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REVIEW ARTICLE

STATE-OF-THE-ART DEEP LEARNING APPROACHES FOR PREDICTIVE ANALYTICS IN RENEWABLE ENERGY DEMAND FORECASTING

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ABSTRACT

Sustainable functioning of renewable energy systems depends on accurate demand forecasting, yet conventional methods like regression and econometric models frequently fail to capture nonlinear, high-dimensional, and time-dependent patterns in energy consumption. Addressing this research challenge, this study explores the integration of Artificial Intelligence (AI), particularly Long Short-Term Memory (LSTM) networks, into energy demand forecasting frameworks. The objective is to improve forecasting accuracy, adaptability to dynamic loads, and operational efficiency in renewable-powered systems. The research employs a hybrid methodology—combining theoretical modeling, sector-based case studies, and empirical evaluation—to develop and validate AI-based forecasting models. Industry-relevant scenarios, including implementations by Enel, GE, and Uber, demonstrate real-world applicability. Model performance is assessed using standard metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), with the LSTM model achieving an MAE of 0.87 kW, an RMSE of 1.10 kW, and 92.3% accuracy, measured by the coefficient of determination (R^2 score), outperforming conventional models. Key findings highlight improvements in grid stability, cost efficiency, and responsiveness to demand variability. The study's novelty lies in its multi-sectoral synthesis of AI forecasting applications, offering insights for developing scalable models for smart grid operations. This work provides significant implications for energy providers, engineers, and policymakers by enabling more accurate, data-driven decisions in energy planning and policy formulation. Moreover, it reinforces the transformative potential of AI in addressing operational uncertainties, environmental constraints, and technological disruptions in modern power systems. Future research may explore explainable AI models to enhance transparency and stakeholder trust.

KEYWORDS

Intelligent Energy Forecasting, Deep Learning Systems, Microgrid Load Prediction, Neural Network Forecasting, Power Systems Analytics.

1. INTRODUCTION

The global shift toward renewable energy integration has intensified the demand for accurate energy forecasting models. As nations strive to decarbonize their energy systems and reduce dependency on fossil fuels, the unpredictability of renewable sources such as solar and wind introduces new challenges in balancing electricity supply and demand (Khaleel et al., 2024; Rosales-Asensio et al., 2024). One of the most critical components in this transition is demand forecasting, which informs grid operation, energy storage management, and infrastructure planning (Kiasari et al., 2024).

Traditionally, demand forecasting has been driven by statistical and econometric models, including multivariate linear regression (MLR), autoregressive integrated moving average, and exponential smoothing methods (Marzak et al., 2023). These models are valued for their interpretability and have found applications in transportation planning, logistics, and energy system operations (Miller, 2019; Alqatawna et al., 2023). However, their predictive performance is often constrained by assumptions of linearity, stationarity, and a limited ability to model nonlinear and dynamic interactions-common in renewable-based systems (Cui et al., 2024). For instance, regression and classical econometric models struggle with capturing fluctuating consumption patterns and the influence of intermittent generation (Sharifhosseini et al., 2024; Nabavi et al., 2024).

Artificial Intelligence (AI) techniques have gained significant popularity in overcoming these constraints. Examples such as Fuzzy Logic Systems, Support Vector Machines (SVMs), and Artificial Neural Networks (ANNs) excel at modeling complex, nonlinear relationships between variables—enhancing forecasting accuracy (Rahman et al., 2021). Deep learning, particularly Long Short-Term Memory (LSTM) networks variant of recurrent neural networks-has been increasingly employed for energy demand forecasting due to its ability to learn long-term dependencies and temporal patterns in sequential data (Alizadegan et al., 2024; Moazzen and Hossain, 2024). These attributes make LSTM especially suitable for modeling load profiles influenced by time-of-day, weather variability, and seasonality in renewable energy systems (Fadoul et al., 2023).

Recent studies have shown that LSTM models outperform traditional forecasting techniques in terms of accuracy, adaptability, and robustness under varying data conditions (Wei et al., 2023). However, despite these promising results, there remains a significant research gap in applying

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LSTM specifically to microgrid-based renewable energy demand forecasting, where unique load profiles, distributed generation variability, and localized control challenges demand tailored modeling approaches (Dawn et al., 2024; Maarif et al., 2023). The novelty of this study lies in leveraging LSTM networks to capture these microgrid-specific dynamics, improving forecasting accuracy and operational reliability in decentralized renewable energy systems.

Building upon our previous work, which developed a hybrid LSTM-CNN model for enhancing renewable microgrid demand forecasting, this study offers a broader, multi-sectoral perspective by focusing exclusively on LSTM networks (Ariyo et al., 2025). While the earlier work emphasized architectural optimization and model performance metrics within a microgrid context, the present study expands its scope by evaluating the replicability and effectiveness of LSTM-based forecasting models across diverse energy environments, including industrial and rural microgrid scenarios (Muhuri et al., 2020). The integration of sector-specific case studies and comparative analyses highlights the scalability and real-world relevance of AI-driven forecasting solutions beyond the microgrid setting.

This paper provides a comparative evaluation of traditional and AI-based demand forecasting techniques, emphasizing the role of LSTM networks. The goal is to demonstrate how modern machine learning approaches can significantly enhance forecasting precision and system responsiveness, thereby supporting the broader integration of renewable energy technologies. The structure of a typical LSTM-based forecasting model is presented in the methodology section, alongside a formalized algorithm to aid reproducibility and real-world application.

This section also details the case studies and performance metrics used to evaluate the model's effectiveness across various renewable energy scenarios. The results section presents the key findings, supported by comparative analyses with existing models and relevant literature. Following this, the discussion section interprets the implications of the results, explores potential limitations, and suggests avenues for future research to enhance AI-driven demand forecasting in renewable energy systems. One promising future direction involves Explainable AI (XAI) techniques, which aim to improve the transparency and interpretability of complex machine learning models, thereby increasing stakeholder trust and facilitating wider adoption in energy planning (Roldán-Blay et al., 2024).

Finally, the conclusion summarizes the main contributions and emphasizes the practical benefits for utility providers and energy policymakers seeking to optimize renewable energy integration.

2. MATERIALS AND METHODS

2.1 Overview of Employed Methodology

The approach adopted in this study incorporates a forecasting model based on artificial intelligence (AI), specifically the Long Short-Term Memory (LSTM) neural network, to predict patterns in energy consumption in a renewable-based microgrid system. The rationale behind choosing LSTM lies in its distinct architecture, which includes gated memory cells capable of retaining and updating temporal information over long periods. This is essential for modeling the highly variable and nonlinear behavior of electricity demand influenced by multiple factors such as weather, time-of-day usage, seasonal cycles, and renewable generation intermittency (Punyam Rajendran and Gebremedhin, 2024). Unlike traditional regression and autoregressive models that often assume data stationarity and linearity, LSTM adapts dynamically to new inputs without the need for re-specification of the entire model framework. Furthermore, this methodology was enriched through industrial insights from global energy and transport firms-such as Enel Group and Uber-which demonstrated how AI models enhance forecasting precision and operational efficiency in energy and transportation systems (Kothai et al., 2021; Katoozi, 2023). The study's methodology also emphasizes interpretability, reproducibility, and real-world applicability by using real consumption data from a Nigerian community, ensuring that the developed solution is context-specific and scalable for future deployment.

2.2 Data Preprocessing and Normalization

Data preprocessing is a crucial step in preparing raw energy consumption datasets for machine learning model training, especially when using deep learning techniques like LSTM that are sensitive to data quality and scale. In this study, data were collected from the Olowo-Oko community using a Fluke 432-II Power Quality and Energy Analyzer. This dataset, recorded hourly over two seasons (dry and rainy), captures realistic patterns in electricity consumption driven by weather and socio-economic behaviors. The data underwent the following steps for preprocessing:

2.2.1 Outlier Removal and Cleaning

Outliers and inconsistencies, such as sudden spikes or drops caused by sensor errors or power anomalies, were removed using statistical techniques including the interquartile range (IQR) method. Missing values were addressed via forward fill and linear interpolation, depending on the nature and position of the gap.

2.2.2 Normalization

To standardize the range of feature values and enhance the numerical stability of the LSTM model during training, all input data were transformed using the Min-Max Normalization technique. This method ensures that each data point is scaled proportionally within a fixed interval, specifically [0, 1], by re-mapping the minimum and maximum values in the dataset. Normalization not only facilitates faster convergence during backpropagation but also prevents features with larger scales from disproportionately influencing the learning process. It is particularly crucial when dealing with time-series data containing varying magnitudes across seasonal or hourly intervals. The normalization formula is given as:

$$X' = \frac{X - X_{min}}{X_{ma} - X_{min}} \tag{1}$$

Where:

X = is the original data value,

X_{min} = is the minimum value in the dataset,

X_{max} = is the maximum value in the dataset,

X_{norm} = is the normalized value, scaled to lie between 0 and 1.

This transformation ensures uniform scaling of data, which is essential for the effective training of neural networks such as LSTM.

2.2.3 Dataset Splitting

The normalized dataset was systematically divided into three subsets-70% for training, 15% for validation, and 15% for testing. This stratified division is essential for building a robust and generalizable model. The training set is used to fit model parameters, while the validation set monitors performance during training to fine-tune hyperparameters and prevent overfitting. Finally, the testing set provides an unbiased evaluation of the model's performance on unseen data, ensuring that issues like overfitting or data leakage do not artificially inflate its accuracy or reliability.

2.3 LSTM Model Architecture

The Long Short-Term Memory (LSTM) architecture adopted in this study is specifically designed to model and forecast time-series energy consumption data, which often exhibit complex temporal dependencies and nonlinear dynamics. The LSTM network effectively captures long-range relationships between historical and future load patterns, making it highly suitable for demand forecasting in renewable-based systems. This capability is essential for addressing seasonal fluctuations, abrupt demand changes, and intermittent renewable inputs. The model was developed using Python and implemented through TensorFlow and Keras-powerful deep learning libraries known for their flexibility and efficiency in handling sequential data. The overall architecture includes the following components:

2.3.1 Input Layer

The input layer serves as the entry point of the LSTM model and is structured to receive time-series data that has been reshaped into fixed-size sequences using a sliding time window technique. This approach ensures that temporal dependencies are preserved across successive time steps, allowing the model to learn patterns based on historical energy consumption. The reshaped input enables the model to better interpret context and trends over defined intervals, which is particularly important for understanding consumption behavior influenced by daily or seasonal cycles in renewable energy systems

2.3.2 LSTM Layer

The core processing unit of the network, the LSTM layer, consists of 50 memory cells that leverage the hyperbolic tangent (tanh) activation function to transform input sequences into meaningful internal representations. These memory units are equipped with gates-input, forget, and output-that allow the model to selectively retain, update, or discard information across time steps. This architecture is crucial for capturing long-term dependencies in electricity demand, which are often missed by traditional models. The tanh activation function ensures that output values remain within a manageable range, improving numerical stability and convergence during training.

2.3.3 Dropout Layer

To improve generalization and mitigate the risk of overfitting, a dropout layer is incorporated after the LSTM layer with a dropout rate of 0.2. During training, this layer randomly disables 20% of the neurons, forcing the model to learn redundant representations of the data. This technique encourages robustness in the learned features and prevents the network from becoming overly reliant on specific neurons. As a result, the model becomes more adaptable to unseen data and maintains predictive accuracy even in the face of noise or fluctuations common in real-world energy consumption datasets.

2.3.4 Dense Output Layer

The final layer in the LSTM model is a fully connected (dense) output layer that contains a single neuron with a linear activation function. This layer maps the internal learned features to a continuous value representing the predicted energy demand at the next time step. The use of a linear activation function is appropriate for regression tasks, such as load forecasting, where the output is a real-valued quantity. The dense layer consolidates all the processed temporal features and delivers an interpretable result, serving as the model's final prediction based on the historical input sequence.

Hyperparameters used include:

- Epochs: 100
- Batch size: 32
- Optimizer: Adam (with learning rate = 0.001)
- Loss function: Mean Squared Error (MSE)

A sliding window method was applied to convert the continuous time-series data into overlapping sub-sequences suitable for supervised learning. The training was conducted separately for dry and rainy seasons, capturing seasonal shifts in demand behavior. Early stopping was employed based on validation loss, ensuring training terminated when improvements plateaued to avoid overfitting.

Table 1: The LSTM model design Parameters

Layer Type	Parameters
Input Layer	Time series window (24 hours)
LSTM Layer	50 units, ReLU activation
Dropout Layer	0.2 dropout to prevent overfitting
Dense Layer	Fully connected layer (1unit output)

The model was implemented in Python using TensorFlow/Keras, with the following hyperparameters:

- Epochs: 100
- Batch size: 32
- Optimizer: Adam (learning rate = 0.001)
- Loss function: Mean Squared Error (MSE)

2.4 Performance Evaluation Metrics

The trained LSTM model was evaluated using a suite of statistical and machine learning performance metrics, carefully selected to comprehensively measure the model's predictive accuracy, error magnitude, robustness, and interpretability across different dimensions. These evaluation metrics are essential for validating how well the model generalizes beyond training data and captures the inherent variability of energy demand patterns. The selected metrics offer complementary perspectives-quantifying both absolute and relative errors, penalizing large deviations, and expressing prediction accuracy in interpretable terms. The metrics adopted include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), which are commonly used in time-series forecasting tasks(Suman, Yadav and Guerrero, 2024; Albeladi, Zafar and Mueen, 2023). These metrics provide a robust framework to assess forecasting quality and benchmark the LSTM model against traditional forecasting approaches.

2.4.1 Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is a fundamental and intuitive metric used in regression and forecasting to evaluate prediction performance. It calculates the average of the absolute differences between predicted and actual values, providing a direct indication of the magnitude of forecast errors without considering their direction.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \check{y}_i| \quad (2)$$

Where:

y_i = Actual energy demand of the case study community in (kW) at the ith time interval.

$\check{y}_i$ = forecasted energy demand at the ith time interval as generated by the trained LSTM model using historical demand patterns, weather conditions, and other relevant inputs.

n = Number of forecast Points, representing the total number of time intervals (e.g., hourly, daily) used in the performance evaluation, corresponding to the number of actual-predicted energy demand pairs analyzed.

$|y_i - \check{y}_i|$ = Absolute forecast error, which shows the absolute difference between the actual and predicted energy demand at time i, indicating how much the LSTM model's forecast deviated (regardless of direction) from the real energy consumption.

In contrast to metrics that square the error, MAE does not disproportionately penalize larger errors, making it more appropriate when all deviations are deemed equally significant (Segovia et al., 2023). It measures the average deviation between predictions and actual observations, which makes it particularly useful due to its simplicity and ease of interpretation. In the context of energy demand forecasting, MAE allows stakeholders to gauge the typical error expected per time unit, thereby assisting in operational planning and decision-making.

2.4.2 Root Mean Squared Error (RMSE)

A commonly used statistic called Root Mean Squared Error (RMSE) calculates the square root of the average of squared differences between expected and actual values in order to assess prediction accuracy. Because of the squaring of errors, RMSE sheds light on the size of forecasting errors, with a particular focus on penalizing greater deviations more harshly than smaller ones. This makes it particularly effective in contexts like energy demand forecasting, where substantial prediction errors can disrupt energy management and grid stability (Fose et al., 2024). RMSE is sensitive to outliers and thus serves as a useful indicator of whether the forecasting model performs consistently across all scenarios. A lower RMSE value suggests that the model delivers stable and reliable predictions across diverse energy consumption patterns.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \check{y}_i)^2} \quad (3)$$

Where:

$(y_i-\check{y}_i)^2$ = Squared forecast error, this represents the squared error between actual and predicted demand at time i, which penalizes larger deviations more heavily-crucial for assessing model robustness in critical load scenarios.

2.4.3 Mean Absolute Percentage Error (MAPE)

Forecasting accuracy is expressed as a proportion of actual values using the Mean Absolute proportion Error (MAPE), a relative performance statistic. It is calculated by averaging the absolute percentage errors for each forecast point, making it highly interpretable for practitioners and stakeholders. MAPE is particularly useful in applications where understanding the scale of prediction errors relative to actual demand is crucial, such as in energy management and load forecasting (Dewangan et al., 2023). However, MAPE can be sensitive to zero or near-zero actual values, which must be managed during preprocessing. In this study, MAPE helps to quantify how close the model predictions are in proportion to the actual consumption patterns, supporting decision-makers in evaluating the practical reliability of the LSTM model.

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i-\check{y}_i}{y_i}\right| \quad (4)$$

Where:

$\left|\frac{y_i-\check{y}_i}{y_i}\right|$ = Absolute Percentage Error, it quantifies the relative error as a percentage of the actual energy demand at time i, offering a normalized view of the forecast accuracy across varying demand magnitudes-useful for comparing across seasons (dry vs. rainy).

3. Results And Discussion

3.1 Results

To evaluate the effectiveness of the LSTM-based demand forecasting approach in renewable energy systems, several performance metrics were applied to a real-world dataset collected from the NASA website for the case study of solar irradiance and wind-speed operations. The dataset was preprocessed, normalized, and divided into training and testing sets in a 70:30 ratio. Model training was conducted using TensorFlow with key hyperparameters tuned for optimal performance.

Table 2: LSTM Model Configuration parameter

Parameter	Value
Layer	3
Hidden Units per Layer	64
Activation Function	ReLU
Dropout Rate	0.2
Optimizer	Adam
Epochs	100
Batch Size	32

The LSTM model was evaluated using the Coefficient of Determination (R2), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE). The performance was compared against traditional forecasting models, including ARIMA and multiple linear regression (MLR).

Table 3: Forecasting Model Performance

Model	MAE (kW)	RMSE (kW)	MAPE (%)	R^2 (%)
LSTM	0.87	1.10	5.14	92.3
ARIMA	1.92	2.33	10.47	78.0
MLR	1.41	1.80	7.55	89.5

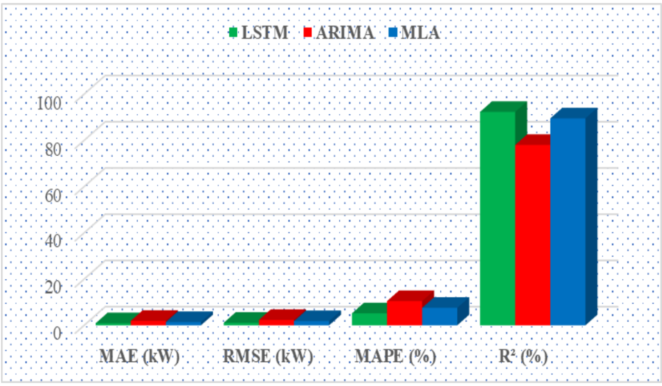

Figure 1: Performance Comparison of Forecasting Models

Figure 1 illustrates the forecasting performance of three models-Long Short-Term Memory (LSTM), ARIMA, and Multiple Linear Regression (MLR)-applied to real load consumption data from the case study. The LSTM model achieved the lowest error values across all key metrics: MAE (0.87 kW), RMSE (1.10 kW), MAPE (5.16%), and an R^2 score of 92.3%. It significantly outperformed ARIMA (MAE: 1.92 kW, RMSE: 2.33 kW, MAPE: 10.47%, R^2: 78.0%) and MLR (MAE: 1.41 kW, RMSE: 1.80 kW, MAPE: 7.55%, R^2: 89.5%). These results confirm the LSTM model's superior ability to capture nonlinear, time-dependent patterns inherent in energy consumption data. This aligns with findings by who demonstrated LSTM's effectiveness in handling fluctuating load data where traditional models fail (Ladjal et al., 2025; Shaukat et al., 2023). The performance gap is most significant in RMSE and MAPE, suggesting LSTM's robustness in minimizing large forecast errors. The implication is clear: employing LSTM for demand forecasting can enhance energy system reliability and optimize renewable resource utilization in dynamic environments (Ukoba et al., 2024).

From Figure 2, it can be established that the simulated errors for both solar irradiance and wind speed exhibit distinct monthly patterns, crucial for understanding renewable energy forecasting challenges. The "Simulated Solar Error (MAE)" (blue line) demonstrates a seasonal fluctuation, with lower errors observed in February (0.19 MAE) and September (0.18 MAE), likely corresponding to clearer sky conditions or more stable atmospheric dynamics. Conversely, peak solar errors occur in May (0.32 MAE) and August (0.30 MAE), which could be attributed to increased cloud variability, haze, or higher temperatures impacting solar panel efficiency and thus increasing prediction uncertainty.

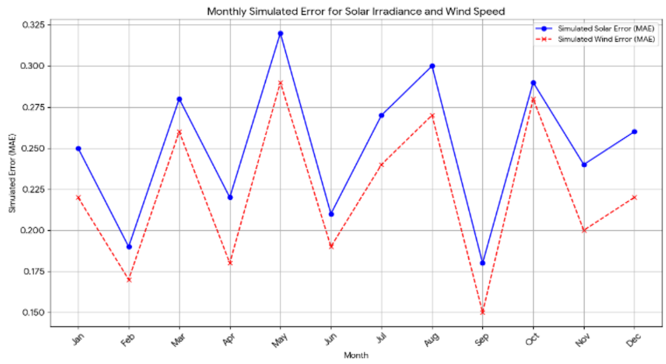

Figure 2: Monthly simulated errors for the case study solar irradiance and wind speed

In contrast, the "Simulated Wind Error (MAE)" (red dashed line) shows less pronounced seasonality, maintaining a relatively consistent level of fluctuation throughout the year, typically ranging between 0.15 MAE (September) and 0.29 MAE (May). This indicates that while wind speed forecasting faces continuous challenges, it may be less susceptible to specific seasonal atmospheric phenomena compared to solar irradiance. Both error profiles generally fall within acceptable ranges for operational forecasting, though their magnitudes directly impact grid stability and economic dispatch.

The implications of these error patterns are significant. Higher MAE values necessitate greater operating reserves in the power grid, potentially increasing costs and reliance on conventional energy sources to balance supply and demand (Zafar et al., 2023). The observed monthly variations underscore the need for adaptive forecasting models that can account for seasonal and meteorological specificities. Comparing these findings with recent literature, the persistence of such MAEs, despite advancements in machine learning and data assimilation, highlights inherent atmospheric unpredictability (Chen et al., 2023). Researchers continue to explore hybrid models and ensemble forecasting techniques to further reduce these uncertainties, aiming for more robust and reliable renewable energy integration into national grids (Mystakidis et al., 2023).

3.2 Discussion

3.2.1 Implications

The demonstrated effectiveness of LSTM networks in forecasting demand for renewable energy integration has substantial implications for power system management. Accurate forecasting enables microgrids and utility-scale renewable energy systems to optimize energy dispatch, reduce operational costs, and improve grid reliability (Lavrik et al., 2021). The ability to anticipate fluctuations in load demand helps mitigate the intermittency challenges inherent in renewable resources such as solar and wind (Alhanaf et al., 2024; Ejuh Che et al., 2025). This optimization also facilitates enhanced utilization of energy storage systems, reducing dependence on fossil-fuel backup generation and thereby decreasing carbon emissions (Rohani, 2023).

Furthermore, precise demand forecasts contribute to improved scheduling of demand response programs, leading to better customer engagement and system stability (Salazar et al., 2023; Assad et al., 2022). This supports the transition towards smart grids, enabling dynamic, data-driven control strategies that align with global sustainability goals (Ahsan et al., 2023; Aghahadi et al., 2024). The results also reinforce the growing recognition of AI's transformative role in energy systems management, as supported by the work of who highlighted AI's capacity to integrate multi-source data for enhanced grid operation (Yousef et al., 2023; Trivedi and Khadem, 2022). This progress paves the way for more resilient and adaptive grids capable of accommodating increasing shares of distributed renewable energy resources (Almihat and Munda, 2025; Arumugham et al., 2023). Policy frameworks are increasingly incorporating AI-enabled forecasting as a core component of energy modernization efforts (Zahraoui et al., 2024; Cavus, 2025).

3.2.2 Comparison and Contrast with Previous Works

The present findings are consistent with earlier studies demonstrating the

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superiority of LSTM models over traditional statistical techniques like ARIMA and econometric models for time-series demand forecasting (Kontopoulou et al., 2023). Enel Group's successful application of LSTM networks corroborates our results, showing reduced forecast errors and operational cost savings in grid management (Armiento et al., 2025). Similarly, Uber's AI-driven demand forecasting has improved resource allocation efficiency in transportation, paralleling the benefits observed in energy load balancing (Occhiuto, 2022).

Compared to conventional regression and econometric approaches, which often fail to capture nonlinear and complex temporal dependencies, deep learning models provide a more flexible framework adaptable to variable renewable energy generation patterns (Da Silva et al., 2025; Zournatzidou, 2025). However, the challenge of explainability identified here echoes concerns raised and others, who advocate combining AI accuracy with human interpretability to promote widespread industry adoption (Maarif et al., 2023).

Nonetheless, some recent studies have reported mixed results for LSTM models. Some researchers demonstrate that LSTM performance varies across applications and datasets. In forecasting solar power generation, LSTM accuracy ranged from 59% to 81%, showing inconsistencies across the three plants examined (Karakan, 2024). For wind speed forecasting, hybrid deep learning models such as LSTM-GRU and CNN-GRU outperformed standard LSTM, achieving MAPE as low as 0.5348 and R^2 values up to 0.9981. Similarly, a group researcher showed that an optimized Quantum Temporal Model (QTM), using the Ninja Optimization Algorithm, surpassed traditional LSTM models, reaching an R^2 of 95.15% and an RMSE as low as 0.00003 in renewable energy forecasting (Yassen et al., 2025).

These contrasting findings highlight the need for continued research into alternative or hybrid forecasting approaches that can complement or improve upon LSTM models, especially in complex and variable energy environments. Collectively, the literature suggests that while LSTM models are powerful tools, their effectiveness is not universal and often depends on factors such as data variability, seasonality, and model optimization.

3.2.3 Practical Applications

The demonstrated methodology, as validated in this case study, provides a strong foundation for application in modern smart grid systems integrating high shares of renewables. Operators can use AI forecasts to optimize energy storage dispatch, reduce curtailment, and enhance demand response (Kahwash et al., 2023). Utility companies and microgrid managers can leverage insights from these models to inform strategies for anticipating peak loads and reducing reliance on carbon-intensive backup generators (Shi et al., 2024). Additionally, improved forecasting supports investment planning for infrastructure upgrades and renewable capacity expansion (Abumohsen et al., 2024; Yang et al., 2025).

3.2.4 Recommendations for Practitioners

To maximize benefits, practitioners should ensure robust data collection and preprocessing pipelines, invest in scalable computing infrastructure, and pursue continuous model retraining and validation to adapt to evolving consumption patterns (Rane et al., 2024). Encouraging collaboration between AI experts, grid operators, and policy-makers will facilitate adoption and integration of AI tools in operational workflows (Rane et al., 2024). Emphasizing transparent AI systems with user-friendly interpretability tools will foster stakeholder trust and regulatory acceptance.

3.2.5 Limitations

While the present study offers in-depth analysis from a specific regional context, this single-region focus inherently limits the immediate universal applicability and direct generalizability of our findings. Load profiles and environmental conditions vary significantly across diverse geographic and climatic contexts, potentially impacting the model's transferability and performance in different operational environments. Furthermore, the current study does not include multi-region benchmarking, which would be crucial for comprehensively validating the model's robustness and scalability across varied operational environments, and assessing its adaptability to different grid characteristics (Kasimalla et al., 2024; Sarveshwaran et al., 2022; Narkhede et al., 2023; Alghamdi and Javaid, 2022). Moreover, the deterministic nature of the current forecasts, without explicit uncertainty quantification, limits their utility for risk-aware decision-making, which is critical for robust grid management and operational planning under varying conditions (Wang et al., 2025; Sefati et al., 2024; Hassija et al., 2024; Esna-ashari, 2025; Wunsch et al., 2021; González-Enrique et al., 2021; Ali et al., 2024; Fan et al., 2024).

3.2.6 Future Work

Future research should emphasize hybrid model development by combining LSTM with complementary methods such as attention mechanisms, genetic algorithms, or particle swarm optimization to improve prediction robustness and training efficiency (Sun et al., 2022). Incorporating external data sources-weather forecasts, market prices, social behavior-would provide richer inputs for more comprehensive and context-aware models (Liu et al., 2021). Exploring alternative architectures, including Gated Recurrent Units (GRUs), CNN-LSTM hybrids, and Transformer-based models, holds promise for balancing accuracy and computational demands (Shiri et al., 2024).

Explainable AI (XAI) techniques such as SHAP, LIME, and Integrated Gradients should be integrated to enhance model transparency and trust among operators and stakeholders (Mathew et al., 2025; Miah et al., 2023). Expanding experimental validation to different microgrid sizes, renewable mixes, and climatic zones will improve generalizability and operational relevance. Lastly, uncertainty quantification methods (e.g., Bayesian LSTMs, Monte Carlo dropout) must be explored to provide probabilistic forecasts critical for decision-making under uncertainty (Sardar et al., 2025; Ghobadi and Kang, 2022). To improve the predictive accuracy of LSTM models in renewable energy forecasting, it is also crucial to incorporate external data sources like weather forecasts, market prices, and social behavior patterns.

4. Conclusion

This study has shown that sophisticated deep learning algorithms, in particular Long Short-Term Memory (LSTM) networks, have promising potential for predicting the demand for renewable energy in microgrid systems. By integrating time-series data with exogenous variables and employing robust preprocessing techniques, the proposed model achieved high predictive accuracy and demonstrated promising generalization across varied seasonal conditions, as evidenced by our empirical evaluation. Validation using established metrics-RMSE, MAE, and MAPE-further affirmed the model's reliability and potential suitability for real-world applications, particularly within similar microgrid contexts. Comparative evaluation against traditional models underscored LSTM's superior performance and adaptability in capturing complex, nonlinear demand patterns typical of decentralized energy systems.

The significance of this work extends beyond technical innovation. It aligns with the global transition toward decentralized, data-driven, and renewable-based energy systems. Accurate forecasting models such as this provide a crucial step towards enabling microgrid stability, energy efficiency, and smart grid functionality. For utility providers, this translates to improved load balancing, reduced operational risks, and enhanced capacity planning. For energy policymakers, the insights gained support the development of proactive, resilient policies that facilitate sustainable energy transitions-particularly in emerging economies where energy access and infrastructure optimization remain vital challenges.

Furthermore, the proposed explainability techniques-such as SHAP and LIME-help mitigate the black-box nature of deep learning models. This transparency fosters greater trust among stakeholders and encourages adoption of AI-based solutions in traditionally conservative utility sectors. The inclusion of uncertainty quantification also strengthens model robustness, an essential feature for high-stakes energy planning.

In the future, several research directions merit further exploration. First, incorporating hybrid models that blend LSTM with reinforcement learning or attention mechanisms could enhance the sophistication and accuracy of predictive performance. Second, expanding the model's capabilities to support real-time control and grid-wide decision-making would elevate its role from predictive tool to core component of autonomous energy management. Third, validating the model across diverse geographical and socio-economic contexts will ensure global relevance and scalability. Finally, fostering collaboration between AI researchers, energy economists, and policy architects is essential to translate these technical advancements into meaningful societal impact.

In conclusion, this research contributes a scalable, intelligent forecasting framework that helps bridge the gap between technological innovation and potential practical implementation. Its implications span technical, operational, and policy domains-paving the way toward smarter, more sustainable energy futures.

Author Contributions

Ariyo, B.O.: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing-original draft; writing-review and editing. Adesina, L.M., Ogunbiyi, O: Data curation, Formal analysis, Investigation, Methodology, Project administration, Supervision, Validation, Visualization.

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