Journal of Information Systems Engineering and Management
2025, 10(56s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

An Electric Load Forecasting Enhancement Using LSTM-RNN Integrated with Genetic Algorithms: A Case Study of SEWA in the Sharjah Emirate

Abdel Rahman Al Ali[1], Danial Md Nor[2], Fahmy Rinanda Saputri[3], Norfaiza Fuad[4]
[124] *Department of Electronic Engineering, Universiti Tun Hussein Onn Malaysia*
[3] *Department of Engineering Physics, Universitas Multimedia Nusantara*

ARTICLE INFO

Received: 30 Dec 2024

Revised: 19 Feb 2025

Accepted: 27 Feb 2025

ABSTRACT

Introduction: Accurate electric load forecasting is essential for power companies to ensure efficient load scheduling and avoid excessive electricity production. However, developing a reliable forecasting model remains a complex task due to the need for training multiple models, selecting the most effective one, engineering informative features, and determining optimal time lags for time series forecasting.

Objectives: This research aims to address the challenges of long-term electric load forecasting by proposing a hybrid model that combines Long Short-Term Memory (LSTM) neural networks with Genetic Algorithms (GA). The objective is to enhance forecasting accuracy through optimal feature selection, time lag determination, and LSTM architecture configuration.

Methods: The methodology involves building baseline models using both linear and non-linear machine learning algorithms. Feature selection is conducted using wrapper and embedded methods to identify the most relevant predictors. Genetic Algorithms are applied to optimize time lags and the number of LSTM layers. The model is trained and evaluated using electricity consumption data from the Sharjah Emirate.

Results: The optimized LSTM-GA model significantly outperforms traditional machine learning models. It achieved a Mean Absolute Error (MAE) of 10 MW and a Root Mean Square Error (RMSE) of 12 MW, compared to 20 MW MAE and 25 MW RMSE from the Random Forest model. Feature selection reduced MAE by 33.3% and RMSE by 40%, demonstrating the effectiveness of GA-based optimization. Temperature analysis revealed that every 1°C increase beyond 30°C results in a 900 MW rise in electricity load, highlighting the importance of incorporating weather data.

Conclusions: The results confirm that the proposed LSTM-GA framework effectively captures the dynamics of long-term electric load forecasting. The integration of feature engineering, optimization algorithms, and weather data enhances prediction accuracy, making it a promising tool for power system planning and management.

Keywords: electric load forecasting, LSTM, genetic algorithm, time series, feature selection, optimization.

INTRODUCTION

Accurate electricity load forecasting (ELF) is vital for the planning, operation, and management of power systems, particularly in the context of increasing energy demands and the integration of renewable energy sources. Load forecasting not only ensures economic optimization of generation and distribution but also enhances public safety and supports the stable operation of society [1]. Misestimations, whether overestimation or underestimation, can lead to costly inefficiencies, blackouts, or resource misallocations, as illustrated by events such as the 2003 Northeast blackout in North America, which affected over 50 million people and resulted in losses exceeding USD 6 billion [2], [3].

Traditional statistical methods such as Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing have been widely used in load forecasting due to their simplicity and effectiveness in short-term, linear, and stationary data contexts [4]. However, these methods often fail to capture non-linear dependencies, seasonal trends, and external factors such as temperature and economic activity, especially in long-term scenarios. The evolving complexity of energy systems necessitates more advanced forecasting tools that can handle large, dynamic datasets and uncover hidden temporal relationships [5].

In response, machine learning (ML) and deep learning techniques, such as Support Vector Machines (SVM), Random Forests, and Artificial Neural Networks (ANN) have been adopted for their superior performance in handling non-linear and high-dimensional data. These models also consider external variables such as weather or holidays to improve prediction accuracy [6]. Among these, Long Short-Term Memory (LSTM) networks, a variant of Recurrent Neural Networks (RNN), have shown promising results in time-series forecasting due to their ability to capture long-range temporal dependencies [7]. LSTM networks maintain memory over time, allowing them to learn complex patterns across various time scales, including daily, weekly, and seasonal variations [8].

Nevertheless, the performance of LSTM models heavily depends on appropriate feature selection and optimal tuning of hyperparameters, such as the number of neurons, learning rate, and time lags. Improper configuration can lead to overfitting or poor generalization. Effective feature selection strategies, such as wrapper and embedded methods have been shown to enhance forecasting accuracy by focusing only on the most relevant predictors [9], [10]. To address the challenge of hyperparameter tuning, heuristic optimization techniques such as Genetic Algorithms (GA) offer robust solutions. GA simulates natural evolutionary processes to search for optimal parameter configurations, enabling efficient tuning of LSTM architectures and improving forecasting accuracy [11], [12].

This study focuses on enhancing long-term electricity load forecasting in the Sharjah Emirate by integrating LSTM networks with GA-based optimization. The model leverages historical electricity consumption data, weather variables, and selected feature subsets to develop a predictive framework. By optimizing time lags and network parameters through GA, the proposed approach aims to outperform conventional forecasting methods and provide a more accurate, scalable, and practical solution for energy system planning [13], [14].

OBJECTIVES

The main objective of this work is to enhance the accuracy and reliability of electricity load forecasting (ELF) through the integration of advanced deep learning techniques and intelligent optimization algorithms. In light of the growing demand for sustainable energy solutions and the increasing complexity of electricity consumption patterns, this research aims to address the limitations of conventional forecasting models by leveraging the strengths of Long Short-Term Memory (LSTM) Recurrent Neural Networks (RNN) and Genetic Algorithms (GA).

This research is based on the belief that a proper forecast model is fundamental to efficient energy planning and market stability. By embedding feature selection strategies and optimization procedures into the forecast pipeline, this research aims to provide a robust, scalable and intelligent system capable of adapting to diverse data scenarios. In addition, an evaluation framework is designed to rigorously validate model performance through comprehensive statistical and performance metrics.

METHODS

This research outlines a comprehensive methodology for electricity load forecasting using a Long Short-Term Memory (LSTM) model enhanced with a genetic algorithm (GA). The process begins with the acquisition of historical electricity load data from SEWA Electric Company (for 2020, 2021, 2023, and 2024), as well as climatological data including temperature, humidity, and other weather parameters.

The next stage is data pre-processing. This step involves merging electricity consumption data with weather data and time-lagged variables. These time-lagged variables are created to capture temporal dependencies, such as how past electricity consumption or weather conditions influence future consumption. The data is then cleaned by handling missing values using imputation techniques (e.g., filling with mean values), and scaled to a [0, 1] range to standardize features and improve the model's training phase. Subsequently, the data is divided into 80% for training and 20% for testing, while maintaining temporal order. Time series stationarity is also checked using the Dickey-Fuller test.

Journal of Information Systems Engineering and Management
2025, 10(56s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Feature engineering and feature selection are crucial subsequent steps. New features are created from previous time steps to help the model predict future electricity consumption. External variables like weather and holidays are also included as time-lagged features due to their influence on consumption patterns. To optimize feature selection and time-lag, a Genetic Algorithm (GA) is employed. The GA identifies the most relevant features and optimal time-lags to minimize forecasting errors. Additionally, Recursive Feature Elimination (RFE) is used to gradually remove less relevant features.

The benchmark model is then selected by evaluating the performance of various machine learning algorithms such as ANN, gradient boosting, random forest, and others. Models are evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The LSTM model enhanced with GA was found to provide the best results and is therefore chosen as the benchmark model.

After the benchmark model is selected, the design and training of the LSTM model are carried out. The LSTM architecture is designed with an input layer for time-lagged features and external variables, one or more LSTM layers, and a dense layer for forecasting. LSTM model hyperparameters, such as the number of layers, neurons per layer, activation function (tanh is used), and optimizer (Adam is used), are tuned to optimize prediction accuracy. Model training is performed using Backpropagation Through Time (BPTT). Early stopping is applied during training to prevent overfitting. Hyperparameters are further tuned using grid search and random search.

Finally, the model is thoroughly evaluated. Model performance is assessed using MAE and RMSE, which provide a measure of average error and give higher weight to significant errors. The model is tested on 20% of the dataset, not used during training, to ensure its generalization capability and effectiveness. Cross-validation is also performed to verify the model's robustness across different data splits. The final output of the proposed LSTM-RNN model is electricity load forecasting, which considers weather conditions to accurately predict peak consumer loads. The proposed research framework for the LSTM-RNN forecasting model with GA and best features selection is shown in Figure 1.

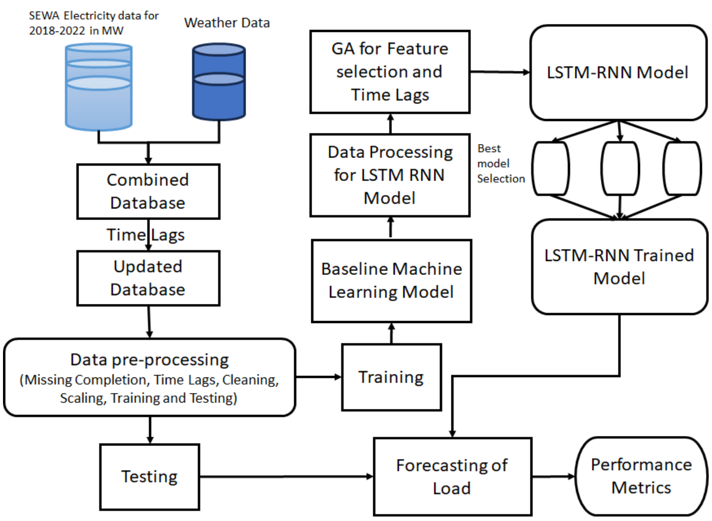

Figure 1. Proposed Research Framework for LSTM-RNN Forecasting Model with GA and Best Features Selection

RESULTS

The experimental setup in this research was designed using a systematic approach that encompassed data collection, preprocessing, feature selection, model training, and performance evaluation. As the study did not involve the development of a physical prototype, the entire experimental process relied solely on historical electricity load data obtained from SEWA.

The dataset consists of Electric Load Data (hourly or daily electricity consumption records collected from SEWA), Weather Data (Temperature, humidity, and wind speed), and Calendar Data (Public holidays, weekdays vs. weekends, and seasonal variations

Journal of Information Systems Engineering and Management
2025, 10(56s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Feature Selection

Preliminary feature selection, incorporating statistical and machine learning techniques like correlation analysis, mutual information, Recursive Feature Elimination (RFE), Principal Component Analysis (PCA), and feature importance from machine learning models, was performed to filter redundant or unimportant features.

Time Lag Selection and Optimization

Time lag selection is important for GA optimization, maintaining important past observations for forecasting. The study utilized ACF, PACF, RFE, and cross-validation to select appropriate time lags, as listed in Table 1, including short-term (1, 3, 6, 12, 24 hours), daily (24, 48 hours), and weekly (168 hours/7 days) intervals. Genetic Algorithm (GA) was employed to fine-tune the hyperparameters of the LSTM model, specifically identifying the optimal number of layers and time lags. This optimization process significantly reduced forecasting errors and enhanced the model's overall performance. As illustrated in Figure 2 and Figure 3, GA-optimized lags notably reduce forecasting errors during peak periods in terms of both timing and magnitude, as further demonstrated in Figure 4 which shows the impact of lag optimization on peak predictions. This confirms their critical role in capturing complex electricity load dynamics for reliable peak prediction and effective grid management, with the quantified improvement shown in Figure 5.

Table 1. Selected Time Lag before GA

Category	Selected Time Lags
Short-term Lags	1-hour, 3-hour, 6-hour, 12-hour, 24-hour
Daily Lags	24-hour, 48-hour
Weekly Lags	168-hour (7 days)

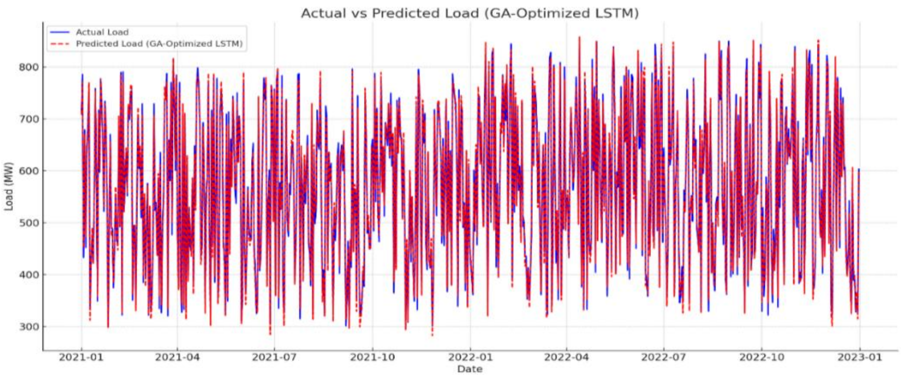

Figure 2. Actual vs Predicted Load (GA-Optimized LSTM)

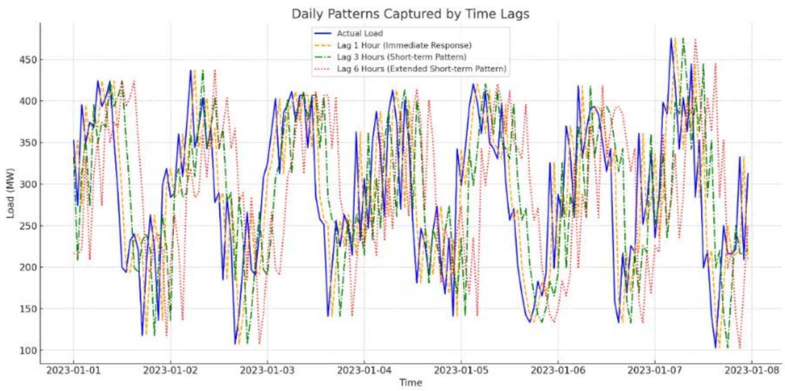

Figure 3. Daily Patterns Captured by Time Lags

Journal of Information Systems Engineering and Management
2025, 10(56s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

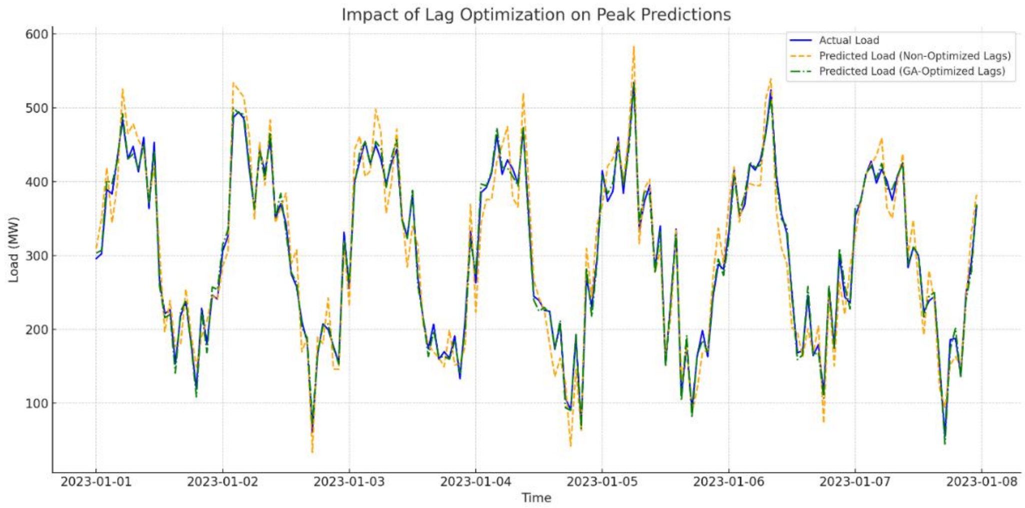

Figure 4. Impact of Lag Optimization on Peak Predictions

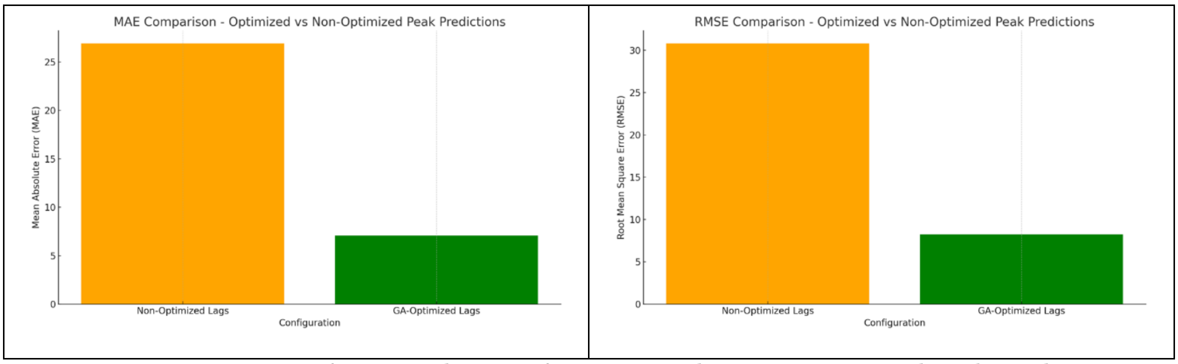

Figure 5. Comparison of MAE and RMSE for Optimized vs Non-Optimized Peak Predictions

Model Training and Evaluation

The experimental framework involved an 80% training and 20% testing data split to maintain sequence integrity. Model optimization using GA parameters for LSTM was evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

Impact of Feature Selection on Model Performance

Feature selection significantly improved model performance across all evaluated models. The improvements are quantified in Table 2 as different models' improvements after feature enhancements and visually represented in Figure 6. For Linear Regression, MAE improved by 20% (from 50 to 40) and RMSE by 21.4% (from 70 to 55). Decision Trees saw a 20% improvement in both MAE (from 35 to 28) and RMSE (from 45 to 36). Random Forest's MAE decreased by 20% (from 25 to 20), and RMSE improved by 20% (from 30 to 24). The Optimized LSTM model showed the most significant improvements, with MAE decreasing to 10 (33.3% improvement from 15) and RMSE reducing by 40% (from 20 to 12). This highlights feature selection's crucial role, especially for complex architectures like LSTM, by enabling better visualization of temporal and environmental dependencies.

Table 2. Different Models Improvements after Features Enhancements

	MAE Values in MW			**RMSE Values in MW**		
Model	**Baseline**	**With Feature Selection**	**Improvement (%)**	**Baseline**	**With Feature Selection**	**Improvement (%)**
Linear Regression [15]	50	40	20%	70	55	21.4%

Journal of Information Systems Engineering and Management
2025, 10(56s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Decision Trees [16]	35	28	20%	45	36	20%
Random Forest [17]	25	20	20%	30	24	20%
Optimized LSTM + best selection + GA (LRSG)	15	10	33.3%	20	12	40%

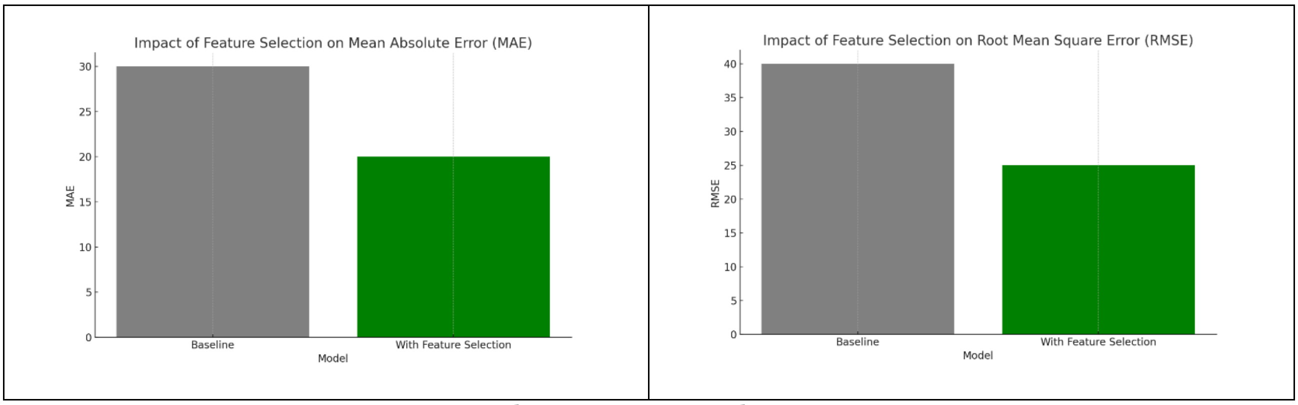

Figure 6. Baseline VS Features Selection Error Rate

Summary of Findings

This research comprehensively analyzed contemporary approaches to electric load forecasting, identifying a gap in the application of deep learning methods specifically tailored for the Sharjah environment. To address the first objective, data was gathered and preprocessed, and the proposed deep-learning model was developed. The Long Short-Term Memory (LSTM) model, optimized with a Genetic Algorithm (GA), was chosen due to its remarkable performance in modeling sequential data and its ability to memorize long-term dependencies and optimize, which is essential for precisely forecasting electric load demand. As highlighted in the second objective, the outcome revealed significant precision improvements compared with other forecasting models. By incorporating weather conditions, time indicators, and historical load data inputs, the LSTM model helped identify several factors that affected load demand. The final objective of this research, achieving low Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values, indicates a high level of prediction accuracy.

Theoretical Implications

Theoretically, this research advances the electric load forecasting knowledge base by demonstrating the effectiveness of LSTM networks in this field. It challenges the traditional understanding of statistical models, showcasing the ability of deep learning to replicate real-world electric load patterns more accurately. Furthermore, an examination of data preprocessing and feature engineering revealed their potential to enhance model performance, thereby expanding our understanding of the effective application of machine learning in energy forecasting.

Practical Implications

From a practical standpoint, the outcomes of this research hold significant potential for enhancing energy management in Sharjah. The higher level of prediction accuracy of the LSTM model could improve the engineering of energy systems for efficient distribution, increase the level of renewable energy integration, and aid in planning for high demand periods. It also has the potential to reduce operational costs for energy suppliers and improve the stability and sustainability of energy for consumers. The study also highlights the need to focus on the data foundation and develop analytic capacity to derive value from sophisticated prediction systems.

CONCLUSION

Limitations and Future Directions

Nevertheless, it is important to fully acknowledge the limitations of the current study. Although the model outperforms traditional practices, its performance depends directly on the quality and granularity of the data it

Journal of Information Systems Engineering and Management
2025, 10(56s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

receives. As with any model, future research could incorporate additional variables, such as socio-economic characteristics or finer weather data, to further enhance the predictive model. Furthermore, there is a relatively low level of knowledge regarding the model's ability to generalize to other regions or contexts. Future studies may refine this method to include distinct locations or distribute load forecasts in commercial or industrial settings where usage is likely to differ from residential use. Future research could also explore using deep learning in conjunction with other classical statistical or machine learning paradigms. Such models could offer a more balanced approach between statistical methods, ensuring easy-to-understand results without sacrificing the predictive power of deep learning techniques, thereby enhancing the versatility of the study.

Concluding Remarks

This research is a step toward using deep learning to forecast electric load demand in Sharjah, UAE. Through the application of LSTM network capabilities, this study provides a more reliable, effective, and possibly revolutionary technique for regulating energy demand. The research has successfully addressed a significant gap and provides a strong base for subsequent research. Future research suggests that combining an energy management approach with the next generation of advanced analytics can significantly enhance the sustainability, reliability, and efficiency of energy solutions.

ACKNOWLEDGMENT

We would like to express our appreciation to Universiti Tun Hussein Onn Malaysia and Universitas Multimedia Nusantara, Indonesia, for their invaluable support and collaboration throughout the research and writing processes of this project. The opportunity to engage in joint academic activities between these institutions has significantly enriched the quality and depth of this work. Their commitment to fostering research excellence and cross-institutional cooperation has been instrumental in the successful completion of this study.

REFERENCES

[1] M. Q. Raza and A. Khosravi, "A review on artificial intelligence-based load demand forecasting techniques for smart grid and buildings," *Renew. Sustain. Energy Rev.*, vol. 50, pp. 1352–1372, 2015, doi: https://doi.org/10.1016/j.rser.2015.04.065.

[2] L. Luka, "The case for improved governance as a tool for sustainable urban development in Malawi," in *ISOCARP Congress*, 2010, pp. 1–13. [Online]. Available: www.isocarp.net/Data/case_studies/1664.pdf

[3] M. Lange, "On the Uncertainty of Wind Power Predictions—Analysis of the Forecast Accuracy and Statistical Distribution of Errors ," *J. Sol. Energy Eng.*, vol. 127, no. 2, pp. 177–184, Apr. 2005, doi: 10.1115/1.1862266.

[4] H. M. Al-Hamadi and S. A. Soliman, "Long-term/mid-term electric load forecasting based on short-term correlation and annual growth," *Electr. Power Syst. Res.*, vol. 74, no. 3, pp. 353–361, 2005, doi: https://doi.org/10.1016/j.epsr.2004.10.015.

[5] M. A. Hammad, B. Jereb, B. Rosi, and D. Dragan, "Methods and Models for Electric Load Forecasting: A Comprehensive Review," *Logist. Sustain. Transp.*, vol. 11, no. 1, pp. 51–76, 2020, doi: 10.2478/jlst-2020-0004.

[6] T. Han, D. Jiang, Q. Zhao, L. Wang, and K. Yin, "Comparison of random forest, artificial neural networks and support vector machine for intelligent diagnosis of rotating machinery," *Trans. Inst. Meas. Control*, vol. 40, no. 8, pp. 2681–2693, 2018, doi: 10.1177/0142331217708242.

[7] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, 1997, doi: 10.1162/neco.1997.9.8.1735.

[8] N. Li, L. Wang, X. Li, and Q. Zhu, "An effective deep learning neural network model for short-term load forecasting," *Concurr. Comput. Pract. Exp.*, vol. 32, no. 7, p. e5595, 2020, doi: https://doi.org/10.1002/cpe.5595.

[9] S. Ghore and A. Goswami, "Short Term Load Forecasting of Chhattisgarh Grid Using Adaptive Neuro Fuzzy Inference System," *Int. J. Sci. Res.*, vol. 4, no. 11, pp. 841–846, 2015, doi: 10.21275/v4i11.nov151305.

[10] D. K. Chaturvedi, A. P. Sinha, and V. P. Singh, "Short Term Load Forecasting using Soft Computing Techniques," vol. 9, no. 4, pp. 491–502, 2013.

[11] X. Wang, D. Wang, Z. Ma, and R. Zhang, "Holiday Load Power Forecasting Based on SOIF-PAMAM method," *J. Electr. Electron. Eng.*, vol. 2, no. 3, 2023, doi: 10.33140/jeee.02.03.12.

[12] K. D. Abeyrathna and C. Jeenanunta, "Hybrid Particle Swarm Optimization With Genetic Algorithm to Train Artificial Neural Networks for Short-Term Load Forecasting," in *Research Anthology on Artificial Neural Network Applications*, I. R. Management Association, Ed., Hershey, PA, USA: IGI Global, 2022, pp. 227–241. doi: 10.4018/978-1-6684-2408-7.ch010.

Journal of Information Systems Engineering and Management
2025, 10(56s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

[13] S. Bouktif, A. Fiaz, A. Ouni, and M. A. Serhani, "Optimal Deep Learning LSTM Model for Electric Load Forecasting using Feature Selection and Genetic Algorithm: Comparison with Machine Learning Approaches †," *Energies*, vol. 11, no. 7, 2018, doi: 10.3390/en11071636.
[14] Y. Hong, Y. Zhou, Q. Li, W. Xu, and X. Zheng, "A Deep Learning Method for Short-Term Residential Load Forecasting in Smart Grid," *IEEE Access*, vol. 8, pp. 55785–55797, 2020, doi: 10.1109/ACCESS.2020.2981817.
[15] H. M. Al-Hamadi, "Long-term electric power load forecasting using fuzzy linear regression technique," *PEAM 2011 - Proc. 2011 IEEE Power Eng. Autom. Conf.*, vol. 3, pp. 96–99, 2011, doi: 10.1109/PEAM.2011.6135023.
[16] M. Hambali, A. Akinyemi, J. Oladunjoye, and N. & Yusuf, "Electric Power Load Forecast Using Decision Tree Algorithms. Computing, Information Systems," *Dev. Informatics Allied Res. J.*, vol. 7, no. 4, pp. 29–42, 2016.
[17] N. Shirzadi, A. Nizami, M. Khazen, and M. Nik-Bakht, "Medium-Term Regional Electricity Load Forecasting through Machine Learning and Deep Learning," *Des. 2021, Vol. 5, Page 27*, vol. 5, no. 2, p. 27, Apr. 2021, doi: 10.3390/DESIGNS5020027.