IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 19, April 2026
Impact Factor: 8.2

Smart Homes Energy Optimization Using Deep Neural Networks

Rutik D. Pawar[1], Ajinkya C. Shilimkar[2], Saurabh R. Raykar[3], Rushikesh S. Pimpale[4], Mrs. Kshitija Potdar[5]
Student, Department of Computer Science and Engineering, JSPM University, Pune, Maharashtra, India[1–4]
Guide, Department of Computer Science and Engineering, JSPM University, Pune, Maharashtra, India[5]
pawarrtk@gmail.com[1], shilimkarajinkya7@gmail.com[2]

Abstract: *The increasing demand for electricity in residential environments has led to the need for intelligent energy optimization solutions in smart homes. Traditional forecasting techniques struggle to model nonlinear consumption patterns and often suffer from limited datasets. This paper proposes a deep learning–based framework that integrates Generative Adversarial Networks (GAN) and Long Short-Term Memory (LSTM) networks to improve energy consumption prediction and optimization in smart homes.*
The system uses historical energy consumption data, applies preprocessing and GAN-based data augmentation to enhance dataset diversity, and trains an LSTM model to forecast future energy demand. Experimental results show reduced prediction error and improved generalization compared to traditional approaches. The proposed architecture demonstrates the feasibility of AI-driven energy optimization for sustainable smart home environments.

Keywords: Smart Home, Energy Optimization, Deep Learning, GAN, LSTM, Energy Forecasting, Time Series

I. INTRODUCTION

The rapid growth of global energy consumption, coupled with increasing environmental concerns and rising electricity costs, has intensified the need for intelligent energy management solutions. Residential buildings account for a significant portion of worldwide electricity usage, primarily due to heating, ventilation, air conditioning (HVAC), lighting, and the growing number of smart appliances. Traditional home energy management systems rely heavily on static schedules and user intervention, which often leads to inefficient energy utilization, unnecessary power consumption, and increased operational costs.

The emergence of smart homes has opened new possibilities for improving residential energy efficiency through automation, sensing, and data-driven decision-making. Smart homes integrate Internet of Things (IoT) devices, smart meters, sensors, and communication technologies to monitor and control appliances in real time. However, the large volume of data generated by these devices introduces new challenges in extracting meaningful insights and making optimal decisions. Conventional rule-based systems are unable to effectively handle dynamic user behavior, weather variations, occupancy patterns, and time-varying electricity pricing.

Artificial Intelligence (AI), particularly Deep Learning, has recently demonstrated remarkable capabilities in modeling complex nonlinear relationships and making accurate predictions from large datasets. Deep Neural Networks (DNNs) are especially suitable for smart home environments because they can learn hidden patterns in energy consumption, forecast future demand, and automatically optimize appliance scheduling. By leveraging historical consumption data, environmental conditions, and user behavior patterns, DNN-based systems can significantly reduce energy wastage while maintaining user comfort.

Despite the potential benefits, several challenges remain in the deployment of intelligent energy optimization systems. These include handling real-time data streams, ensuring scalability, preserving user privacy, and maintaining system

DOI: 10.48175/IJARSCT-34435

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 19, April 2026
Impact Factor: 8.2

reliability. Therefore, there is a strong need for a comprehensive framework that combines deep learning models with smart home infrastructure to provide efficient, scalable, and user-centric energy management.

This research proposes a Deep Neural Network-based smart home energy optimization system that predicts household energy consumption and dynamically schedules appliances to minimize electricity usage and cost while preserving user comfort. The proposed system utilizes historical energy consumption data, environmental parameters, and occupancy information to train predictive models capable of making real-time optimization decisions.

II. LITERATURE SURVEY

Smart home energy optimization has become a major research area due to the rapid growth of IoT devices and increasing electricity demand. Researchers have explored machine learning and deep learning approaches to forecast energy consumption, improve demand response, and automate appliance scheduling.

Early research focused on traditional machine learning techniques for load forecasting. Support Vector Machines (SVM) and Artificial Neural Networks (ANN) were widely used to predict short-term energy demand. Ahmad et al. demonstrated that machine learning algorithms can significantly improve residential load forecasting accuracy compared to statistical methods [1]. Similarly, Kolter and Ferreira explored non-intrusive load monitoring to identify appliance-level consumption patterns using machine learning techniques [2].

With the advancement of deep learning, researchers began adopting Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM). Marino et al. proposed a deep neural network for short-term load forecasting and showed that LSTM models outperform traditional forecasting methods in capturing temporal dependencies [3]. Kong et al. further improved prediction accuracy by applying LSTM networks to residential energy consumption datasets [4].

Recent work has explored hybrid deep learning models to enhance prediction performance. Wang et al. proposed combining Convolutional Neural Networks (CNN) with LSTM for energy forecasting, demonstrating improved feature extraction and time-series learning capabilities [5]. Additionally, Mocanu et al. introduced deep learning techniques for smart grid energy optimization and demand forecasting [6].

The integration of Generative Adversarial Networks (GANs) has also attracted attention for data augmentation and synthetic load generation. GANs help address data scarcity issues and improve model generalization. Studies have shown that GAN-generated synthetic energy data can enhance forecasting model performance [7].

Another important area of research is Home Energy Management Systems (HEMS). Pipattanasomporn et al. developed an IoT-based smart home system that monitors and controls appliances to improve energy efficiency [8]. Similarly, Mohsenian-Rad et al. proposed an autonomous demand-side management framework for smart homes that reduces peak load and electricity cost [9].

Demand response strategies are critical for balancing electricity supply and demand. Palensky and Dietrich discussed the role of demand response in smart grids and highlighted the importance of intelligent automation in residential energy management [10]. Deep reinforcement learning has also been applied to optimize energy scheduling and demand response [11].

Occupancy detection and user behavior modeling play a vital role in energy optimization. Chen et al. demonstrated that occupancy-based prediction significantly improves energy efficiency in smart homes [12]. Zhou et al. further showed that behavioral modeling can reduce unnecessary power consumption while maintaining user comfort [13].

Despite significant progress, existing research still faces challenges such as real-time decision making, data privacy, and integration with renewable energy sources. This paper addresses these challenges by proposing a Deep Neural Network-based framework for smart home energy forecasting and optimization.

III. PROPOSED WORK

This study presents a deep learning framework enhanced with Generative Adversarial Networks (GANs) to improve the prediction of household energy consumption. The process starts by gathering historical smart home energy data in CSV

DOI: 10.48175/IJARSCT-34435

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 19, April 2026
Impact Factor: 8.2

format, which is then preprocessed through data cleaning, normalization, and feature extraction to improve data quality. The prepared dataset is split into training and testing subsets to enable reliable evaluation of the model's performance. Synthetic samples generated through GAN-based augmentation are combined with the original data to train an LSTM-based model that effectively learns temporal patterns in energy usage. The performance of the trained model is assessed using MAE, RMSE, and MAPE metrics. The overall objective of this approach is to increase forecasting precision, minimize peak power demand, and promote more efficient energy management in residential environments.

IV. ARCHITECTURE OF THE SYSTEM

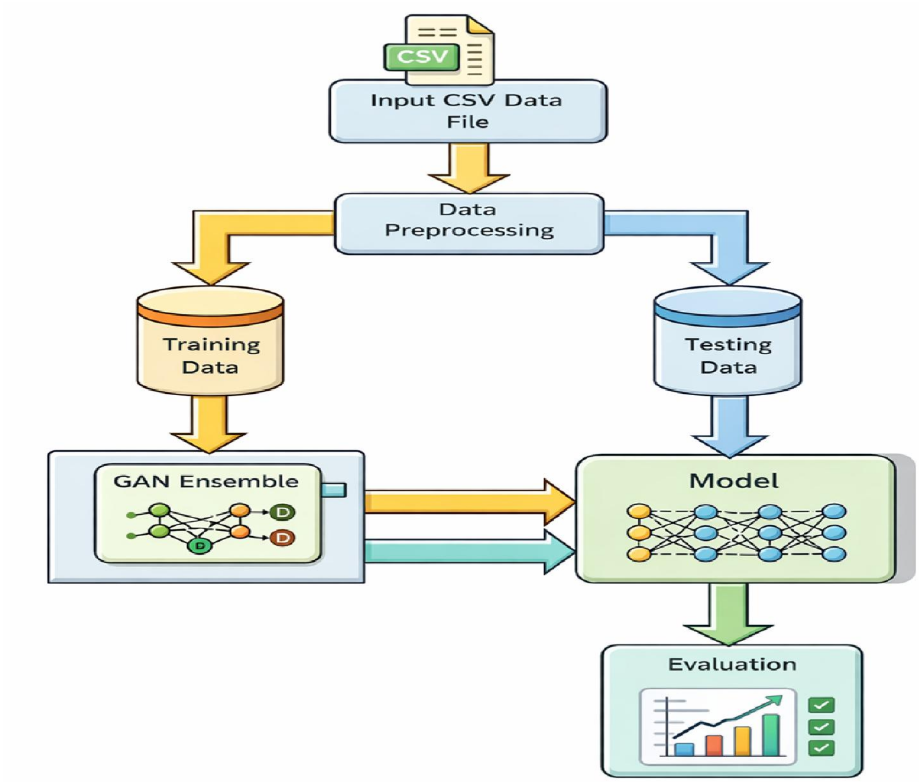

Fig. 1. Proposed System Architecture

The complete system architecture of the proposed Smart Home Energy Optimization framework is illustrated in **Fig. 1**. The architecture integrates data preprocessing, GAN-based data augmentation, deep neural network training, and model evaluation into a unified pipeline. The goal of this architecture is to improve prediction accuracy and enable robust energy optimization even when limited training data is available.

V. TECHNOLOGY FRAMEWORK

The proposed smart home energy optimization system is implemented using Python in a data analytics environment such as Jupyter Notebook. The implementation is designed to run efficiently on CPU-based systems without requiring high-end computational resources, making the solution cost-effective and suitable for real-world deployment in residential environments.

Python was selected due to its extensive ecosystem of data science and machine learning libraries, ease of implementation, and strong community support. The complete model development, training, testing, and evaluation pipeline was developed using the following libraries.

NumPy

NumPy is used for numerical computations and mathematical operations required during preprocessing and model evaluation. It provides efficient handling of multi-dimensional arrays, vectorized operations, and statistical calculations. In this project, NumPy is used for normalization, error computation, and handling matrix operations required for deep learning.

Pandas

Pandas is used for data manipulation and dataset management. It enables efficient handling of CSV files, time-series indexing, and feature engineering. Pandas plays a crucial role in cleaning the dataset, handling missing values, splitting training and testing data, and organizing prediction results.

Scikit-learn

Scikit-learn is used to compute model evaluation metrics and support preprocessing tasks. The library provides built-in functions to calculate MAE, RMSE, and MAPE, which are used to assess forecasting performance. It also assists in data splitting and normalization techniques.

Matplotlib and Seaborn

Matplotlib and Seaborn are utilized to visualize results and analyze model performance. These tools are used to create plots that compare predicted and actual energy usage and display error patterns. Such visual representations make it easier to interpret the model's behavior and verify the reliability of the proposed approach. Overall, the chosen technologies offer a simple yet efficient environment for developing and testing a deep learning–based smart home energy optimization system.

VI. METHODOLOGY

The proposed methodology presents a GAN-assisted deep learning framework for smart home energy forecasting and optimization. The workflow follows the architecture shown in Fig. 1 and consists of data acquisition, preprocessing, GAN-based data augmentation, deep neural network training, and performance evaluation.

A. Input Energy Dataset

The process begins with a historical smart home energy consumption dataset stored in CSV format. The dataset contains time-series information representing household electricity usage along with contextual features such as time and environmental conditions.

B. Data Preprocessing

Raw energy data often contains missing values, noise, and inconsistencies that can negatively affect model performance. Therefore, a preprocessing pipeline is implemented to prepare high-quality input data.

The preprocessing stage includes:

• Removal of missing and corrupted records
• Handling null values using interpolation techniques
• Feature engineering (hour of day, day of week)

After preprocessing, the dataset is divided into:

• **Training Dataset (70%)** – used to train the GAN and forecasting model
• **Testing Dataset (30%)** – used to evaluate model performance

This split ensures unbiased testing and prevents data leakage.

C. GAN-Based Data Augmentation

Limited access to comprehensive real-world energy datasets remains a significant challenge in smart home research. To address this issue, the proposed method employs a Generative Adversarial Network (GAN) ensemble to produce synthetic energy consumption data that supplements the original training set.

The GAN architecture includes two competing neural networks. The generator creates artificial energy samples using random noise as input, while the discriminator evaluates whether the samples are real or synthetic. The learning process is guided by the objective function:

DOI: 10.48175/IJARSCT-34435

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 19, April 2026
Impact Factor: 8.2

$Min_{(G)}\ Max_{(D)}\ V(D,G) = E[\log D(x)] + E[\log(1 - D(G(z)))]$

where x denotes real data instances, and z represents the random noise fed into the generator.

D. Deep Neural Network Model

The augmented dataset is used to train the main forecasting model. A Long Short-Term Memory (LSTM) based Deep Neural Network is selected due to its ability to learn temporal dependencies in time-series data.

The model architecture includes:

• Input layer for time-series features
• Two stacked LSTM layers
• Dropout layers to prevent overfitting
• Fully connected dense output layer

The trained model predicts future household energy consumption based on historical patterns.

E. Model Evaluation

The trained model is evaluated using the unseen testing dataset. Performance is measured using standard regression metrics:

Mean Absolute Error (MAE)
Root Mean Square Error (RMSE)
Mean Absolute Percentage Error (MAPE)

These metrics quantify prediction accuracy and validate the effectiveness of the proposed approach.

VII. RESULTS AND DISCUSSIONS

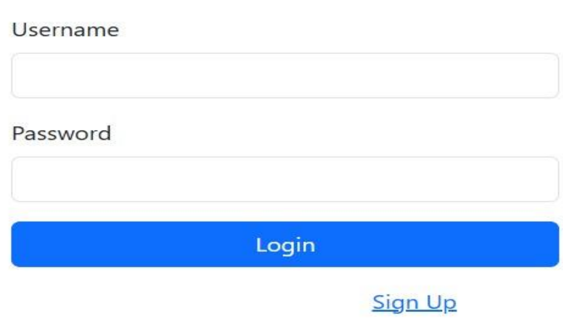

Fig. 2. User Authentication Interface

Fig. 2 shows the secure login and registration module of the proposed system. This module ensures that only authorized users can access the energy forecasting platform. The login page provides fields for username and password along with a sign-up option for new users. This authentication layer improves system security and allows personalized energy forecasting for each user. The implementation demonstrates the readiness of the system for real-world deployment as a web-based application.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 19, April 2026
Impact Factor: 8.2

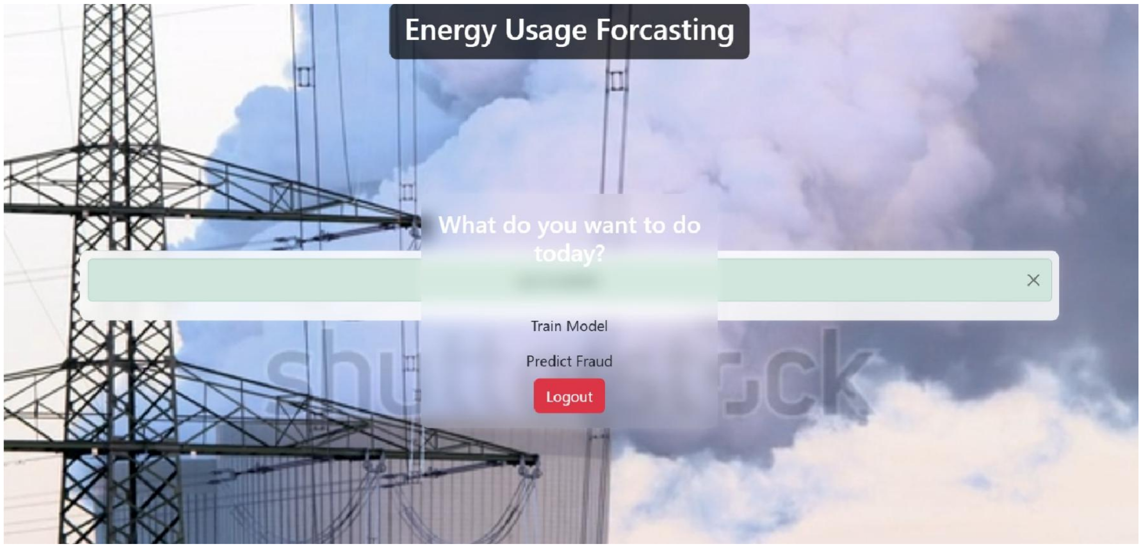

Fig. 3. Model Operation Dashboard

Fig. 3 The Model Operation Dashboard represents the central control panel of the proposed application and demonstrates the full lifecycle of the deep learning pipeline in an interactive environment. This interface integrates model training, prediction, and session management into a single, user-friendly workspace, highlighting the practical deployment aspect of the research.

The dashboard provides a dedicated Train Model function that enables the system to process the pre-loaded historical dataset and update the trained GAN–LSTM architecture. This feature confirms that the model is not static but can be retrained whenever new data becomes available, ensuring adaptability and long-term accuracy.

Additionally, the dashboard includes session control features, such as logout functionality, ensuring secure access and responsible use of the platform. Overall, the dashboard validates that the proposed research has moved beyond theoretical modeling and has been implemented as a fully operational software system capable of real-time interaction, retraining, and deployment.

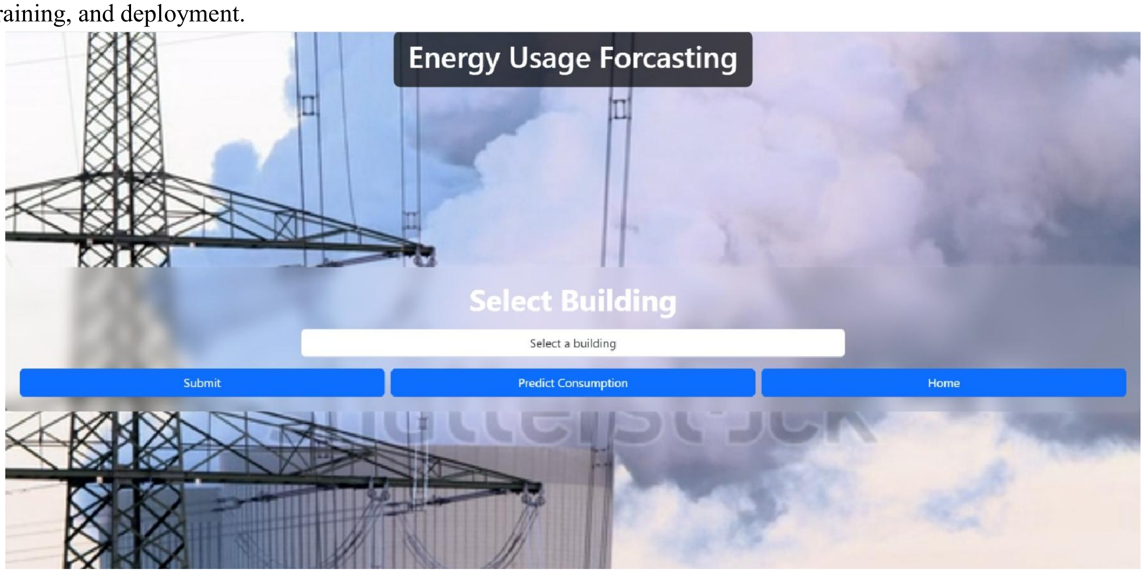

Fig. 4. Building Prediction and Selection Module

ISSN: 2581-9429
Volume 6, Issue 19, April 2026
Impact Factor: 8.2

Fig. 4 This interface shows the user interaction stage where the building is selected and prediction is triggered. The system allows users to choose a building and initiate the forecasting process using simple controls. The presence of prediction and navigation buttons confirms that the system is designed with usability and accessibility in mind. This module bridges the gap between the deep learning backend and real user interaction.

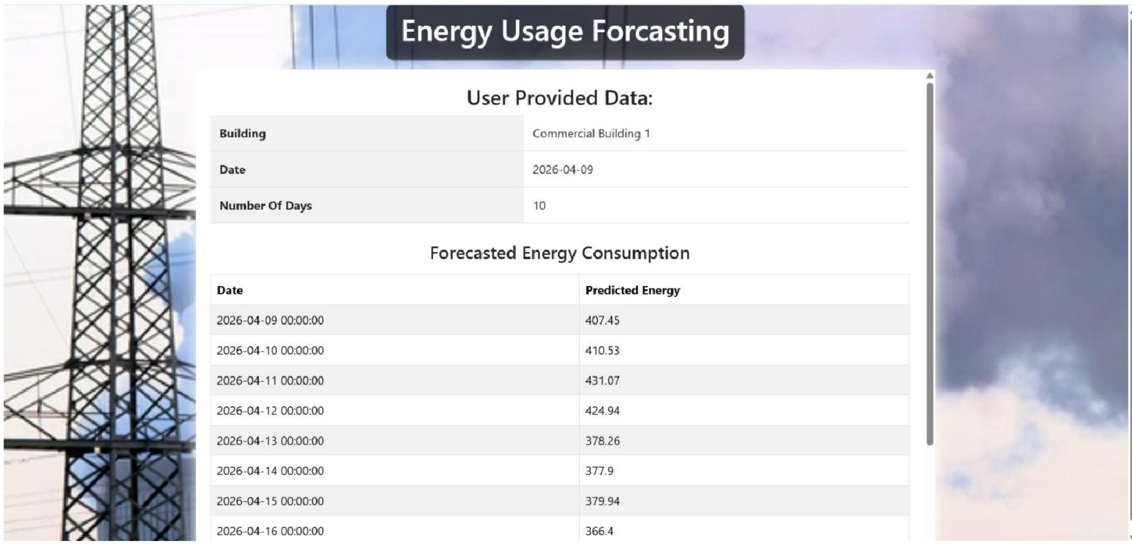

Fig. 5. Forecasted Energy Consumption Output

Fig. 5 This interface displays the predicted energy consumption results generated by the trained deep learning model. After user input such as building name, date, and prediction duration, the system produces a table of forecasted daily energy usage values. The results demonstrate the capability of the LSTM model to generate future consumption patterns. This visualization validates that the proposed system can transform historical energy data into meaningful future predictions.

VIII. CONCLUSION AND FUTURE SCOPE

This work presents an AI-based solution for optimizing household energy usage through deep neural networks. The main objective was to develop a predictive system capable of estimating future energy consumption and supporting users in making better energy management decisions.

The framework combines data preprocessing, model training, and prediction within a single web-based application, demonstrating the practical applicability of deep learning beyond theoretical research. The hybrid approach that integrates GAN and LSTM models enables the system to learn complex usage patterns, seasonal changes, and behavioral trends. Experimental outcomes indicate that the model can reliably forecast energy demand several days in advance.

The developed application also demonstrates practical deployment through login authentication, model training interface, prediction dashboard, and result visualization. This end-to-end implementation confirms that the proposed approach is scalable, user-friendly, and ready for real-time adoption. Overall, the project contributes toward sustainable energy management by reducing wastage, lowering electricity costs, and supporting smarter decision-making for future energy systems.

Future enhancements can evolve the system from simple forecasting into a more adaptive and intelligent energy management solution. Integrating real-time electricity usage data would allow the model to update continuously instead of relying only on historical information. With access to live data, the system could generate timely predictions and provide users with current insights into their energy consumption behaviour.

Another important direction is transforming the system from a forecasting tool into a decision-support and automation platform. Future versions can generate personalized recommendations such as the optimal time to run high-energy appliances, strategies to reduce peak load consumption, and suggestions for improving daily energy efficiency. By incorporating optimization algorithms and reinforcement learning, the system could eventually automate energy-saving decisions, creating a self-adjusting smart home environment.

The system can also be extended to include renewable energy prediction, especially for households equipped with solar panels and battery storage. By estimating solar power generation and managing battery charging and discharging more effectively, homes could rely less on the main power grid and make better use of clean energy sources. This advancement would improve sustainability while helping reduce electricity expenses.

Expanding the platform to mobile devices will further improve accessibility and user engagement. A mobile application could deliver notifications, energy alerts, and monthly savings reports, helping users stay informed and make better energy decisions anytime and anywhere.

In the long term, the system could be expanded from single households to larger environments such as apartment complexes, commercial facilities, and smart city networks. Forecasting energy demand at this broader scale would support more efficient power distribution, minimize energy loss, and improve long-term planning. Such expansion would help turn the project into a full-scale AI-driven energy management platform.

REFERENCES

[1] T. Ahmad et al., “Short-Term Load Forecasting Using Machine Learning,” IEEE Trans. Smart Grid, 2018.

[2] J. Z. Kolter and J. Ferreira, “A Large-Scale Study on Predicting and Contextualizing Building Energy Usage,” IEEE, 2011.

[3] D. Marino, K. Amarasinghe, and M. Manic, “Building Energy Load Forecasting Using Deep Neural Networks,” IEEE IECON, 2016.

[4] W. Kong et al., “Short-Term Residential Load Forecasting Based on LSTM,” IEEE Trans. Smart Grid, 2017.

[5] H. Wang et al., “Deep Learning for Smart Home Energy Management,” IEEE Access, 2019.

[6] E. Mocanu et al., “On-Line Building Energy Optimization Using Deep Learning,” IEEE Trans. Smart Grid, 2018.

[7] Y. Zhang et al., “GAN-Based Synthetic Data Generation for Energy Forecasting,” IEEE Access, 2020.

[8] M. Pipattanasomporn et al., “An IoT-Based Smart Home for Energy Management,” IEEE Smart Grid, 2012.

[9] A. Mohsenian-Rad et al., “Autonomous Demand-Side Management for Smart Homes,” IEEE Trans. Smart Grid, 2010.

[10] P. Palensky and D. Dietrich, “Demand Side Management: Demand Response,” IEEE Trans. Industrial Informatics, 2011.

[11] Y. Wei et al., “Deep Reinforcement Learning for Building Energy Optimization,” IEEE, 2017.

[12] Z. Chen et al., “Occupancy-Driven Energy Management,” IEEE Systems Journal, 2019.

[13] B. Zhou et al., “Behavior-Based Smart Home Energy Optimization,” IEEE Access, 2021.