study focuses primarily on the development and validation of the forecasting framework (Objective 1). The controlled experimental setup using a synthetic dataset allows for rigorous evaluation of the proposed LSTM architecture and preprocessing pipeline. More advanced comparative models, such as ARIMA and CNN-based approaches, as well as validation under real-world uncertainty conditions, will be investigated in subsequent studies as part of the extended research framework.

4. Experimental Setup

This section describes the experimental configuration used to evaluate the proposed LSTM-based forecasting framework.

4.1. Implementation Environment

The forecasting framework was implemented using the Python programming language within a Jupyter Notebook environment. The deep learning model was developed using the TensorFlow and Keras libraries, while data preprocessing and analysis were performed using NumPy, Pandas, and Scikit-learn.

All experiments were conducted using a multivariate time-series dataset with a 15-minute temporal resolution, representing typical operational data intervals used in smart grid monitoring and energy market systems.

4.2. Forecasting Configuration

The forecasting model was trained using historical sequences generated through a sliding window approach. The lookback window length was set to 96 time steps, corresponding to 24 hours of historical data.

Separate forecasting models were trained and evaluated for each prediction horizon (15-minute, 1-hour, and 24-hour ahead forecasts). This approach enabled independent assessment of forecasting performance across different operational timescales while maintaining a consistent network architecture and training procedure.

Three forecasting horizons were evaluated in **Table 2** in order to assess the model's performance across different operational planning scenarios:

Table 2. Forecasting horizons evaluated.

Forecast Horizon	Time Interval
Short-Term	15 Minutes Ahead
Intra-Hour	1 Hour Ahead
Day-Ahead	24 Hours Ahead

These horizons represent common decision-making intervals used in energy management systems and grid operation planning.

4.3. Model Training Parameters

The LSTM forecasting model was configured with a stacked architecture comprising two LSTM layers and dropout regularisation. The key training parameters are summarised in Table 3.

Table 3. LSTM training parameters.

Parameter	Value
Lookback Window	96-Time Steps
LSTM Units per Layer	64
Dropout Rate	0.2
Batch Size	64
Optimiser	Adam
Loss Function	Mean Squared Error
Early Stopping Patience	5 Epochs

Early stopping was used during training to prevent overfitting by monitoring validation loss and restoring the best-performing model weights.

5. Results and Discussion

This section presents the forecasting performance of the proposed LSTM model across different prediction horizons. The training behaviour of the proposed LSTM forecasting model was analysed by examining the evolution of training and validation loss values during the learning process. As illustrated in Figure 7, both the training and validation losses decrease steadily across training epochs, indicating that the model successfully learns the temporal patterns present in the dataset. The relatively small gap between the curves suggests good generalisation performance without significant overfitting.

The objective is to evaluate the model's ability to produce accurate short-term

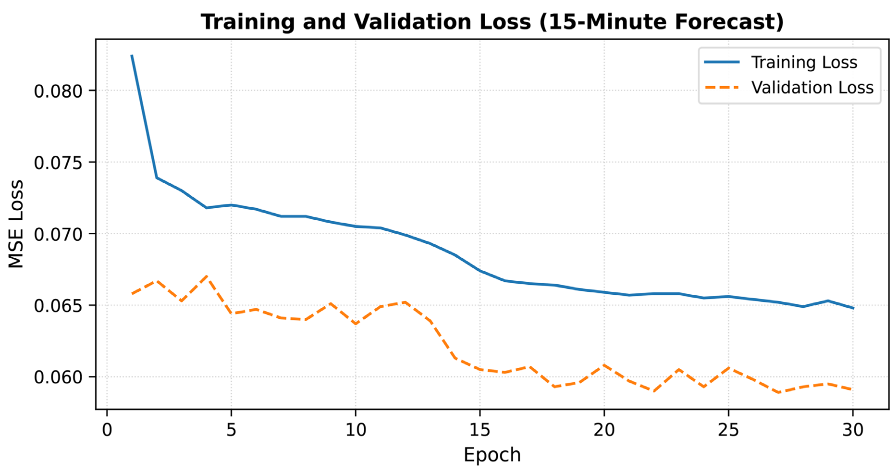

Figure 7. Training and validation loss curves for the LSTM forecasting model.

electricity demand predictions across multiple operational time scales.

5.1. Forecasting Performance

The forecasting accuracy was evaluated using three widely adopted metrics in energy forecasting studies: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics provide complementary measures of prediction accuracy and are commonly used to assess the performance of load forecasting models.

The experimental results obtained from the proposed LSTM forecasting framework are summarised in **Table 4**.

Table 4. LSTM forecasting performance across prediction horizons.

Horizon	MAE (MW)	RMSE (MW)	MAPE (%)
15 Minutes	126.55	159.42	2.58
1 Hour	120.71	151.59	2.45
24 Hours	120.97	151.41	2.46

The results indicate that the LSTM model achieves consistent forecasting accuracy across all evaluated prediction horizons. The Mean Absolute Percentage Error (MAPE) remains approximately 2.5%, which indicates a high level of predictive accuracy for short-term electricity demand forecasting.

In practical smart grid operation, forecasting models with MAPE values below 5% are generally considered suitable for operational planning and energy management applications. The obtained results, therefore, demonstrate that the proposed multivariate LSTM framework provides sufficiently accurate forecasts for real-time decision support in smart grid environments.

Furthermore, the relatively small variation in forecasting error across the three prediction horizons suggests that the model is capable of capturing the dominant temporal patterns embedded in the dataset. This behaviour indicates that the proposed architecture successfully learns the periodic structure of electricity demand and renewable generation dynamics.

The comparison between actual and predicted load values demonstrates strong alignment in overall trend, peak demand periods, and temporal fluctuations. The LSTM model successfully captures both the amplitude and phase of the load variations, although minor deviations are observed during sudden transitions, which are expected in time-series forecasting (**Figure 8**). This confirms the model's effectiveness in learning underlying temporal dynamics while maintaining stable predictive performance.

5.2. Analysis of Forecasting Behaviour

The relatively similar forecasting errors observed across the 15-minute, 1-hour, and 24-hour prediction horizons are largely influenced by the strong periodic structure embedded within the synthetic dataset. Because the generated load profiles exhibit stable daily and weekly cycles with limited abrupt behavioural changes, the forecasting task becomes less challenging than real-world smart grid forecasting scenarios. Consequently, the forecasting performance reported in this study should be interpreted primarily as validation of the proposed forecasting framework under controlled conditions rather than direct evidence of equivalent real-world forecasting accuracy across all prediction horizons. A zoomed comparison over a shorter test interval is presented in Figure 9, further highlighting the ability of the LSTM model to track short-term variations in electricity demand.

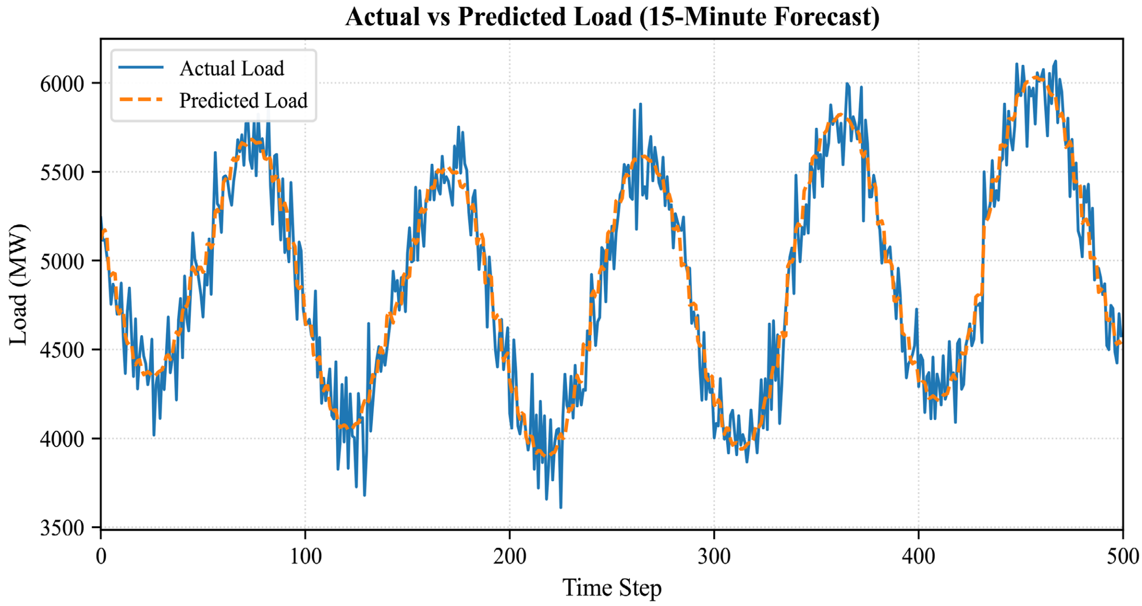

Figure 8. Comparison between actual load values and LSTM-predicted load values for the test dataset.

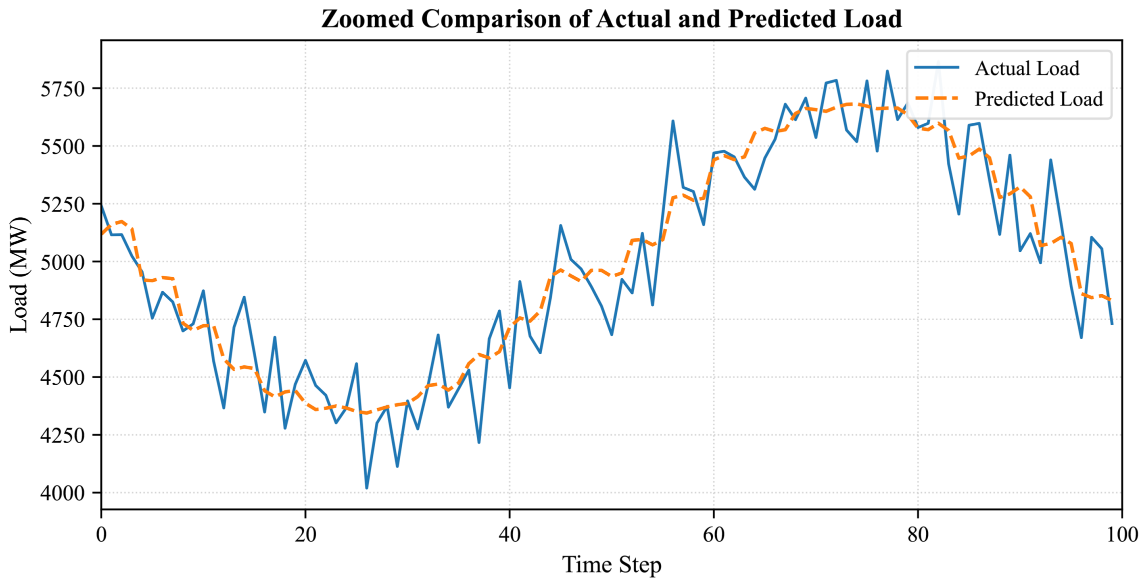

Figure 9. Zoomed comparison of actual and predicted load values for a selected time interval.

In real-world power systems, however, forecasting errors typically increase as the prediction horizon becomes longer. This occurs because longer horizons introduce additional uncertainty due to factors such as weather variability, renewable generation fluctuations, and stochastic demand behaviour. Although the synthetic dataset used in this study exhibits relatively smooth periodic patterns, the results nevertheless demonstrate that the proposed LSTM architecture is capable of capturing complex temporal dependencies and producing stable multi-horizon forecasts.

To further analyse the statistical behaviour of the forecasting model, the distribution of prediction errors was examined. The residual error distribution, defined as the difference between the actual load values and the corresponding predicted values, is illustrated in **Figure 10**.

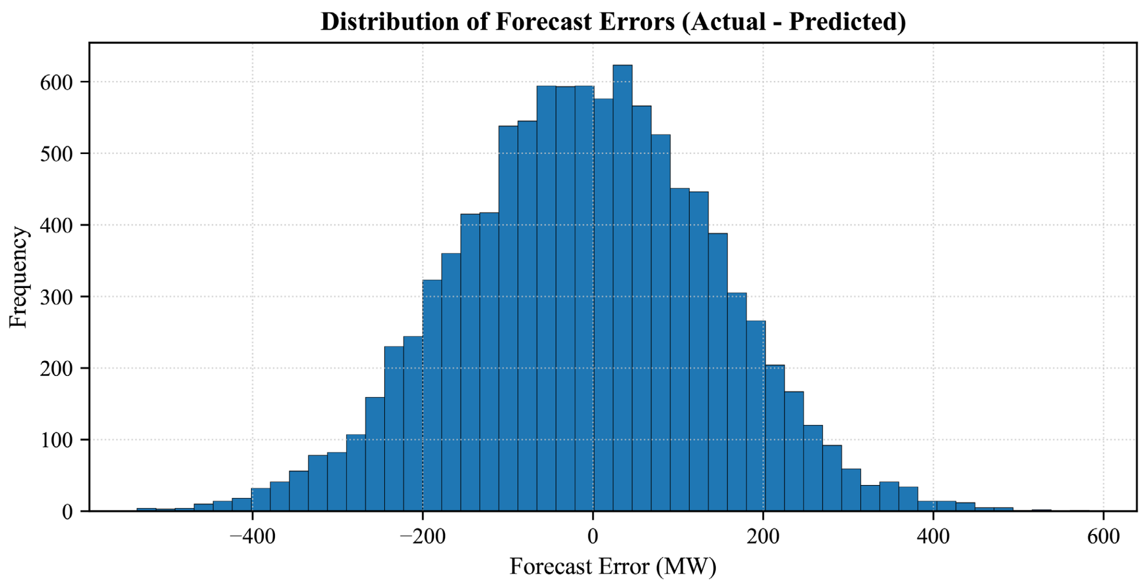

Figure 10. Distribution of forecasting residual errors (Actual − Predicted load) for the LSTM model.

The distribution is approximately centered around zero, indicating that the LSTM model does not exhibit systematic overestimation or underestimation of load values. This behaviour suggests that the model produces unbiased forecasts and captures the underlying temporal structure of the dataset effectively.

To further illustrate forecasting performance across multiple operational timescales, a comparison of the predicted load profiles for 15-minute, 1-hour, and 24-hour forecasting horizons is presented in **Figure 11**. The figure demonstrates that the proposed LSTM model is capable of tracking the overall load dynamics consistently across different prediction horizons.

5.3. Implications for Smart Grid Optimisation

Accurate short-term forecasting plays a critical role in enabling intelligent decision-making within smart grid environments. Reliable predictions of electricity demand allow energy management systems to anticipate future system states and

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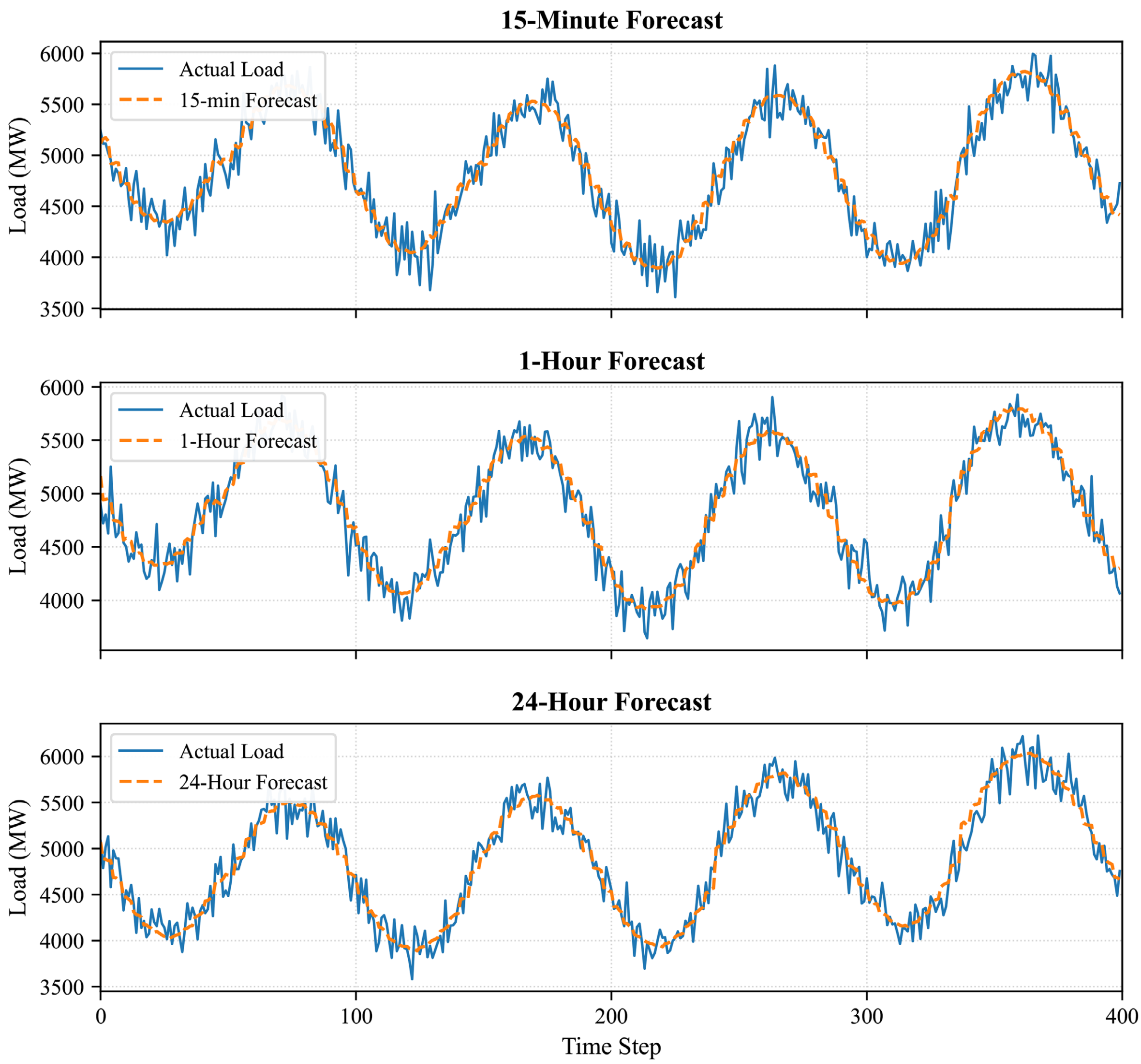

Figure 11. Multi-horizon comparison of actual load and LSTM forecasts for 15-minute, 1-hour, and 24-hour prediction intervals.

perform proactive operational adjustments. The forecasting module developed in this study is designed to function as the predictive input layer of a broader multi-objective smart grid optimisation framework. In such a system, the predicted electrical load outputs generated by the LSTM model serve as input parameters to optimisation algorithms responsible for determining optimal operational strategies, including generator dispatch, energy storage scheduling, and demand response control.

By providing reliable multi-horizon forecasts, the proposed LSTM-based forecasting framework supports real-time energy management strategies aimed at improving grid efficiency, operational reliability, and sustainable integration of renewable energy resources. The forecasting architecture developed in this work, therefore, forms a foundational component of the integrated smart grid optimisation framework that will be presented in subsequent research.

6. Conclusions and Future Work

This paper presented a multivariate Long Short-Term Memory (LSTM)-based framework for short-term multi-horizon electrical load forecasting in smart grid environments. The proposed approach integrates a structured preprocessing pipeline including cyclical temporal feature encoding, chronological dataset partitioning, feature standardisation, and sliding-window sequence generation to support robust time-series forecasting.

The forecasting model was evaluated using 15-minute, 1-hour, and 24-hour prediction horizons. Experimental results demonstrated that the proposed LSTM framework effectively captures the dominant temporal patterns embedded within the dataset and produces stable forecasting performance across multiple operational timescales.

The use of a synthetic dataset provided a controlled experimental environment for validating the proposed forecasting methodology and ensuring reproducibility of the experimental setup. However, the relatively similar forecasting errors observed across different prediction horizons are influenced by the strong periodic structure of the generated dataset. Consequently, the forecasting performance reported in this study should be interpreted primarily as validation of the proposed forecasting framework under controlled conditions rather than direct evidence of equivalent real-world forecasting accuracy.

The forecasting framework developed in this work is intended to function as the predictive input layer of a broader smart grid optimisation architecture. The generated load forecasts will support future optimisation models responsible for real-time energy management, generator scheduling, and operational decision-making under uncertainty.

Future work will therefore focus on validating the proposed framework using real-world smart grid datasets and integrating the forecasting model with multi-objective optimisation techniques for intelligent smart grid energy management.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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