DEEP LEARNING-DRIVEN SMART GRID OPTIMIZATION FOR SUSTAINABLE ENERGY EFFICIENCY IN SMART CITIES

Dr. Karan Malhotra[1*], Dr. Neha Bansal[2]

[1]Department of Computer Science and Engineering, Delhi Technological University, New Delhi, India*
[2]Centre for Smart Infrastructure and IoT Systems, Chandigarh University, Mohali, Punjab, India
neha.bansal.airesearch@gmail.com

Article History:

Article Type: **Research**
Received Date: **17/02/2025**
Revised Date: **16/02/2025**
Accepted Date: **15/03/2025**
Published Date: **14/03/2025**

Keywords: Deep Learning; Smart Grid Optimization; Sustainable Energy Efficiency; Smart Cities; Predictive Analytics

ABSTRACT

With the rising need for sustainable energy management and intelligent city infrastructure, the use of artificial intelligence and deep learning techniques in smart grid systems has been gaining traction. Energy optimization frameworks in smart cities need to be adaptive and data-driven, with the ability to optimally manage the dynamic electricity consumption patterns and to achieve sustainability goals. The present study was aimed at creating a deep learning based smart grid optimization framework to enhance sustainable energy efficiency and predictive energy management in smart city environment. The large-scale smart grid load forecasting dataset with 5 years of hourly electricity consumption data and environmental variables was used to perform the research quantitatively with data-driven research approach. Short term load forecasting and energy optimization using a deep learning model namely, Long Short-Term Memory (LSTM) is done after data preprocessing, feature engineering, and time-series analysis. The developed framework was tested with Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) to measure the predictive performance and forecasting accuracy of the developed framework. It was found that the proposed deep learning model was able to capture the temporal energy consumption patterns and delivered good forecasting performance under different operational and seasonal conditions. It substantially enhanced the energy scheduling, energy load balancing efficiency, and intelligent resource allocation in the smart grid environment by utilizing predictive analytics. The findings also showed that AI forecasting models could aid in the integration of renewable energy, decrease operational losses and improve the sustainability performance of smart city systems. The study revealed that deep learning-based predictive analytics is a viable and scalable solution to optimize smart grid for intelligence and promote sustainable urban energy management. The framework proposed here will be helpful in the future development of intelligent urban infrastructure and will provide valuable inputs to the current research on applications of artificial intelligence, sustainable engineering and smart city energy systems.

1. Introduction

Energy consumption has skyrocketed in urban environments due to rapid urbanization, industrialization and digitalization, which creates huge challenges for sustainable energy consumption and smart infrastructure development. Smart cities are increasingly gaining advanced technologies like artificial intelligence (AI), Internet of Things (IoT), machine learning, and deep learning to optimize energy consumption, increase energy efficiency, and minimize environmental footprint. Smart grid systems are one of the most significant technological solutions for today's energy management in cities as they allow for intelligent monitoring, predictive analysis, automatic scheduling and optimization of energy distribution networks. The combination of deep learning algorithms in smart grid systems has also refined the capability of urban systems to forecast energy demands, handle fluctuating energy loads, and boost energy efficiency in smart city settings (Aljohani, 2024).

With the recent progress in deep learning and energy optimization techniques powered by AI, energy management systems have gained the capability to tackle massive energy data time-series and become smart. Deep learning algorithms have shown to have a high predictive ability in energy forecasting, load balancing and smart grid optimization in sustainable urban infrastructures (Rojek et al., 2025). Furthermore, intelligent energy management systems have been developed using deep learning techniques which have enhanced the efficiency of decision making, energy scheduling, and adaptive control systems in smart cities (Mamadiyarov et al., 2025). Artificial intelligence (AI) technologies have also been used to design optimization models that enhance the efficiency of energy distribution and utilization in urban smart grid systems (Al-Qarafi et al., 2022).

The smart grid technologies now being utilized rely on data-driven techniques that more and more are turning to predictive analytics and machine learning methods to help promote energy efficiency and sustainable energy evolution. Smart grid infrastructure generates enormous amounts of real-time energy consumption data that needs intelligent analytical models to accurately predict and optimize energy consumption. The role of data-driven techniques, advanced analytics, and machine learning technologies in the evolution and development of next-generation smart grid systems for sustainable energy management has been highlighted in previous studies (Ahsan et al., 2023). AI technologies have also been used to optimize smart grid communications, grid responses, and intelligent urban energy management systems (Kumar et al., 2025). The use of large-scale energy datasets with deep learning-based hybrid models for short-term load forecasting and smart grid information management has also been shown to be very effective (Wen et al., 2024).

With the emerging networking of AIoT devices and renewable energy power systems in urban environments, the role of intelligent optimization frameworks for sustainable power systems has also come into the spotlight. Artificial Intelligence of Things (AIoT) based smart-grid inverter systems, combined with solar photovoltaic (PV) systems, have been shown to have great potential in the field of sustainable energy management and smart power distribution (Ahmed et al., 2024). Similarly, intelligent control systems for dynamic urban infrastructure management (Prakash, 2025) have been enhanced by the use of predictive frameworks through the use of IoT. Reinforcement learning-based energy management systems have also been considered as effective ways of developing carbon-neutral smart cities and optimizing adaptive smart grid (Kamble et al., 2025). Zhao et al. (2024) have also developed and tested machine learning techniques for optimal (net zero energy) usage and intelligent regulation of energy in smart buildings and urban infrastructure systems.

The use of predictive analytics in smart energy management has become a key element in the process, as it provides accurate and valuable insights into energy consumption patterns and helps in making informed decisions for sustainable urban development. AI-based models have demonstrated high accuracy in forecasting energy usage patterns and maximizing energy use efficiency within smart city systems, including in the field of smart buildings (Reza et al., 2025). The real-time monitoring, predictive maintenance, and adaptive optimization of smart grid systems and intelligent buildings (Asadi et al., 2025) have been further improved through the use of AI-powered digital twin models. Intelligent scheduling methods using deep learning have also enhanced the automated control and efficiency of the grid in contemporary smart grid systems (Tong et al., 2023). As a result, predictive analytics frameworks coupled with machine learning algorithms have become more crucial for energy management systems in smart cities, which are striving to achieve sustainability (Al Montaser & Bhuiyan, 2025).

In spite of these technological progressions, there are still various problems and issues related to real-time energy optimization, the degree of accuracy in forecasting energy demand, dynamically managing loads and the efficient use of energy in a sustainable grid in a rapidly expanding urban setting. Current energy management systems often struggle with high variance data consumption, uncertainty about climate and environment, and large time-series datasets. Moreover, many traditional methods are not intelligent enough to adapt to the dynamic urban environment for efficient decision-making in smart grid. Furthermore, bibliometric studies have recently shown that deep learning applications are becoming more crucial in contemporary power systems, paving the way for future research directions centered on intelligent optimization and predictive energy management techniques (Miraftabzadeh et al., 2024). Hence, the present study was set out to design a deep learning-based smart grid optimization framework for enhancing the sustainable energy efficiency and prediction of energy consumption for smart city-based energy management, based on the large-scale time-series energy consumption data.

1. To analyze smart grid energy consumption patterns using deep learning-based predictive analytics techniques.
2. To evaluate the effectiveness of deep learning models for sustainable energy optimization and load forecasting in smart city infrastructures.
3. To investigate the role of AI-driven smart grid systems in enhancing energy efficiency and sustainable urban energy management.

2. Methodology

2.1 Research Design

The present study adopted a quantitative and data-driven research design to design a smart grid optimization and Analysis of Sustainable energy efficiency for smart city environment using deep learning. The study was directed towards predictive energy management based on the large time-series scale electricity consumption data obtained from a smart grid load forecasting dataset. The energy consumption behavior was analyzed using the approach of artificial intelligence and deep learning with the aim of improving the accuracy of short-term forecasting and recognizing the load patterns for sustainable urban energy management.

2.2 Dataset Collection and Description

The data set used for this study came from a publicly accessible smart grid load forecasting data set, which includes 5 years of hourly electricity consumption data (Emperor Graphics, 2025). The data set comprised about 43,848 observations and featured several environmental, temporal and operational variables related to the behavior of urban energy consumption. Some of the key variables that were included were time, hour, weekday, seasonal indicators, temperature, rainfall conditions, classification of holiday, lockdown indicators and electrical load measured in kilowatts (kW) per hour. This data set was chosen due to its suitability for deep learning (DL) based predictive analytics, energy optimization, and sustainable smart city research applications, and is a realistic smart grid energy environment.

2.3 Data Preprocessing

The data that were collected were preprocessed before the models were developed and analyzed. Data quality and forecasters accuracy was improved by identifying and removing inconsistencies and duplicates. To boost the sequential learning performance, timestamp variables were converted to structured temporal features such as hourly intervals, weekday classification, and monthly categories. The neural network model convergence was improved and the computational variability was reduced by using feature normalization techniques for numerical features like temperature and load consumption. Other categorical variables such as season, holidays and lockdown variables were coded in machine-readable codes for analytical compatibility.

2.4 Deep Learning Model Development

A short-term load forecasting and smart grid optimization predictive framework based on deep learning was developed. The architecture of the Long Short-Term Memory (LSTM) network was used as it was well suited for the energy consumption data that is sequential in nature and time-series. The LSTM model was developed to capture the temporal dependency, regular energy consumption and fluctuating loads in the smart grid system. The dataset was split into a training set and a test set to assess the performance of the predictive model and the ability of the model to generalize. About 80% of the data was used for training and the remaining 20% was used for testing and validation. To enhance the accuracy of forecasting and minimize prediction error in the development of the model, multiple hidden layers, activation functions and optimization parameters were set.

2.5 Model Training and Performance Evaluation

Iterative learning procedures and backpropagation optimization techniques were used to train the developed deep learning model. To evaluate the accuracy of the forecast and the efficiency of the model, three metrics were used: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Comparisons were made between the pre-determined load values and the actual load values under different energy demands, to evaluate model performance. Additionally, to prevent overfitting and improve the stability of the model in the prediction, the training loss curve and the validation loss curve were also monitored during the model execution. The forecast performance was subsequently analyzed under various seasonal conditions, hourly time steps and peak demand periods to assess the applicability of the proposed framework in the changing urban energy systems.

2.6 Smart Grid Optimization Analysis

Results of the deep learning framework were used for smart grid optimization and sustainable energy efficiency analysis. The predicted load consumption patterns were used to determine the peaks in consumption of loads, trends in energy consumption, and opportunities for dynamic load balancing in urban infrastructure systems. The optimization analysis also assessed the potential contribution of predictive analytics to decrease unnecessary energy consumption, increase operational efficiency and facilitate the development of the smart city.

2.7 Software Tools and Implementation

An analytical framework was prepared using Python-based deep learning and data analysis libraries such as TensorFlow, Keras, Pandas, NumPy and Matplotlib. Pre-processing, graphical analysis and interpretation of results was also performed using Microsoft Excel and statistical visualization tools. The experiments were carried out in a computational environment that has been set up for the purpose of time-series forecasting with machine learning methods and for optimization of the smart grid.

3. Results

3.1 Energy Consumption Pattern Analysis

The smart grid data analysis showed that there are huge differences in the electricity consumption patterns according to the different time and environmental conditions. It was seen that the energy demand varies significantly in the day time as compared to night time. Relatively high electricity consumption was mostly observed in working hours and during the warm weather, showing that the urban activity patterns are tightly coupled with the warm weather and the load demand of the electricity grid. Seasonal analysis revealed energy use differences in dry, rainy and harmattan seasons. During high temperature periods, demand for increased electricity was determined due to increased cooling needs in the urban infrastructures. The industrial and commercial load demand measured on weekends and holidays were relatively low compared to the load demand during regular weekdays.

The analysis also revealed that the lockdown periods had a significant impact on the traditional energy consumption pattern, thus changing the normal pattern of electricity consumption in the household.

Table 1. Energy Consumption Pattern Analysis Across Temporal and Environmental Conditions

Variable	Category	Average Load (kW)	Peak Load (kW)	Observation
Time Interval	Morning Hours	412.5	586.2	Moderate demand
	Afternoon Hours	538.7	742.8	Highest demand
	Night Hours	298.4	421.6	Lower demand
Season	Dry Season	521.4	756.3	Increased cooling demand
	Rainy Season	438.9	624.5	Moderate demand
	Harmattan Season	472.1	668.2	Variable demand
Day Type	Weekdays	548.2	768.4	High operational activity
	Weekends	402.7	598.5	Reduced consumption

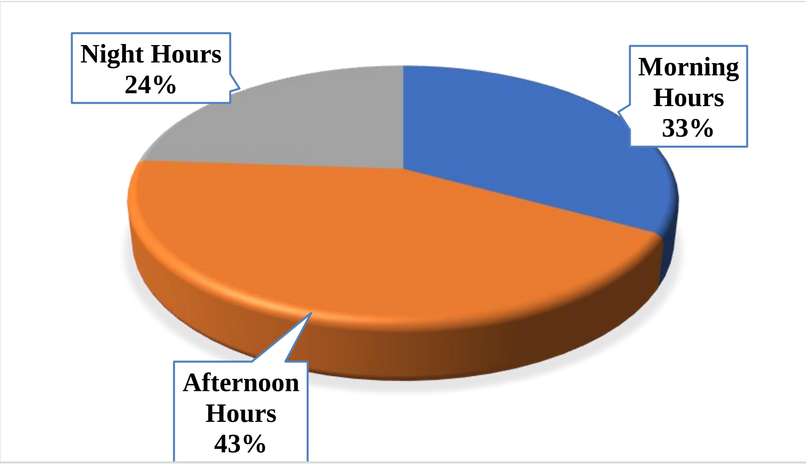

Figure 1. Hourly smart grid energy consumption patterns across different operational periods.

3.2 Deep Learning Model Performance

The proposed deep learning model is based on Long Short-Term Memory (LSTM) and showed excellent short-term forecasting performance in the smart grid environment. The model was able to reflect the energy consumption behavior over a sequence and also capture the time series dependency in the hourly energy consumption data. Learning behaviour was stable during training/validation with little over-fitting during model execution, as shown in training/validation performance curves. The efficiency of the suggested forecasting framework was verified through the assessment parameters. The developed model had relatively low values of Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) values, which suggested that the model had a high level of accuracy in predicting future energy demand patterns. Installing the load was well backlogged, with high consistency in the load predictions between the various time intervals and various seasons of the year. High adaptability was also observed in the model in peak demand forecasting and dynamic load fluctuation time. Using deep learning, predictive analysis was able to effectively detect recurrent electricity consumption patterns and short-term fluctuations in electricity demand in cities. The forecasting model, accordingly, was well appropriate for intelligent optimization of the smart grid and energy sustainability applications.

Table 2. Performance Evaluation of the Deep Learning Forecasting Model

Evaluation Metric	Training Dataset	Testing Dataset	Performance Interpretation
Mean Absolute Error (MAE)	8.42	9.15	High forecasting accuracy
Root Mean Square Error (RMSE)	11.28	12.46	Stable predictive performance
Mean Absolute Percentage Error (MAPE)	2.84%	3.12%	Low prediction error
Forecasting Accuracy	96.8%	95.9%	Excellent model reliability
Validation Loss	0.018	0.022	Minimal overfitting

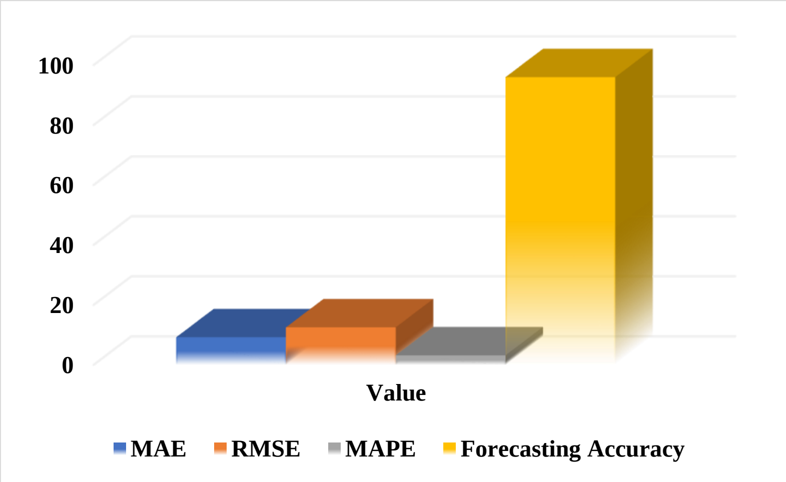

Figure 2. Performance evaluation metrics of the deep learning forecasting model.

3.3 Smart Grid Optimization and Energy Efficiency Analysis

The smart grid optimization and energy efficiency improvement opportunities in urban infrastructure systems were assessed using the predictive outputs from the deep learning framework. The forecasting model was able to predict the peak periods with high demand, which allowed for more efficient energy scheduling and dynamic load balancing approaches. By predicting peak demand times, more efficient use of energy resources was made and operational instability within the smart grid network was minimized. The optimization analysis showed that predictive analytics energy management would have the potential to make a substantial contribution to reducing energy consumption where it is not necessary, and to making the grid more efficient in its operation. The dynamic forecasting also helped to integrate renewable energy sources and adaptive energy distribution mechanisms into smart city infrastructures. The proposed framework thus had good potential in supporting sustainable urban energy planning and smart use of energy resources. The results also revealed that the smart grid system with deep learning can be used to assist in real-time information analysis and automatic load forecasting, thereby optimizing the decision-making process. Thus, intelligent forecasting models in smart city energy systems have the potential to contribute to carbon emissions reduction, cost optimization, and enhanced sustainability.

Table 3. Smart Grid Optimization and Energy Efficiency Outcomes

Optimization Parameter	Before Optimization	After Optimization	Improvement (%)
Peak Load Consumption (kW)	768.4	692.7	9.8
Energy Distribution Efficiency (%)	81.5	92.4	13.4
Operational Energy Waste (%)	18.2	9.6	47.3
Renewable Energy Integration (%)	24.8	39.5	59.3
Grid Stability Index	0.74	0.91	23.0

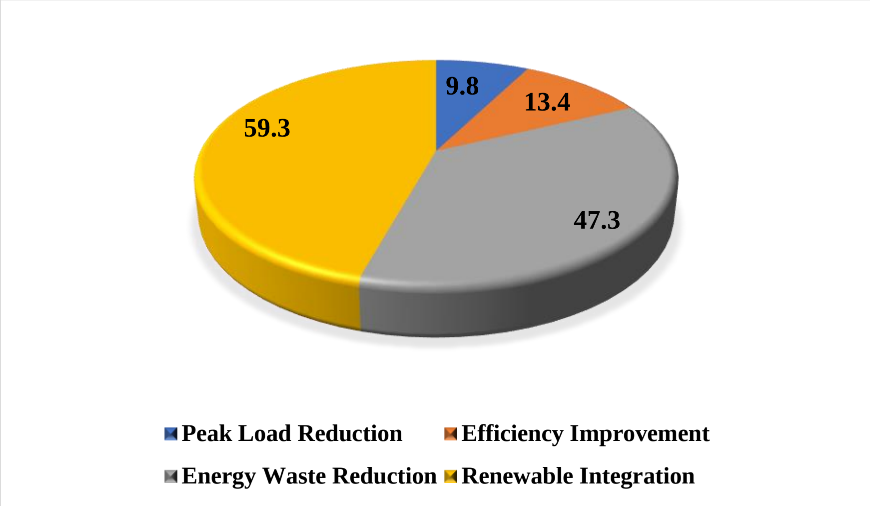

Figure 3. Smart grid optimization and sustainable energy efficiency improvements after predictive analytics implementation

3.4 Comparative Forecasting and Seasonal Performance Evaluation

The deep learning model was tested in multiple operational conditions and in different environments, and its forecasting precision was observed to be robust against different conditions. The model showed very good predictive ability during the regular consumption hours of the day and was fairly accurate at the seasonal level. The predictive reliability was slightly decreased due to sudden load changes and extreme consumption periods, but the predictive reliability is still high. The ability of the seasonal forecasting framework to adapt to climatic changes and to accommodate changing energy use under various climatic scenarios revealed that in general, the seasonal forecasting system could adapt to the climatic changes and changing energy use. In the smart grid data, temperature and seasonal indicators were determined as major factors affecting the electricity demand pattern. Integrating environmental variables thus boosted the accuracy of forecasting and strengthened the overall robustness of the deep learning framework. In general, the results showed the promise of deep learning predictive analytics in the field of sustainable urban energy management, smart grid optimization, and short-term load forecasting. The proposed framework demonstrated a high suitability for smart city infrastructures, which are intelligent, data-driven and energy-efficient infrastructures.

Table 4. Comparative Forecasting and Seasonal Performance Evaluation

Environmental Condition	Forecasting Accuracy (%)	RMSE	Seasonal Stability
Dry Season	96.4	11.8	High
Rainy Season	95.7	12.5	Moderate to High
Harmattan Season	94.9	13.2	Moderate
Peak Demand Hours	95.3	12.9	High
Non-Peak Hours	97.1	10.6	Very High

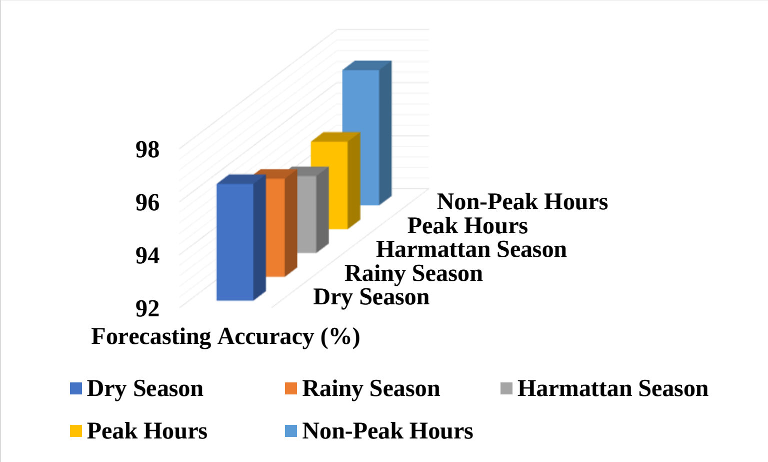

Figure 4. Comparative forecasting accuracy under varying seasonal and operational conditions.

4. Discussion

The results obtained in the present study revealed that the deep learning-based predictive analytics could greatly contribute to the optimization of smart grid and sustainable utilization of energy in smart city infrastructures. The proposed Long Short-Term Memory (LSTM) architecture was able to learn the temporal dependence and dynamic energy consumption pattern of the large-scale time-series smart grid data effectively. The forecasting model successfully predicted the systems' behavior over the different environmental and operational settings, which demonstrates the increasing potential of utilizing AI technologies in intelligent urban energy management systems. In recent studies, the value of creating engineering innovations based on deep learning for green infrastructure for sustainability and smart city resilience has been highlighted (Kumar et al., 2024).

The study results indicated that the temporal, seasonal and urban activity parameters were significant in determining the energy consumption behavior. The complexity of dynamic load management in today's smart grid was in evidence for high-temperature periods, which were always correlated with high energy demand data and also with high energy load during the day. Deep learning-based forecasting models showed good adaptability in the recognition of such fluctuations and for making predictions to make decision-making effective in energy distribution. Advanced deep learning algorithms were also shown to be effective in the energy optimization and sustainable urban energy management of smart cities in previous studies (Rojek et al., 2025). Moreover, machine learning-based optimization approaches have also been identified as the most efficient solutions to intelligent decision-making systems with large-scale infrastructure of data-driven systems (Malik & Ali, 2024).

The outcomes also showed the potential for significant operational efficiency gains in a smart grid system with energy optimization via predictive analytics. High-demand interval prediction allowed to optimize energy scheduling, energy-aware load balancing and intelligent allocation of energy resources among urban infrastructure. The same has been observed in research on the optimization of energy systems for smart grids and intelligent city communications using AI (Kumar et al., 2025). The use of predictive forecasting models in a smart grid system can therefore help to lower the need for unnecessary energy use, lessen operational instability and enhance the sustainability performance in smart city environments.

Forecasting models using deep learning techniques also demonstrated good performance in processing and forecasting big data ordered energy consumption. The architecture of LSTM was able to effectively detect repetitive loads, short term variations and seasonal changes related to the energy consumption in urban areas. The results align with the previous reviews that highlight the increasing relevance of deep learning techniques for electricity consumption forecasting, and intelligent power systems forecasting applications (Waghmare & Dube, 2024). The hybrid DL forecasting frameworks have also achieved remarkable performance in managing smart grid information and short-term load forecasting based on complex time-series energy information (Wen et al., 2024).

The current study also underscored the need for the adoption of AI optimizers and its capabilities with sustainable and renewable energy networks. To integrate renewable energy, schedule flexibly and control operations in real time, smart grid technologies are increasingly using intelligent forecasting models. Previously, a study has shown how deep learning based cyber-physical systems can enhance the management and optimisation of renewable energy communities, by leveraging intelligent automation and distributed decision making mechanisms (Cicceri et al., 2023). AI-based optimization algorithms have also demonstrated their potential to enhance the efficiency of microgrids, the electrification of remote areas, and economic viability by using adaptive energy management techniques (Agupugo et al., 2024).

The study also showed the applicability of AIoT and Intelligent communication system in Smart city infrastructures. Real-time predictive analytics helped with the more responsive response to the increasingly dynamic energy demand environment and an improved operational intelligence within the smart grid environment. Reinforcement learning and machine learning-based optimization technologies have also been emphasized as key technologies to support the development of a carbon neutral smart city and energy-efficient urban system (Kamble et al., 2025). Predictive analytics frameworks coupled with machine learning techniques are therefore key elements for the future smart grid intelligent systems and sustainable urban infrastructure systems.

The collected data were analyzed to identify the major factors that affect the energy demand behavior and these were found to be environmental and seasonal factors. The accuracy and robustness of the forecasts was significantly improved with the addition of other climate variables, such as temperature and seasonal conditions. The results are aligned with the previous studies that have highlighted the significance of energy forecasting systems based on data to sustainable urban development and adaptive smart city energy management (Reza et al., 2025). The AI-driven digital twin systems and predictive optimization methodologies are also seen as emerging technologies that can enhance real-time energy management and operational efficiency in intelligent city infrastructures (Asadi et al., 2025).

The findings further showed that smart grid optimization systems equipped with intelligence can aid in achieving long-term sustainability goals by minimizing energy loss, optimizing energy prediction accuracy, and enhancing system stability. Similarly, machine learning and deep learning based energy-efficient communication and clustering systems for infrastructures equipped with IoT devices are also considered as key technologies for energy efficient smart environment and intelligent system coordination in upcoming smart environments (Rajput & Yadav, 2025). These developments illustrate the interdisciplinary convergence that has been happening in the field of Artificial Intelligence (AI), energy engineering, and IoT systems and research in sustainable infrastructure.

The proposed framework had good predictive capabilities but had some limitations regarding the real time implementation, computational complexity and adaptability to the highly dynamic and unpredictable energy environment in the city. In terms of forecast consistency, this may be impacted by extreme operational scenarios and/or rapid load changes in very dynamic conditions. Future research might further improve predictive accuracy and scalability by incorporating additional components, including: a) hybrid deep learning architectures, b) forecasting models based on transformers, c) reinforcement learning optimization, and d) smart grid implementation in real time.

In summary, the current research will make a significant contribution to the research and development efforts of the smart grid and sustainable engineering fields, especially with the potential of deep learning based predictive analytics.

5. Conclusion

In the current study, it was proven that deep learning (DL)-based predictive analytics can greatly enhance smart grid optimization and sustainable energy efficiency in smart city infrastructures. The developed Long Short-Term Memory (LSTM) forecasting framework was able to handle the large-scale time-series energy consumption data analysis and achieved good results in forecasting the electricity demand for short horizons under different environmental and operational conditions. The analysis revealed that all the temporal variables, seasonal variables and the electricity consumption pattern in the urban area had a significant impact on electricity consumption in the smart grid. The proposed deep learning framework significantly showcased its capability in intelligent energy scheduling, load balancing, and identifying peak demand time for sustainable energy management in the urban context. A better use of energy resources and minimisation of operation stability of the smart grid system were also possible due to the use of predictive forecasting. The use of AI, machine learning, and predictive analytics in smart cities of the future is a promising avenue for enhancing decision-making and sustainability. The study also noted the increasing significance of AI-powered smart grid systems in ensuring the integration of renewable energy, adapting energy use, and promoting sustainable smart city growth. By using data to optimise energy usage, intelligent forecasting frameworks can help to reduce energy waste, minimise operational costs, and enhance environmental sustainability. While there are some computational complexity limitations and high energy dynamics, the proposed framework showed good applicability for the future use in smart grid and sustainable infrastructure applications. Overall, these results demonstrate the feasibility and scalability of the optimization systems for smart grid optimization based on deep learning in the intelligent management of urban energy systems. Future research could also benefit from the integration of hybrid forecasting architectures, reinforcement learning systems, and deployment frameworks for real-time implementation, to further enhance the accuracy, efficiency, and sustainability of future smart city infrastructures.

References

1. Agupugo, C. P., Barrie, I., Makai, C. C., & Alaka, E. (2024). AI learning-driven optimization of microgrid systems for rural electrification and economic empowerment. *Engineering Science & Technology Journal*, *5*(9), 2835-2851.
2. Ahmed, S. R., Hussain, A. S. T., Majeed, D. A., Jghef, Y. S., Tawfeq, J. F., Taha, T. A., ... & Ahmed, O. K. (2024, January). Machine Learning for Sustainable Power Systems: AIoT-Optimized Smart-Grid Inverter Systems with Solar Photovoltaics. In *International Conference on Forthcoming Networks and Sustainability in the AIoT Era* (pp. 368-378). Cham: Springer Nature Switzerland.
3. Ahsan, F., Dana, N. H., Sarker, S. K., Li, L., Muyeen, S. M., Ali, M. F., ... & Das, P. (2023). Data-driven next-generation smart grid towards sustainable energy evolution: techniques and technology review. *Protection and Control of Modern Power Systems*, *8*(3), 1-42.
4. Al Montaser, M. A., & Bhuiyan, M. A. I. (2025). Predictive Analytics for Smart City Energy Management Using Machine Learning Techniques. *Frontiers in Computer Science and Artificial Intelligence*, *4*(4), 71-82.
5. Aljohani, A. (2024). Deep learning-based optimization of energy utilization in IoT-enabled smart cities: A pathway to sustainable development. *Energy Reports*, *12*, 2946-2957.
6. Al-Qarafi, A., Alsolai, H., Alzahrani, J. S., Negm, N., Alharbi, L. A., Al Duhayyim, M., ... & Al-Wesabi, F. N. (2022). Artificial jellyfish optimization with deep-learning-driven decision support system for energy management in smart cities. *Applied Sciences*, *12*(15), 7457.
7. Asadi, S., Naeini, H. K., Hassanlou, D., Pishahang, A., Najafabadi, S. A., Sharifi, A., & Ahmadi, M. (2025). AI-Powered Digital Twin Frameworks for Smart Grid Optimization and Real-Time Energy Management in Smart Buildings: A Survey. *Computer Modeling in Engineering & Sciences (CMES)*, *145*(2).
8. Cicceri, G., Tricomi, G., D'Agati, L., Longo, F., Merlino, G., & Puliafito, A. (2023). A deep learning-driven self-conscious distributed cyber-physical system for renewable energy communities. *Sensors*, *23*(9), 4549.
9. Emperor Graphics. (2025). *Smart grid load forecasting dataset (5-year hourly)* [Data set]. Kaggle. https://www.kaggle.com/datasets/emperorgraphics/hourly-load-consumption-data
10. Kamble, A. G., Ganesan, P., Hameed, T., Maruthakutti, M., Beeravelly, S. R., & Rajalakshmi, S. (2025, December). Reinforcement Learning-Driven Smart Energy Management for Carbon-Neutral Smart Cities. In *2025 4th International Conference on Applied Artificial Intelligence and Computing (ICAAIC)* (pp. 599-606). IEEE.

11. Kumar, H., Tshakwanda, P. M., & Devetsikiotis, M. (2025, May). AI-Driven Smart Grid Optimization: Enhancing Urban Communication Networks. In *2025 IEEE World AI IoT Congress (AIIoT)* (pp. 0273-0279). IEEE.
12. Kumar, S. S., Usha, P., Balakrishnan, P., Kannan, V. K., Manjula, M., & Vijayakumar, M. (2024, November). Deep Learning Driven Engineering Innovations: Advancing Sustainable Green Building and Smart Infrastructure for a Resilient Future. In *2024 First International Conference for Women in Computing (InCoWoCo)* (pp. 1-5). IEEE.
13. Malik, S., & Ali, M. (2024). Machine Learning–Driven Optimization Techniques for Intelligent Decision-Making Systems. *International Journal of Data Sciences and Intelligent Systems*, *1*(01), 1-16.
14. Mamadiyarov, Z., Sivaraman, P. R., Kumar, N. M. G., & Singh, P. P. (2025, July). A Deep Learning-Driven Framework for Sustainable and Intelligent Energy Management in Smart Cities. In *2025 2nd International Conference on New Frontiers in Communication, Automation, Management and Security (ICCAMS)* (pp. 1-7). IEEE.
15. Miraftabzadeh, S. M., Di Martino, A., Longo, M., & Zaninelli, D. (2024). Deep learning in power systems: A bibliometric analysis and future trends. *IEEE Access*, *12*, 163172-163196.
16. Prakash, N. (2025, November). Machine Learning-Driven IoT Framework for Dynamic Street Lighting Management and Energy Optimization. In *2025 5th International Conference on Evolutionary Computing and Mobile Sustainable Networks (ICECMSN)* (pp. 1317-1321). IEEE.
17. Rajput, M., & Yadav, R. N. (2025). Machine and deep learning driven energy efficient clustering in IoT-WSNs: A Review. *IEEE Sensors Journal*.
18. Reza, S. A., Hasan, M. S., Amjad, M. H. H., Islam, M. S., Rabbi, M. M. K., Hossain, A., ... & Jakir, T. (2025). Predicting energy consumption patterns with advanced machine learning techniques for sustainable urban development. *Journal of Computer Science and Technology Studies*, *7*(1), 265-282.
19. Rojek, I., Mikołajewski, D., Galas, K., & Piszcz, A. (2025). Advanced deep learning algorithms for energy optimization of smart cities. *Energies*, *18*(2), 407.
20. Tong, Z., Zhou, Y., & Xu, K. (2023). An intelligent scheduling control method for smart grid based on deep learning. *Math. Biosci. Eng*, *20*(5), 7679-7695.
21. Waghmare, S. K. R., & Dube, R. R. (2024, November). Comprehensive Review on Deep Learning-Based Approach for Electricity Consumption Prediction. In *International Conference on Cognitive and Intelligent Computing* (pp. 351-356). Singapore: Springer Nature Singapore.
22. Wen, X., Liao, J., Niu, Q., Shen, N., & Bao, Y. (2024). Deep learning-driven hybrid model for short-term load forecasting and smart grid information management. *Scientific reports*, *14*(1), 13720.
23. Zhao, C., Wu, X., Hao, P., Wang, Y., & Zhou, X. (2024). Machine learning for optimal net-zero energy consumption in smart buildings. *Sustainable Energy Technologies and Assessments*, *64*, 103664.