SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V12I4P110

Volume 12 Issue 4, 110-118, April 2025

Original Article

Development of a Smart Energy Management System Using Machine Learning and Solar panels

German Alberto Echaiz Espinoza[1], Miguel Angel Sanchez Valencia[2], Carlos Benjamin Huillca Velásquez[3]

[1,2,3]*Universidad Nacional de San Agustin de Arequipa, Arequipa, Perú.*

[1] *German Alberto Echaiz Espinoza : gechaiz@unsa.edu.pe*

Received: 07 February 2025 Revised: 09 March 2025 Accepted: 09 April 2025 Published: 29 April 2025

Abstract *- Households should use good and efficient energy management practices to minimize energy consumption and maximize the use of renewable energy sources. This paper describes a novel approach to regulating household energy consumption that combines solar panels and machine learning approaches. The suggested system estimates energy demand and solar power generation with high accuracy using past data on energy consumption and weather forecasts. The machine learning model dynamically adjusts energy usage patterns and storage solutions, thereby maximizing solar energy utilization and minimizing grid dependency. In addition, the local grid tariff cost is compared to determine the time required in which the implemented system becomes self-sufficient. Simulation results demonstrate significant improvements in energy efficiency and cost savings for residential users.*

Keywords *- Home Energy Management, Machine learning, Energy efficiency, Solar panels.*

1. Introduction

Interest in renewable energy sources has grown dramatically as a result of the global movement towards sustainability. Since solar panels can generate clean energy directly from sunlight, their popularity in domestic environments has increased. Integrating solar energy into Home Energy Management Systems (HEMS) is challenging due to its intermittent nature, changing household energy consumption patterns, and the need for sufficient energy storage options. To solve these problems, sophisticated management techniques are needed to harness solar energy and optimize its use [1].

Machine learning has become a powerful tool in various fields, including energy management, due to its ability to analyze large data sets, identify patterns, and make accurate predictions. Machine learning algorithms can be applied to HEMS to estimate solar power generation, anticipate household energy consumption and improve the performance of energy storage systems. These capabilities enable more efficient use of resources by reducing grid dependence and improving overall household energy efficiency [2, 3]. Applying machine learning to energy management systems has been the subject of numerous studies. For instance, predictive models that forecast solar energy production using weather data have been created to manage energy storage and consumption better [4]. In addition, machine learning algorithms have been used to categorize and forecast household energy consumption patterns, enabling real-time adjustments that reduce energy waste and increase efficiency [5]. These advances demonstrate how machine learning could make energy management systems smarter and more flexible, allowing them to independently regulate energy flow and reduce overall costs [6].

Despite these advances, there are still large gaps in fully integrating solar energy systems in residential environments. Without sufficiently addressing the complex interactions between these components, much of the current research focuses on individual aspects of energy management, such as demand forecasting or storage optimization [7]. In addition, extensive testing in real-world environments is needed to validate the scalability and efficiency of ML-based HEMS [8, 9].

This research seeks to address these shortcomings and provide efficient energy management for homes with solar panels through a unique machine learning-based home energy management system and an embedded system. The proposed system forecasts household energy consumption, predicts solar power generation and maximizes the use of energy storage devices by integrating machine learning models previously trained with data obtained from sensors. Considering the interdependencies among these components, the system may dynamically adjust energy flows, reducing grid dependency and optimizing solar energy consumption at the lowest feasible cost. The rest of the document is organized as follows: Related work in the area of energy management with solar energy and machine learning is presented in Section 2. The methodology for this work, including the machine learning techniques, is presented in Section 3.

Section 4 presents an explanation of the experimental development of the problem. Section 5 presents the simulation and analysis results, demonstrating the effectiveness of the proposed system. Finally, Section 6 concludes the article with a discussion of the results and future lines of research.

2. Related Works

In recent years, there has been a significant increase in research focused on integrating renewable energy sources, especially solar energy, into Home Energy Management Systems (HEMS) due to serious pollution problems. Numerous strategies using machine learning have been proposed to improve the reliability and efficiency of these proposed systems integrating solar energy in the home. Several studies can be found in the state of the art that focuses on solar energy forecasting, energy consumption prediction, energy storage optimization, and the development of comprehensive energy management frameworks.

Accurate prediction of solar energy production is essential to maximize the efficiency of HEMS systems, especially in homes with photovoltaic (PV) systems, one of the most widely used methods of obtaining renewable energy. Applying machine learning techniques to improve solar energy forecasting has been the subject of numerous studies. For example, Alvarez-Alvarado et al. [10] created a model to predict solar irradiance based on past meteorological data using support vector machines (SVM).

Their results showed that SVM could perform better than conventional statistical techniques, providing more accurate projections necessary to organize energy storage and consumption. Similarly, the detailed analysis of solar radiation prediction models by Diagne et al. [11] showed how well machine learning (ML) algorithms, such as ensemble approaches and neural networks, capture nonlinear correlations between rainfall and solar energy output. These techniques have been particularly effective in short-term forecasting when accurate estimates are required for real-time energy management.

Hybrid models, which combine machine learning and physical models to increase forecast accuracy, have been the focus of recent advances. Voyant et al. [12] proposed a hybrid strategy combining machine learning techniques with a physical solar model to increase forecast accuracy under various meteorological circumstances. By combining the best features of the two methodologies, this hybrid methodology provides a reliable solution for solar energy prediction in solar energy management systems.

Another essential component of HEMS is its ability to forecast household energy consumption, which improves the match between energy supply and demand. Several researchers have modeled and predicted trends in residential energy consumption using machine learning methods. For example, in the paper by Zhang et al., they employed Artificial Neural Networks (ANNs) to predict short-term household energy demand [13]. This demonstrated that complex usage patterns that depend on various factors, such as occupancy, weather, power grid, and time of day, could be captured by Machine Learning (ML) models. In a related study, Tahereh and Alireza [14] developed a model to forecast the long-term energy use of residential structures using deep learning techniques. Their method performed better than more conventional models, such as Autoregressive Integrated Moving Averages (ARIMA), especially when consumption patterns were highly varied. Deep learning algorithms are particularly well suited for estimating energy consumption in electric power metering systems, as they can learn from large data sets and adapt to changing conditions. In addition, to improve forecasting accuracy, this and other studies have analyzed the integration of machine learning with smart meter data. In their study, Wang et al. [4] created a system that forecasts energy consumption at the appliance level by combining data from smart meters with machine learning methods, including decision trees and random forests. This incredibly exact level of prediction allows for the use of more focused energy-saving strategies, which boosts the system's overall efficiency.

Efficient management of Energy Storage Systems (ESS) is necessary to use solar energy in HEMS best. The application of ML techniques to improve the performance of ESSs has been the subject of numerous studies. For example, Yingchun et al. [8] described an optimal method to dynamically control battery storage in PV-equipped homes using Reinforcement Learning (RL). Based on real-time data, this approach discovered the optimal charging and discharging patterns, resulting in remarkable improvements in cost and energy efficiency. Another notable addition is the work of Siva et al. [15], who developed a model using machine learning (ML) to predict the battery state of charge (SOC) and maximize energy storage in a microgrid environment. Their results showed that ML-based predictions could improve battery lifetime and reliability by preventing deep drain and overcharging, which are common problems with traditional monitoring methods.

Machine learning has been used to optimize the integration of various energy storage systems and manage batteries. Riffonneau et al. [16] presented a hybrid Energy Storage System (ESS) combining supercapacitors and batteries in another study. The appropriate distribution of energy storage tasks between the two technologies is decided by machine learning.

Researchers have created comprehensive HEMS frameworks that combine solar forecasting, consumption prediction and storage optimization into a single cohesive system, going beyond discrete ML applications in these areas. These frameworks aim to optimize energy management at all levels (generation, consumption, and storage). Recalde et al. [17], for example, presented a complete HEMS architecture that combines machine learning (ML)-based solar forecasting, demand prediction, and energy storage system management. To ensure efficient energy use and minimize costs, their system combines supervised and unsupervised learning algorithms to adapt to changing household conditions, which achieves good results. Real scenarios were used to test the framework's ability to reduce energy costs and improve the reliability of the system they proposed in their work.

Another significant addition is the work of Li et al. [18], who developed a cloud-based HEMS for real-time energy management in smart homes using machine learning and the Internet of Things. In addition, the study by Muhammad et al. [19] presents an intelligent energy management system that combines the Internet of Things (IoT) and machine learning (ML). Their technology uses machine learning to predict energy consumption and improve the performance of networked devices, such as smart appliances and HVAC systems. The efficiency and responsiveness of the system are further improved by integrating IoT, which enables real-time monitoring and control of household energy consumption. However, the system remains to be enhanced to predict solar patterns.

3. Methodology

The methodology section presents the proposed framework for home energy management using machine learning (ML) and solar panels, detailing the system architecture, data preprocessing techniques, ML models employed, and evaluation metrics used to assess system performance. With an emphasis on projecting household energy usage, anticipating solar power generation, and maximizing the efficiency of energy storage devices, the methodology is intended to maximize energy use in homes with solar energy systems. Figure 1 displays the entire system.

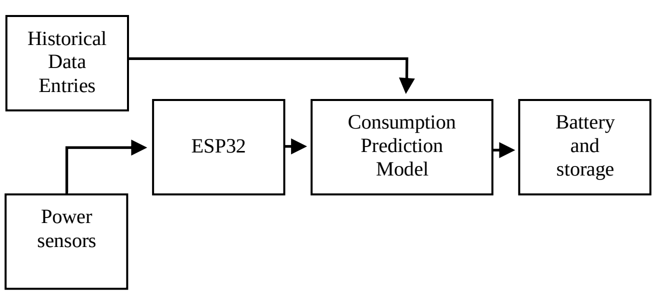


Fig. 1 Methodology of the proposed system

3.1. System Architecture

The architecture of the proposed system consists of three main components: solar energy forecasting, domestic energy consumption prediction, and energy storage optimization. A centralized Home Energy Management System (HEMS) that incorporates all of these elements dynamically modifies energy flows in response to real-time data.

- Solar power forecasting module: This module predicts the amount of solar power generated based on historical solar data, weather forecasts and environmental conditions. The forecast plans the optimal use of solar energy and storage.
- Household energy consumption forecasting module: Based on occupancy statistics, weather, time of day, and past consumption trends, this component predicts the energy demand of households. In order to balance the supply and demand for energy, these forecasts are crucial.
- Energy storage optimization module: Using predictions from the first two modules, this module determines when to charge or discharge batteries in order to maximize battery storage system performance. By storing excess solar energy during peak generation hours and employing it during times of low solar generation or high demand, it seeks to reduce the cost of power.

Each module relies on machine learning algorithms to provide accurate predictions and optimizations. Combining these elements allows the system to dynamically control energy flows, optimizing solar energy utilization and reducing grid reliance.

3.2. Data Collection and Pre-Processing

The system requires several data sets to operate effectively, including solar energy data, weather data, and household energy consumption data. Below is a description of the preprocessing procedures for each kind of data:

3.2.1. Solar Energy Data and Weather Data

Historical solar energy data are obtained from solar panel production records. To increase the precision of solar energy estimates, this data is paired with meteorological data, including temperature, cloud cover, and sunshine hours. Local weather services or open APIs are the sources of weather data. To guarantee consistency, the data set is cleaned by eliminating outliers, adding missing values, and normalizing the data.

3.2.2. Household Energy Consumption Data

Household energy use history is provided by smart meters, which collect precise and thorough readings on a regular basis. This data collection offers a thorough grasp of household energy consumption trends, including patterns of use of individual appliances when applicable, as well as overall household energy consumption. To guarantee consistency and dependability of analysis, the data is pooled at hourly intervals during a pre-processing step. This makes a clearer examination of consumption patterns throughout the day possible. Furthermore, normalization techniques are employed to take into consideration variations in home size, appliance kinds, and consumption habits.

3.2.3. Division of the Data

Training, validation, and test sets are created from the gathered data. Machine learning models are trained on the training set, hyperparameters are fitted on the validation set, and model performance is assessed on the test set. The models were split into 70% training, 15% validation, and 15% testing to ensure they generalize well to unknown data.

3.3. Machine Learning Models

The following machine learning models are used to perform key system tasks: solar energy forecasting, energy consumption prediction and energy storage optimization.

3.3.1. Solar Energy Forecasting Model

A neural short-term memory (LSTM) network was used to forecast solar energy due to its ability to capture temporal dependencies in time series data. Meteorological factors, such as temperature, solar irradiance, and historical solar production statistics, are examples of input features. The model is trained to forecast solar power generation over the next 24 hours to provide information on expected energy availability for the next day.

3.3.2. Household Energy Consumption Prediction Model

A Random Forest (RF) regression model predicts household energy consumption. The model inputs historical consumption patterns, time of day, weather conditions, and occupancy data. The RF model was chosen for its robustness to overfitting and its ability to handle complex, nonlinear relationships in the data.

3.3.3. Storage Optimization Model

A reinforcement learning (RL) algorithm is used to optimize the charging and discharging of the battery storage system. Through interaction with the environment, including anticipated solar generation and family consumption, the RL agent learns the best course of action (i.e., when to charge or discharge). By effectively using the stored energy and lowering reliance on the grid, the RL agent seeks to decrease energy expenses.

3.3.4. Model Training and Validation

The solar energy consumption prediction and forecasting models are trained using the training datasets described above. Cross-validation is used to fit hyperparameters such as the number of trees in the random forest and the number of layers in the LSTM model. The reinforcement learning model is trained using the simulation and iteratively adjusts its policy in response to energy-saving incentives.

3.4. Energy Management Strategy

This system's global energy management strategy merges solar production and home use projections with sophisticated storage optimization through Reinforcement Learning (RL). This system is structured in different levels of operation. In daily scheduling, the solar energy projection model projects the expected production for the next 24 hours, while a predictive model calculates the household energy need for the same time frame. To maximize the home's energy efficiency, the RL agent uses these calculations to configure the battery charge and discharge cycles, prioritizing minimizing dependence on the grid and maximizing the use of stored energy. The device continuously monitors household consumption and solar production throughout the day and makes changes in real-time. If initial projections differ, the RL agent modifies its approach to ensure efficient energy consumption. The technology also effectively controls peak demand by using stored energy during periods of high demand, reducing costs and pressure on the grid. When solar production exceeds storage capacity and demand, the system sends additional energy to the grid, allowing households to borrow or reduce their energy costs.

4. Experimental Development

In this development, an experimental home environment was used to build the proposed home energy management system (HEMS), allowing for real-world condition simulation. The system incorporated smart meters, solar panels, batteries for storage, and machine learning algorithms to manage energy flow efficiently. A virtual 5 kW photovoltaic (PV) system was designed to replicate a standard household installation. The power generated by these solar panels was based on real weather data, including temperature, cloud cover, and hours of sunshine, ensuring realistic solar power generation patterns. The experimental setup also included a 10-kWh virtual battery, which was designed to store excess energy during periods of high solar generation and supply power to the home when demand was high or solar production was low. A reinforcement learning (RL)-based optimization model was implemented to regulate battery charge and discharge processes, with the objective of maximizing solar energy utilization while minimizing grid energy dependency. Household energy consumption was simulated using energy profiling data from real smart homes. These datasets collected energy usage from various appliances, including lighting, HVAC systems, and household devices. The energy consumption patterns were structured to vary throughout the day, with higher usage in the mornings and evenings.

4.1. System Architecture

Figure 2 presents the flowchart of the complete algorithm for the proposed HEMS. The system operates in the following stages:

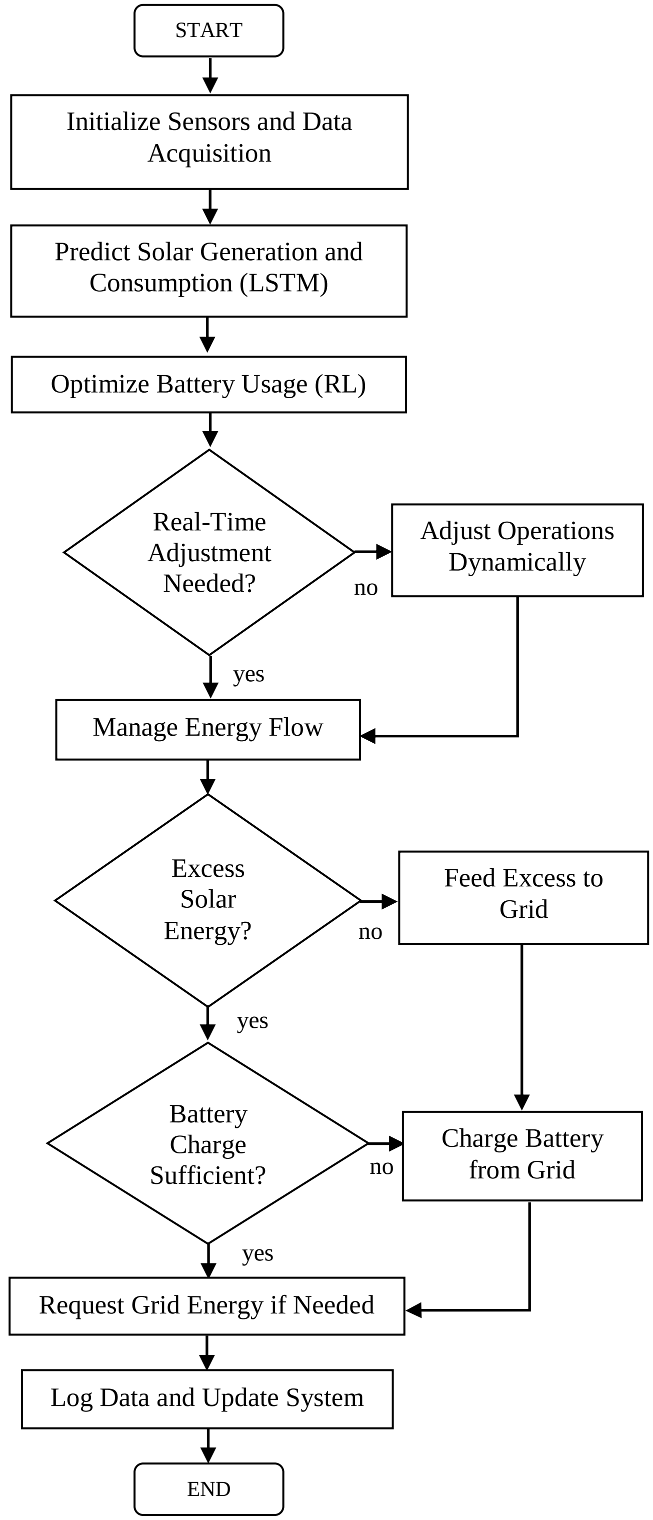
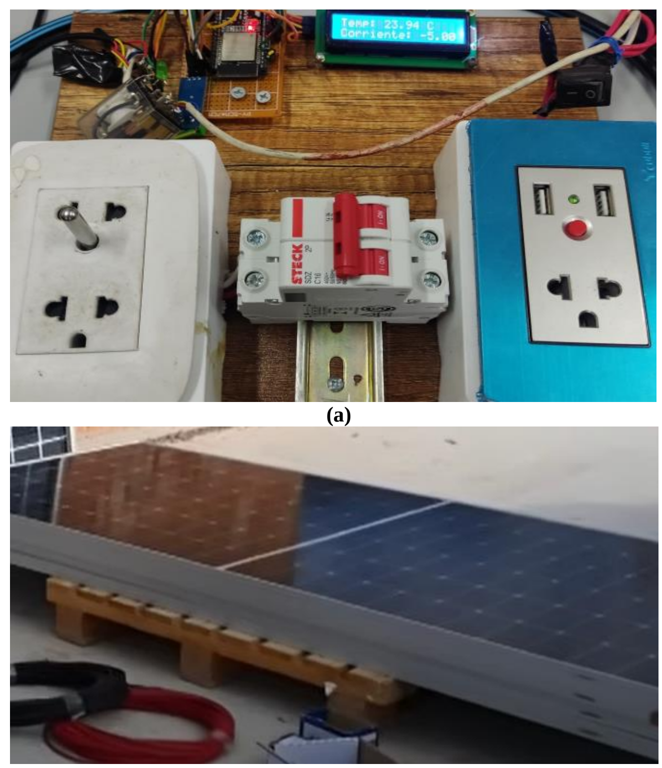


Fig. 2 Flowchart of the proposed system

The datasets were preprocessed, including cleaning, normalization, and partitioning into training, validation, and test sets (80/10/10 split) to ensure the models were trained and evaluated on separate data for accurate performance assessment.

4.2. Hardware Description

The system's hardware infrastructure included an ESP32 microcontroller, which served as the central unit for data acquisition and wireless communication. SCT-013 current sensors were deployed to measure real-time household energy consumption, providing accurate, current flow readings that enabled precise power calculation. Smart meters also tracked the import and export of energy from the grid and measured overall energy use. A virtual 10 kWh battery was integrated to control energy storage and ensure power availability during times of low solar generation, while a 5 kW photovoltaic (PV) system replicated actual solar generating patterns. The ESP32 microcontroller interfaced with the SCT-013 sensors, continuously collecting energy consumption data from the devices comprising the system hardware. Figure 3(a) shows the system installed on the household sockets to monitor and regulate energy consumption, while Figure 3(b) presents the installation of solar panels on the roof of the test house.



(a)

(b)

Fig. 3 System installed on the home. (a) installation on the outlet. (b) installation of the solar panel on the roof.

4.3. Experimental Evaluation

Once the models were trained, the complete system was tested in a simulated home environment. The evaluation focused on three key aspects:

- Grid Energy Reduction: The system's ability to minimize dependence on grid electricity was analyzed.

- Energy Cost Optimization: The impact of ML-based decision-making on reducing electricity expenses was assessed.
- Battery Storage Efficiency: The effectiveness of reinforcement learning-based charge/discharge control was evaluated.

For performance comparison, the proposed system was tested against a rule-based benchmark system that operated without machine learning. This comparison demonstrated the advantages of ML-based optimization over traditional rule-based energy management methods.

5. Results and Discussion

This section provides details on the results of the proposed Home Energy Management System (HEMS), emphasizing the impact of incorporating ML models on a number of key performance metrics, such as prediction accuracy, battery consumption, energy cost savings, and reduced grid dependency. Each section discusses these findings by assessing the implications for efficient energy management in residential environments, emphasizing the direct gains achieved. The advantages of the recommended approach to improving the energy sustainability of homes are further demonstrated by comparing these results with those of other model standards.

5.1. Prediction Accuracy

The system's capacity to estimate household power consumption using the Random Forest model and solar power output using the LSTM model was crucial to its operating efficiency. The LSTM model demonstrated good accuracy in capturing fluctuations in solar power production across various weather conditions and times of day, with a mean absolute error (MAE) of 0.15 kW and a root mean square error (RMSE) of 0.25 kW. The models' prediction comparison is displayed in Table 1.

Table 1. Prediction accuracy of the energy forecasting models analyzed in the system

Model	Metric	Forecast
LSTM	MAE (kW)	0.15
LSTM	RMSE (kW)	0.25
Random Forest	R^2	0.87
Random Forest	RMSE (kW)	0.3

Table 2 shows that the LSTM model predictions match the actual data when comparing predicted and actual solar power generation. This accuracy is essential for battery storage design and energy efficiency since it allows the system to use solar energy more efficiently and reduce grid dependence. Compared to the rule-based reference model, which was based on historical averages, the LSTM model drastically reduced prediction errors by almost 30%, suggesting an improvement in the accuracy of the developed system.

Table 2. Comparison of Real and Predicted Solar Energy Generation Using LSTM Model

Time (Hour)	Real Generation (kW)	Predicted Generation (kW)	Error (kW)
08:00	1.5	1.45	0.05
10:00	3.2	3.10	0.10
12:.00	4.8	4.75	0.05
14:00	5.0	5.10	0.10
16:00	3.6	3.65	0.05
18:00	1.8	1.85	0.05

Similarly, based on data such as temperature, occupancy, and time of day, the Random Forest model demonstrated an excellent match for predicting residential energy usage, with an R-squared value of 0.87 and an RMSE of 0.3 kW.

Table 3 shows a visualization of the model's forecast accuracy versus the actual consumption of a family on a normal day. By accurately anticipating consumption, the device dynamically adjusted the energy supply to residential demand, optimizing the value of stored solar energy during peak consumption hours.

In addition to helping the system optimize home energy flows, the model's improved accuracy over rule-based approaches that solely utilized averages to estimate demand highlights the importance of machine learning models for real-time energy management and boosts the created system's efficiency.

Table 3. Comparison of Real and Predicted Household Energy Consumption

Time (Hour)	Real Consumptio n (kW)	Predicted Consumpti on (kW)	Error (kW)
06:00	0.8	0.78	0.02
09:00	1.2	1.15	0.05
12:00	1.5	1.52	0.02
15:00	1.7	1.65	0.05
18:00	2.3	2.28	0.02
21:00	1.9	1.88	0.02

5.2. Energy Cost Savings

The energy cost savings were assessed by comparing the ML-based HEMS's energy expenses to those of the rule-based reference system. The results showed that by dynamically altering battery utilization to favor stored solar energy during peak charging hours, the ML-based HEMS reduced energy consumption by almost 25%. In Figure 4, the graph compares the energy costs of a Baseline System and a machine learning-based home energy management system (ML-based HEMS).

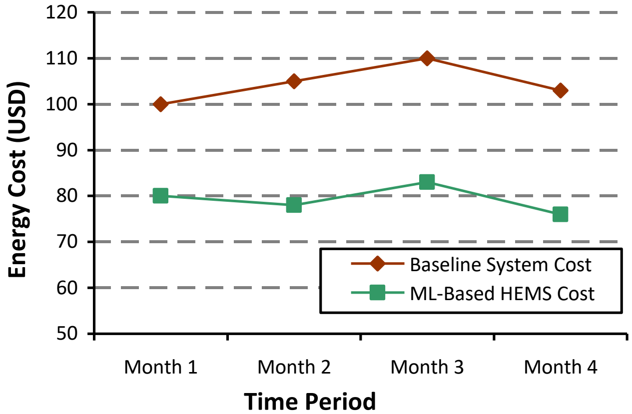


Fig. 4 Comparison of energy cost between baseline system and ML-based HEMS

The RL model's real-time response to changing conditions allowed the system to limit exposure to high electricity costs by reducing the need to draw power from the grid during peak hours. The flexibility and variable pricing are a major advance over the baseline system, which relied on set battery usage plans. By reducing reliance on the grid during peak hours, the RL-based approach generated significant cost savings and improved the system's resilience to variations in electricity prices.

Furthermore, it is observed that over the months, the ML system maintains consistently lower costs compared to the baseline system, reflecting significant savings that support the effectiveness of implementing machine learning in residential energy management.

5.3. Grid Dependency Reduction

Grid reliance is defined as the proportion of a household's total energy use that can be satisfied by solar energy. According to the results, the machine learning-based HEMS system was able to satisfy 60% of the household's energy demands using solar energy and battery storage, compared to 45% for the reference system.

Figure 5 illustrates how the ML-based approach reduced grid reliance by breaking out the energy sources for both systems. Through precise forecasting of solar energy output and effective battery storage management, HEMS could handle fluctuations in both generation and demand.

Because the system stored surplus solar energy and purposefully discharged the battery at peak hours, it decreased reliance on the grid even during moments of high demand. The advantages of incorporating machine learning into home energy management systems are evident in this greater self-sufficiency, which enables homes to depend less on outside energy sources while fostering resilience and sustainability.

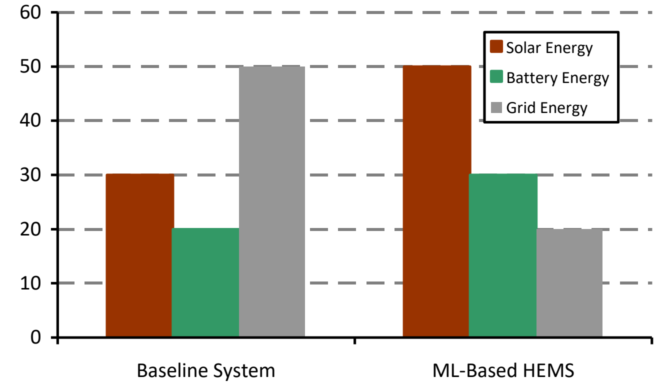


Fig. 5 Breakdown of energy sources for baseline and ML-based HEMS

5.4. Battery Utilization Efficiency

Thanks to the ML-based approach, the battery consumption efficiency was 20% higher than the reference system. The RL model's optimized charging and discharging method made the more efficient battery usage possible, which successfully reduced unnecessary charge cycles and increased battery life. Figure 6, which illustrates the ideal consumption patterns that the RL model was able to attain in comparison to the reference system, shows the battery's state of charge (SOC) over the course of a normal day.

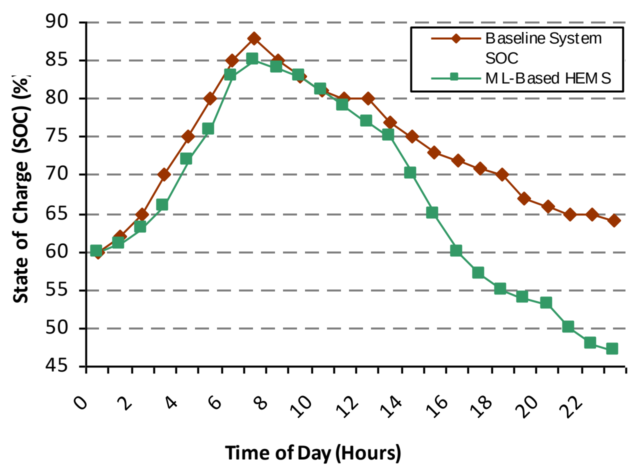


Fig. 6 Comparison of battery SOC - baseline vs RL model

The long-term sustainability of renewable energy systems depends on proper battery management, as frequent and inefficient charging cycles can gradually deplete battery capacity. The battery was able to maintain ideal SOC levels thanks to the adaptive management strategy of the RL model, which guaranteed effective use of stored energy. Since decreasing battery wear and tear prolongs battery life, which reduces replacement costs and improves system sustainability, this efficiency also has long-term financial ramifications. The capacity of machine learning to maximize the efficiency of renewable energy supplies is further demonstrated by increased battery efficiency, which raises the practicality and financial sustainability of renewable energy systems for houses.

6. Conclusion

The implementation of a machine learning (ML)-based home energy management system (HEMS) demonstrates significant advances in efficient residential energy management, especially by integrating renewable sources such as solar energy through photovoltaic (PV) panels. The proposed method effectively reduces energy prices, minimizes grid dependence, and maximizes battery usage by using predictive models, such as LSTM for solar generation and Random Forest for domestic demand, along with reinforcement learning for battery usage optimization. The findings demonstrate the advantages of predictive analytics and adaptive management over traditional rule-based systems, enabling higher solar energy consumption, notable cost reductions, and greater energy self-sufficiency. These results suggest that ML-based HEMS systems could be highly beneficial for improving sustainability and resilience in home energy management using ML to predict and improve the system.

The system's ability to adapt to changing conditions not only helps households reduce their dependence on the grid but also encourages the deployment of decentralized renewable energy sources and reduces pressure on the grid. This paradigm can be expanded in future studies to investigate the scalability and integration of more renewable resources into larger community energy grids, which will spur further innovation in cost-effective and sustainable energy solutions.

Acknowledgments

The authors of this document wish to express their sincere gratitude to the Universidad Nacional de San Agustin de Arequipa for the knowledge provided throughout this research. This research would not have been possible without the commitment and encouragement provided by the university, for which the authors are deeply grateful.

References

[1] Kumar Siddhant et al., "Solar Energy Forecasting Using Artificial Neural Network," *2022 IEEE Students Conference on Engineering and Systems*, Prayagraj, India, pp. 1-5, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[2] Prashant Anand et al., "Occupancy-Based Energy Consumption Modelling Using Machine Learning Algorithms for Institutional Buildings," *Energy and Buildings*, vol. 252, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] Masood Rizvi, Bhanu Pratap, and Shashi Bhushan Singh, "Optimal Energy Management in a Microgrid under Uncertainties Using Novel Hybrid Metaheuristic Algorithm," *Sustainable Computing: Informatics and Systems*, vol. 36, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[4] Yi Wang et al., "Review of Smart Meter Data Analytics: Applications, Methodologies, and Challenges," *IEEE Transactions on Smart Grid*, vol. 10, no. 3, pp. 3125-3148, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[5] Marc Beaudin, and Hamidreza Zareipour, "Home Energy Management Systems: A Review of Modelling and Complexity," *Renewable and Sustainable Energy Reviews*, vol. 45, pp. 318-335, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[6] Chibuike Peter Ohanu, Salihu Ahmed Rufai, and Ugbe Christiana Oluchi, "A Comprehensive Review of Recent Developments in Smart Grid through Renewable Energy Resources Integration," *Heliyon*, vol. 10, no. 3, pp. 1-17, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[7] Muhammad Fahad Zia, Elhoussin Elbouchikhi, and Mohamed Benbouzid, "Microgrids Energy Management Systems: A Critical Review on Methods, Solutions, and Prospects," *Applied Energy*, vol. 222, pp. 133-1055, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[8] Yingchun He, Jun Liu, and Tian Zhang, "Home Energy Management System Optimization Strategy Based on Reinforcement Learning," *Proceedings of the 5th International Conference on Control Engineering and Artificial Intelligence*, Sanya, China, pp. 24-30, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[9] Vipashi Kansal et al., "Optimizing Energy Consumption in Smart Buildings through Reinforcement Learning-Based Demand Response Strategies," *2024 International Conference on Communication, Computer Sciences and Engineering (IC3SE)*, Gautam Buddha Nagar, India, pp. 1616-1621, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[10] José Manuel Álvarez-Alvarado et al., "Hybrid Techniques to Predict Solar Radiation Using Support Vector Machine and Search Optimization Algorithms: A Review," *Applied Sciences*, vol. 11, no. 3, pp. 1-17, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[11] Maimouna Diagne et al., "Review of Solar Irradiance Forecasting Methods and a Proposition for Small-Scale Insular Grids," *Renewable and Sustainable Energy Reviews*, vol. 27, pp. 65-76, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[12] Cyril Voyant et al., "Machine Learning Methods for Solar Radiation Forecasting: A Review," *Renewable Energy*, vol. 105, pp. 569-582, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[13] Haonan Zhang et al., "Artificial Neural Network for Predicting Building Energy Performance: A Surrogate Energy Retrofits Decision Support Framework," *Buildings*, vol. 12, no. 6, pp. 1-18, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[14] Tahereh Shojaei, and Alireza Mokhtar, "Forecasting Energy Consumption with a Novel Ensemble Deep Learning Framework," *Journal of Building Engineering*, vol. 96, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[15] S. Siva Suriya Narayanan, and S. Thangavel, "Machine Learning-Based Model Development for Battery State of Charge–Open Circuit Voltage Relationship Using Regression Techniques," *Journal of Energy Storage*, vol. 49, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[16] Yann Riffonneau et al., "Optimal Power Flow Management for Grid-Connected PV Systems with Batteries," *IEEE Transactions on Sustainable Energy*, vol. 2, no. 3, pp. 309-320, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[17] Angel Recalde et al., "Machine Learning and Optimization in Energy Management Systems for Plug-In Hybrid Electric Vehicles: A Comprehensive Review," *Energies*, vol. 17, no. 13, pp. 1-39, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[18] Zhikang Li, Amro Alsabbagh, and Chengbin Ma, "A Cloud-Based Energy Management Framework with Local Redundancy Control Capability," *2021 4th IEEE International Conference on Industrial Cyber-Physical Systems*, Victoria, BC, Canada, pp. 873-878, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[19] Muhammad Saidu Aliero et al., "Smart Home Energy Management Systems in Internet of Things Networks for Green Cities Demands and Services," *Environmental Technology & Innovation*, vol. 22, 2021. [CrossRef] [Google Scholar] [Publisher Link]