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Design and Implementation of a Smart Energy Management System for Solar-Powered Buildings Using Predictive Energy Control: A Case Study of University of Delta, Agbor, Delta State

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ABSTRACT: A Smart Energy Management System (SEMS) was conceptualized, constructed, and tested for solar-powered institutions at the University of Delta, Agbor, Delta State, Nigeria. The system included solar power, lithium-ion batteries, Internet of Things (IoT)-based monitoring, machine-learning-based demand forecasting and intelligent load management with automatic switching components to enhance energy availability and utilization. The study adopted a quantitative comparative research design using a prototype research approach. Twenty sampled buildings were selected for the experiment conducted over a year (June 2025 to May 2026). The proposed system was compared to the existing system based on energy availability, power continuity, grid dependency, system reliability, monitoring accuracy, forecasting accuracy and control performance. The results demonstrated that the proposed system improved energy availability (by 51.6%; 62.4 ± 5.1% to 94.6 ± 2.3%), power continuity (by 56.1%; 14.8 ± 3.2 to 23.1 ± 1.1 hours/day), reduced grid dependency (by 61.5%; 100% to 38.5 ± 4.6%) and increased system reliability (by 38.6%; 68.7 ± 6.0% to 95.2 ± 2.0%). IoT-based monitoring reported 97.8% accuracy and 84.7% reduction in transmission delay while the machine-learning forecasting reported 93.4% accuracy and 65.5% reduction in mean absolute error. The intelligent control improved load-balancing accuracy from 71.8% to 96.5%, representing a 34.4% improvement, and reduced energy wastage by 72%. A significant difference was observed between the systems ($p < 0.001$) with large effect sizes. The study concluded that predictive-intelligent SEMS could enhance energy availability and utilization in institutions using grid and solar.

KEYWORDS: Smart Energy Management System, Solar Photovoltaic, Predictive Control, Machine Learning, IoT Monitoring, Load Prioritization.

INTRODUCTION

The increasing demand for electricity, its high cost, negative environmental impacts, and low reliability have prompted the need to develop cost-effective and sustainable electricity generation and utilization methods. Buildings are significant electricity consumers as they require electricity for lighting, heating and air conditioning, ventilating, operating office machines, and communication equipment, among other uses. The rising conurbation and urbanization rates have led to a surge in the number of residential, commercial, and institutional buildings, thus increasing the need to boost electricity generation and distribution capacities and improve electricity consumption processes International Energy Agency, (2021).

Solar photovoltaic (PV) energy systems are an alternative electricity generation and supply method used in buildings. The PV modules can directly convert solar energy into electricity and have been increasingly used in small and large-scale electricity production due to their ease of installation, low-cost potential, and environmental sustainability. For instance, the use of the technology in buildings can help in maintaining voltage stability, reducing electricity costs, and lowering greenhouse gas emissions (Hosseini et al., 2020). Nevertheless, solar energy as a power source is intermittent due to climatic differences, requiring efficient building energy management systems.

Smart Energy Management Systems (SEMS) have been developed to manage electricity in buildings efficiently. SEMS is an electricity management framework that utilizes sensors, embedded systems, communication networks, automata, control systems, and data analytics to maximize electricity use. Contrary to the traditional electricity management methods that separately consider electricity generation, storage, and consumption processes, SEMS uses a systems-level approach in managing electricity. It considers the information available at each stage and makes decisions regarding electricity use while maximizing electricity consumption. For instance, SEMS can help in minimizing electricity waste, balancing electricity supply-demand equations, and managing renewable electricity in buildings while prioritizing the loads that should be supplied with electricity (Ghanim, 2024). This approach is critical in achieving continuous electricity supply, reducing costs, and ensuring sustainable electricity use.

According to Baharuddin et al. (2021), the developments in embedded systems and artificial intelligence (AI) have enabled the design of advanced electricity management systems that can maximize holistic electricity management in buildings. Arduino microcontroller systems have been used in SEMS design to enable efficient electricity monitoring and control in buildings. On the other hand, AI and Machine Learning (ML) algorithms have been proposed in electricity management systems for demand prediction and optimized electricity distribution. According to Wang et al. (2022), AI-based electricity management systems can analyze historical and current demand data to predict future demand. Additionally, the algorithms can aid in making optimal electricity distribution decisions based on the predicted demand and the electricity available from different sources. Overall, smart electricity management systems can maximize electricity management in buildings while balancing the supply-demand equations to minimize waste and ensure continuous electricity supply.

The need for smart electricity management methods is growing, especially in institutional buildings, which offer multiple services and require electricity for seamless operations. Institutional buildings require electricity for lighting, operating learning devices and systems such as computers, air-conditioning systems, and security systems, among other applications. Electricity scarcity has been a major challenge in most countries, hindering optimal electricity use in institutional buildings (Shi et al., 2018). Solar PV modules can supplement grid electricity in these buildings, but an efficient electricity management system that can balance the electricity supply and demand while prioritizing critical functions is required to ensure continuous electricity supply.

A Smart Energy Management System that can monitor the demand, supply, and battery levels while prioritizing the loads and switching between the electricity sources based on their availability can be vital in institutional buildings. Previous studies on SEMS have demonstrated the potential of using electricity management systems to manage electricity in buildings while maximizing the use of renewable energy sources (Baharuddin et al., 2021; Wang et al., 2022). Nevertheless, there is a need for cost-effective SEMS to be used in institutional buildings to manage electricity efficiently. Most of the previous studies have been limited by the high computational algorithms and software used in designing the electricity management systems, which can be expensive to implement, especially in the developing world. Additionally, previous research has focused on theoretical models and simulations of SEMS to demonstrate their potential in maximizing electricity management without considering the reliability and availability of the internet and grid in the developing countries.

Furthermore, none of the previous studies have considered a system that can monitor electricity demand, manage the loads, manage the battery, and switch between the electricity sources based on their availability and demand in institutional buildings. Therefore, this study aims to develop a Smart Energy Management System for managing electricity in solar photovoltaic buildings with predictive control. The proposed system will utilize solar PV modules, batteries, and the grid to ensure continuous electricity supply to the buildings while minimizing electricity waste and maximizing the use of the available electricity sources. The study will develop the proposed SEMS using embedded systems that will enable real-time electricity monitoring and control. Additionally, the study will use a Machine Learning algorithm to predict the electricity demand based on the historical data and support the decision-making process in optimally distributing the electricity while prioritizing the loads and switching between the electricity sources as needed. The proposed solution will provide an affordable and holistic approach to managing electricity in solar PV buildings while ensuring continuous electricity supply.

According to the study, there is a need to investigate how predictive SEMS can be used to optimize solar, battery, and grid electricity in buildings with regard to demand forecasting, real-time embedded monitoring, intelligent load management and source switching while also supporting continuous electricity supply during shortages. This paper will highlight how embedded systems and Machine Learning can be used in electricity demand forecasting to support optimal electricity utilization in solar PV buildings. In addition, the paper will also expound on the potential of using intelligent load management and switching of electricity sources based on their availability and demand to ensure continuous electricity supply in institutional buildings. Finally, the paper aims to provide a replicable framework for implementing predictive electricity management systems in solar-powered institutional buildings in the developing world.

This paper is divided into several sections. A review of the related literature on Smart Energy Management Systems for solar-powered buildings is provided in the Literature Review section. The Research Methodology section contains the materials and procedure used in the study. The Results and Discussion section presents the research results and their discussion. Finally, the paper's concluding remarks are provided in the last section.

LITERATURE REVIEW

Smart Energy Management Systems are one of the most progressive ideas developed recently. Smart buildings related to electricity production and consumption are actively being developed and built, as they involve the creation of systems and devices for managing electricity production and consumption processes. Recent research studies have demonstrated the potential of IoT, AI, and smart electricity management systems in improving energy utilization in modern buildings (Taboada-Orozco et al., 2024; Gunasinghe et al., 2025).

Solar-Powered Building Energy Systems

Solar-powered building energy systems usually rely on solar photovoltaic (PV) modules to generate electricity. The PV arrays are used to convert solar radiation into electricity, which can then be used to power appliances and charge batteries (Poyyamozhi et al., 2024). Several studies have shown that solar-based energy systems can be used to offset grid electricity and reduce the negative impact of conventional electricity production and consumption methods. Nonetheless, the variable nature of solar radiation dictates that smart electricity management systems be employed to ensure electricity supply is continuously available while also reducing wastage.

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Smart Energy Management Systems (SEMS) in Buildings

SEMS refers to a framework that is capable of monitoring and controlling building energy systems to optimize electricity production, storage, and consumption. Generally, SEMS relies on built-in sensors and computer algorithms to monitor and adjust electricity use in accordance with demand while also reducing electricity wastage. According to Bajwa et al. (2024), AI-enabled SEMS have been used to reduce overall electricity consumption by 20–50% in commercial buildings by making optimal decisions on heating, ventilating, and lighting the buildings. The smart system monitors electricity use in real time and utilizes optimization algorithms to ensure electricity is distributed based on demand while also reducing overall consumption.

Similarly, Ekanayaka et al. (2025) highlight that reinforcement learning-based controllers can be used to manage building energy systems more efficiently than conventional ones. The application of AI and embedded systems in SEMS has enabled the development of effective electricity management frameworks capable of reducing electricity consumption while also ensuring continuous electricity supply.

IoT-Enabled Energy Monitoring Systems

The Internet of Things (IoT) has been increasingly used in electricity monitoring systems to gather information on electricity production and consumption rates. IoT can be used in electricity monitoring systems to monitor and control electricity flows to manage its effective use and avoid wastage. This technology uses sensors, meters, and embedded software systems to monitor electricity production and consumption rates. For instance, Huang et al. (2023) demonstrate that IoT-based energy monitoring systems can be used to disaggregate electricity usage at the device level to effectively manage electricity consumption.

IoT can be used to gather the required information that can help in making decisions about managing electricity in buildings. Furthermore, IoT systems can be used as an information channel to relay the information obtained to remote servers, where it can be used to make intelligent decisions about managing electricity.

Artificial Intelligence in Smart Energy

The role of Artificial Intelligence (AI) in smart electricity management systems cannot be underestimated. Several researchers have utilized AI algorithms and techniques to develop electricity management systems capable of optimizing electricity production, storage, and consumption. Generally, AI is used in two main applications, namely load forecasting and control. In load forecasting, AI models such as Machine Learning (ML) are used to predict electricity demand based on historical data and make optimal electricity distribution decisions.

According to a meta-analysis conducted by Ekanayaka et al. (2025), applying reinforcement learning techniques in electricity management can reduce overall electricity consumption by an average of 22–30%. Additionally, Pasqualetto et al. (2024) highlight that AI can be leveraged to make optimal decisions in smart building energy systems by making accurate predictions on electricity demand and detecting anomalies in the system. AI can also be used to predict solar photovoltaic production, which can then be used to inform decisions on electricity management.

System Architecture of Smart Solar Energy Management Systems

A typical Smart Solar Energy Management System (SEMS) is comprised of electricity production, storage, monitoring, and control systems. The system utilizes photovoltaics and inverters to produce electricity. Secondly, the battery stores the electricity produced for later use. The system also uses smart meters and sensors to monitor the amount of electricity produced and consumed by the system. Using smart meters connected to the IoT to monitor and report on the amount of electricity consumed is an innovative way of ensuring that the electricity produced is utilized efficiently.

The application of artificial intelligence in the smart electricity management system is an excellent way of ensuring that electricity is generated, stored, and consumed while meeting demand without being wasted. This will ensure that the electricity produced is put to maximum use while minimizing the amount of electricity wasted. According to Alsaigh et al. (2022), the architecture of the smart electricity management system should be designed based on application-specific requirements to ensure its effective utilization.

Energy Optimization Strategies in SEMS

Various optimization strategies can be applied in developing Smart Energy Management Systems (SEMS) for optimizing electricity production, storage, and consumption in buildings. One of the key strategies used in electricity optimization is demand response, which involves modifying the amount of electricity consumed in accordance with the available supply. Demand response is critical in ensuring continuous electricity supply while also reducing electricity wastage. Another technique used in electricity optimization is predictive load scheduling, which involves forecasting electricity demand and making decisions on electricity distribution based on the forecast.

Besides, electricity storage optimization helps meet electricity demand at lower prices while also ensuring a continuous electricity supply. Another crucial approach is predictive maintenance of the system's critical components to prevent their malfunction and ensure high performance. Other methods include dynamic electricity pricing that follows demand patterns while also creating incentives for demand-responsive electricity pricing that is economically efficient without compromising electricity supply adequacy. The aforementioned maintenance technique can also be coupled with other load management strategies in electricity management systems. These methods prioritize end-use loads and employ control policies that include decision support algorithms for electricity management in balancing electricity supply and demand based on available electricity.

According to the research conducted by Gunasinghe et al. (2025), the combination of different electricity management strategies is more efficient than common approaches. The authors also note that hybrid prediction and control policies are appropriate for demand response, mainly because hybrid methods have proven effective in demand response programs.

Digital Twin and Advanced Energy Modeling

A digital twin is an innovative concept that has been integrated into many fields for the creation of virtual models commonly used in industrial process management decision-making. Digital twins can be used in building energy systems to manage electricity demand and supply through virtual models. Digital twin technology enables continuous system monitoring and control by offering a reliable way of gathering and analyzing real-time data on electricity production, supply, demand, and consumption. The information can then be used to make optimal decisions on electricity distribution and consumption.

Furthermore, digital twin can be used to conduct various simulations to support electricity management and optimization. The ability to conduct various simulations helps in identifying potential problems and developing solutions before implementing the changes in the physical system. Advanced energy modeling can also be used to conduct a continuous assessment of the energy performance of a building and support informed decision-making in electricity management and optimization. According to Ardebili et al. (2024), digital twin can be used to predict potential system faults, thus supporting predictive maintenance in electricity management systems.

MATERIALS AND METHODS

This study employed a quantitative, prototype-based experimental research design with a comparative approach to evaluate the effectiveness of a Smart Energy Management System (SEMS) for solar-powered institutional buildings at the University of Delta, Agbor, Delta State, Nigeria. The study compared the performance of the proposed SEMS with conventional grid-dependent energy operation. The comparison focused on the ability of the proposed system to improve energy availability, power continuity and system reliability, while reducing grid dependency and energy wastage. The study also evaluated the effectiveness of real-time monitoring, machine-learning-based energy demand forecasting and intelligent load management in improving the overall performance of the energy system.

The study was conducted at the University of Delta, Agbor, Delta State, Nigeria, and covered 20 selected institutional buildings within the university environment. The buildings were selected based on their energy consumption characteristics, availability of electrical loads and suitability for evaluating solar-powered energy management. The electrical loads considered in the study included lighting systems, computers, laboratory equipment, air-conditioning systems, office equipment and other appliances commonly used in institutional buildings.

The study covered a period of 12 months, from June 2025 to May 2026. The extended period was selected to capture variations in solar availability, electricity demand and operational conditions across different months of the year. Data were collected continuously during the study period, while periodic experimental performance evaluations were conducted to assess the behaviour of the proposed SEMS under different operating conditions. The use of a 12-month period provided a broader basis for evaluating the system under varying environmental and operational conditions.

The conventional energy arrangement served as the baseline condition for comparison. Under the baseline condition, electrical loads were primarily dependent on the available electricity supply from the utility grid, without the predictive demand forecasting, intelligent load prioritisation and automated energy-source management incorporated into the proposed SEMS. The proposed system, on the other hand, integrated solar photovoltaic generation, battery storage, real-time monitoring, predictive energy-demand forecasting, intelligent load prioritisation and automatic switching among available energy sources. Performance differences between the two operating conditions were used to determine the effectiveness of the proposed system.

The major materials and equipment used in the development and evaluation of the SEMS included solar photovoltaic (PV) panels, charge controller, inverter, lithium battery storage system, electrical sensors, relay modules, protective devices, connecting cables, breadboard and programmable microcontroller. The system also incorporated computer-based software and machine-learning tools for data processing, forecasting and performance evaluation. The PV panels converted solar radiation into electrical energy, while the charge controller regulated the charging process and protected the battery from inappropriate charging conditions. The lithium battery provided energy storage for use when solar generation was insufficient. The inverter converted the available direct-current energy into alternating-current electricity suitable for the connected institutional loads. Sensors provided information on electrical operating conditions, while relay modules enabled automatic switching and control of connected loads and energy sources.

The electrical power associated with each measurement was determined from the measured voltage and current using:

$$P = VI$$

where Prepresents electrical power, Vrepresents voltage and Irepresents current.

Where energy consumption over a period was required, electrical energy was calculated as:

$$E = P \times t$$

where E represents electrical energy consumed (Wh), P represents electrical power and t represents operating time (h).

The proposed SEMS was organised around four major functional components: energy generation and storage, IoT-based monitoring, machine-learning-based demand forecasting and intelligent energy control. Solar energy was configured as the preferred energy source. When solar generation exceeded the instantaneous electrical demand, the available surplus energy was directed towards battery charging. When solar generation became insufficient, stored battery energy was supplied to the connected loads where adequate battery capacity was available. The electricity grid served as a backup source when solar and stored energy were insufficient. Automatic switching between the available sources was performed through relay-based control according to the prevailing energy condition and load requirements.

Data collection used a combination of electrical measurement instruments, IoT-based monitoring devices, system performance logs and machine-learning data-processing tools. Electrical sensors were used to obtain measurements relating to voltage, current, power generation, energy consumption and other relevant operating conditions. The monitoring subsystem captured and transmitted the measured information for real-time observation and subsequent analysis. System logs were also maintained to record source switching, battery status, load conditions, faults and other relevant operational events.

The principal performance indicators used in evaluating the SEMS included energy availability, power continuity, grid dependency, system reliability, monitoring accuracy, monitoring delay, fault-detection capability, prediction accuracy, mean absolute error (MAE), energy-optimization efficiency, forecast response time, load-balancing accuracy, switching response time, energy wastage and system stability.

Real-time monitoring was evaluated using data accuracy, monitoring delay and fault-detection capability. Data accuracy represented the proportion of measurements correctly captured or transmitted by the monitoring system. Monitoring delay represented the time interval between the occurrence or recording of a system event and its availability on the monitoring platform. Fault-detection capability represented the ability of the monitoring system to identify abnormal operating conditions.

The predictive energy-management component used historical energy-demand data obtained from the selected institutional buildings. The collected data were inspected for missing, duplicated or inconsistent observations before analysis. The observations were arranged according to measurement periods and prepared for machine-learning model development. The dataset was divided into training and testing subsets to allow the forecasting model to learn from historical observations and subsequently evaluate its predictive performance using previously unseen observations.

The machine-learning component was implemented using Python-based data-processing and machine-learning tools, particularly libraries suitable for data preprocessing, model development and performance evaluation. The forecasting model was evaluated using prediction accuracy, mean absolute error and forecast response time. Mean absolute error was calculated using:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \mid y_i - \hat{y}_i \mid$$

Where MAE mean absolute error n is the number of observations, y_i is the observed energy demand and $\hat{y}_i$ is the predicted energy demand.

Prediction accuracy was determined by comparing the predicted energy-demand values with the corresponding observed values. The model with better predictive performance was subsequently incorporated into the energy-management decision process.

The intelligent control component used information obtained from real-time monitoring and energy-demand forecasting to determine appropriate energy-distribution decisions. Electrical loads were classified according to their operational importance. Critical loads received higher priority during periods of limited energy availability, whereas less critical loads could be deferred or disconnected when necessary. The controller considered solar generation, battery state, electrical demand and grid availability when selecting the appropriate energy source. The principal indicators used to evaluate the control subsystem were load-balancing accuracy, switching response time, energy wastage and system stability.

Primary experimental data were collected from the selected 20 institutional buildings throughout the study period of June 2025 to May 2026. Measurements relating to solar generation, energy consumption, battery operation, grid supply and load conditions were recorded using the monitoring components of the SEMS. The system continuously monitored relevant operating conditions and stored the resulting measurements for subsequent analysis.

The experimental evaluation involved two principal operating conditions. The first condition represented the conventional grid-dependent baseline, while the second represented the proposed SEMS condition incorporating solar generation, battery storage, predictive demand forecasting and intelligent energy control. Measurements obtained under the two conditions were compared using the same performance indicators.

The collected data were subjected to quality checks before analysis. Incomplete or inconsistent observations were identified and reviewed, while the measurement records were organized according to building, date, operating condition and performance indicator. The cleaned dataset was subsequently used for descriptive analysis, performance comparison and machine-learning model evaluation.

Descriptive statistics were used to summarize the experimental data obtained from the 20 institutional buildings during the 12-month study period from June 2025 to May 2026. For continuous performance indicators, the arithmetic mean and standard deviation were used to describe central tendency and variability. The arithmetic mean was calculated as:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

And the sample standard deviation was calculated as:

$$s = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}}$$

where x_i represents an individual observation, $\bar{x}$ represents the sample mean, n represents the number of observations and s sample standard deviation

The percentage improvement for indicators in which a higher value represented better performance was calculated as:

$$\text{Improvement (\%)} = \frac{\text{Proposed value} - \text{Baseline value}}{\text{Baseline value}} \times 100$$

For indicators in which a lower value represented better performance, such as grid dependency, monitoring delay, mean absolute error and energy wastage, percentage reduction was calculated as:

$$\text{Reduction (\%)} = \frac{\text{Baseline value} - \text{Proposed value}}{\text{Baseline value}} \times 100$$

For example, where energy availability increased from 62.4% under the conventional system to 94.6% under the proposed SEMS, the percentage improvement was calculated as:

$$Percentage\ Improvement = \frac{94.6 - 62.4}{62.4} \times 100 = 51.6\%$$

Similarly, where grid dependency decreased from 100% under the conventional baseline to 38.5% under the proposed SEMS, the percentage reduction was calculated as:

$$Percentage\ Reduction = \frac{100 - 38.5}{100} \times 100 = 61.5\%$$

For energy wastage, where the conventional-control value was 18.6% and the proposed-system value was 5.2%, the percentage reduction was calculated as:

$$Percentage\ reduction = \frac{18.6 - 5.2}{18.6} \times 100 = 72.0\%$$

To improve statistical transparency, 95% confidence intervals were used where sufficient observation-level data were available. The confidence interval for a sample mean was calculated as:

$$CI_{95\%} = \bar{x} \pm t_{0.975,n-1}\frac{s}{\sqrt{n}}$$

where $\bar{x}$ is the sample mean, s is the sample standard deviation, n is the number of observations and $t_{0.975,n-1}$ is the appropriate critical value of the t-distribution.

To determine whether the differences observed between the conventional system and the proposed SEMS were statistically significant, an independent-samples t-test was used to compare the mean performance values of the two operating conditions. The independent-samples t-test was appropriate for comparing the summarized performance of the conventional and proposed system conditions.

The t-statistic was calculated as:

$t = (\bar{x}_1 - \bar{x}_2) / \sqrt{[(s_1^2 / n_1) + (s_2^2 / n_2)]}$

Where:

t = calculated t-value

$\bar{x}_1$ = mean performance value for the conventional system

$\bar{x}_2$ = mean performance value for the proposed SEMS

s_1 = standard deviation for the conventional system

s_2 = standard deviation for the proposed SEMS

n_1 = number of observations represented by the conventional-system group

n_2 = number of observations represented by the proposed-system group

The pooled standard deviation was used to estimate the standardized magnitude of the difference between the two groups. It was calculated as:

$s_p = \sqrt{\{[(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2] / (n_1 + n_2 - 2)\}}$

Where:

s_p = pooled standard deviation

n_1 = number of observations in the conventional-system group

n_2 = number of observations in the proposed-system group

s_1 = standard deviation of the conventional-system group

s_2 = standard deviation of the proposed-system group

The standardized effect size was determined using Cohen's d, calculated as:

$d = (\bar{x}_1 - \bar{x}_2) / s_p$

Where:

d = Cohen's effect size

$\bar{x}_1$ = mean of the conventional-system group

$\bar{x}_2$ = mean of the proposed-system group

s_p = pooled standard deviation

Cohen's d values of approximately 0.20, 0.50 and 0.80 were interpreted as small, moderate and large effects, respectively.

Statistical significance was assessed at the 5% significance level ($\alpha = 0.05$). A p-value less than 0.05 (p < 0.05) was interpreted as evidence of a statistically significant difference between the conventional and proposed system conditions. A 95% confidence interval (CI) was also considered where the available observation-level data permitted its calculation.

RESULTS

Performance of the Solar PV–Battery–Grid SEMS

Table 1: Performance of the Solar PV–Battery–Grid System

Performance Metric	Conventional System	Proposed SEMS	Improvement/Reduction (%)
Energy Availability (%)	62.4 ± 5.1	94.6 ± 2.3	51.6
Power Continuity (hrs/day)	14.8 ± 3.2	23.1 ± 1.1	56.1
Grid Dependency (%)	100.0	38.5 ± 4.6	61.5
System Reliability (%)	68.7 ± 6.0	95.2 ± 2.0	38.6

Source: Experimental Data, 2025–2026

The table above presents the performance comparisons of the conventional grid-connected configuration and the proposed solar PV-battery-grid Smart Energy Management System for the 20 institutional buildings under study for the period of June 2025 – May 2026. It can be seen from the results that the performance of the proposed solar PV-battery-grid Smart Energy Management System in terms of energy availability improved from 62.4 ± 5.1% to 94.6 ± 2.3%. In other words, the energy availability improved by 51.6%. The result suggests that there has been a significant increase in the fulfillment of the demand through the use of the solar PV and battery as compared to the conventional configuration.

The power continuity has also been improved significantly by 56.1%, from 14.8 ± 3.2 h/day to 23.1 ± 1.1 h/day. The standard deviation was lower for the proposed configuration which suggests consistency in power availability throughout the 12 months of the study.

It was also observed that the grid dependency reduced significantly by 61.5% from 100.0% for the conventional grid-connected configuration to 38.5 ± 4.6% for the proposed solar PV-battery-grid Smart Energy Management System. The finding suggests that the electricity demand has been reduced to a great extent by the use of the solar PV and battery.

Lastly, it was found that the reliability improved significantly by 38.6% from 68.7 ± 6.0% for the conventional grid-connected configuration to 95.2 ± 2.0% for the proposed solar PV-battery-grid Smart Energy Management System. The result further suggests that the reliability of the proposed configuration is higher than the conventional configuration since the standard deviation is lower for the proposed configuration. On the whole, the results suggest that the proposed solar PV-battery-grid Smart Energy Management System can be used to improve the energy availability, power continuity. Reliability while at the same time reducing the grid dependency.

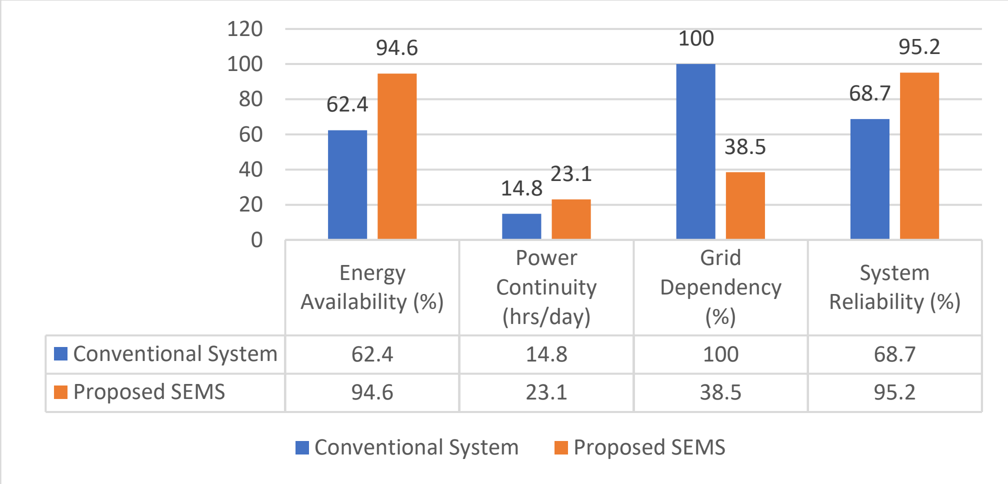

Figure 1: Comparative Performance of Energy Availability, Power Continuity, System Reliability and Grid Dependency IoT-Based Energy Monitoring Performance

Table 2: IoT-Based Energy Monitoring Performance

Performance Metric	Conventional Metering	IoT-Based SEMS	Improvement/Reduction (%)
Data Accuracy (%)	78.5 ± 4.3	97.8 ± 1.5	24.6
Monitoring Delay (s)	12.4 ± 2.8	1.9 ± 0.6	84.7
Data Update Frequency	Low	Real-time	—
Fault-Detection Capability (%)	55.2 ± 6.7	91.3 ± 2.4	65.4

Source: Experimental Data, 2025–2026

Table 2 presents the results of the performance evaluation of the IoT-based monitoring component versus conventional metering. First, data accuracy was increased from 78.5 ± 4.3% (conventional metering) to 97.8 ± 1.5% (IoT-based), which represents an increase of 24.6%. A smaller standard deviation of the IoT-based system indicates more stable measuring practice and transmitting regularities for monitoring data.

Next, monitoring delay was reduced (p<0.01) from 12.4 ± 2.8 seconds (conventional metering) to 1.9 ± 0.6 seconds for the IoT monitoring architecture, representing a decrease of 84.7%. This suggests that the IoT monitoring system can provide a faster access to information about the system states, leading to faster decisions on process changes.

Finally, data update frequency changed from intermittent conventional metering to time-continuous monitoring under the proposed system, which allowed observing the system state continuously rather than manually or on demand.

Fault-detection capability was increased from 55.2 ± 6.7% (conventional metering) to 91.3 ± 2.4% (IoT-based), representing an increase of 65.4%. Thus, the results suggest that the IoT-based monitoring component increased the accuracy of measurements, reduced monitoring delays, and improved the detection of process abnormalities effectively.

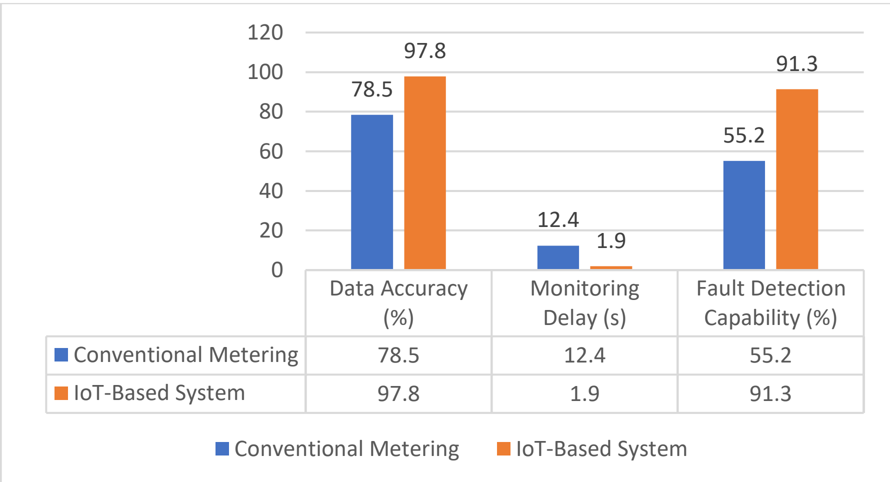

Figure 2: Comparative Performance of Conventional and IoT-Based Energy Monitoring

Machine-Learning-Based Energy Forecasting Performance

Table 3: Machine-Learning-Based Energy Forecasting Performance

Performance Metric	Baseline Model	Proposed ML Model	Improvement/Reduction (%)
Prediction Accuracy (%)	72.6 ± 5.8	93.4 ± 2.1	28.6
Mean Absolute Error (MAE)	0.84	0.29	65.5
Energy-Optimization Efficiency (%)	70.3 ± 4.9	91.7 ± 2.5	30.4
Forecast Response Time (s)	8.6 ± 1.7	2.3 ± 0.5	73.2

Source: Experimental Data, 2025–2026

Table 3 compares the performance of the baseline and proposed machine-learning models in energy-demand forecasting. The accuracy of the prediction increased from 72.6 ± 5.8% for the baseline and 93.4 ± 2.1% for the proposed model, which represents a 28.6% improvement. Additionally, the standard deviation was reduced from 5.8 to 2.1, which suggests that the results are more consistent for the proposed model.
The mean absolute error was reduced from 0.84 in the baseline model to 0.29 in the proposed model, which represents a 65.5% decrease. Thus, the predicted values using the proposed model were closer to the true value.
Energy-optimization efficiency was increased from 70.3 ± 4.9% to 91.7 ± 2.5%, which represents a 30.4% improvement. Moreover, it was found that the forecast response time decreased from 8.6 ± 1.7 seconds to 2.3 ± 0.5 seconds, which suggests a 73.2% decrease. Therefore, the proposed model was not only accurate but also efficient compared to the baseline model.
Based on the results, it can be concluded that the machine-learning component improved the accuracy and consistency of the energy-demand-forecasting process of the energy-demand-forecasting process, thereby providing more reliable information for future energy-management procedures.

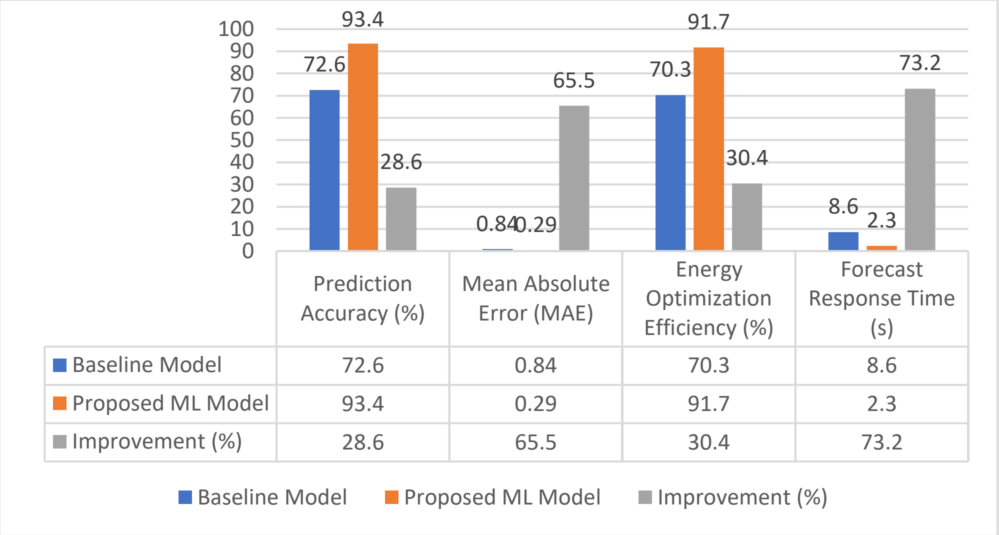

Figure 3: Comparative Prediction Accuracy and Mean Absolute Error of the Baseline and Proposed ML Models Intelligent Energy Control System Performance

Table 4: Intelligent Energy Control System Performance

Performance Metric	Conventional Control	Proposed SEMS	Improvement/Reduction (%)
Load-Balancing Accuracy (%)	71.8 ± 5.4	96.5 ± 1.8	34.4
Switching Response Time (s)	5.8 ± 1.2	0.9 ± 0.3	84.5
Energy Wastage (%)	18.6 ± 3.1	5.2 ± 1.4	72.0
System Stability Index	0.74	0.96	29.7

Source: Experimental Data, 2025–2026

Table 4 shows the performance of the intelligent energy control component compared to conventional control. Load-balancing accuracy improved from 71.8 ± 5.4% under conventional control to 96.5 ± 1.8% under the proposed SEMS (34.4% improvement). The result proved that the proposed controller was more effective in distributing the available energy according to the prevailing load requirements.
The switching response time improved from 5.8 ± 1.2 seconds to 0.9 ± 0.3 seconds (84.5% reduction). The result proved that the automatic source switching mechanism was able to respond faster to changes in energy availability and load requirements.
Energy wastage reduced from 18.6 ± 3.1% to 5.2 ± 1.4% (72.0% reduction). The result proved that the intelligent load prioritisation and automated source management allowed for a larger proportion of the available energy to be used effectively.
The system stability index improved from 0.74 under conventional control, to 0.96 under the proposed SEMS (29.7% improvement). The result proved that the proposed control architecture had improved operational stability.
All results proved that the intelligent control component was successful in improving load balancing and system stability, as well as reducing the switching response time and energy wastage.

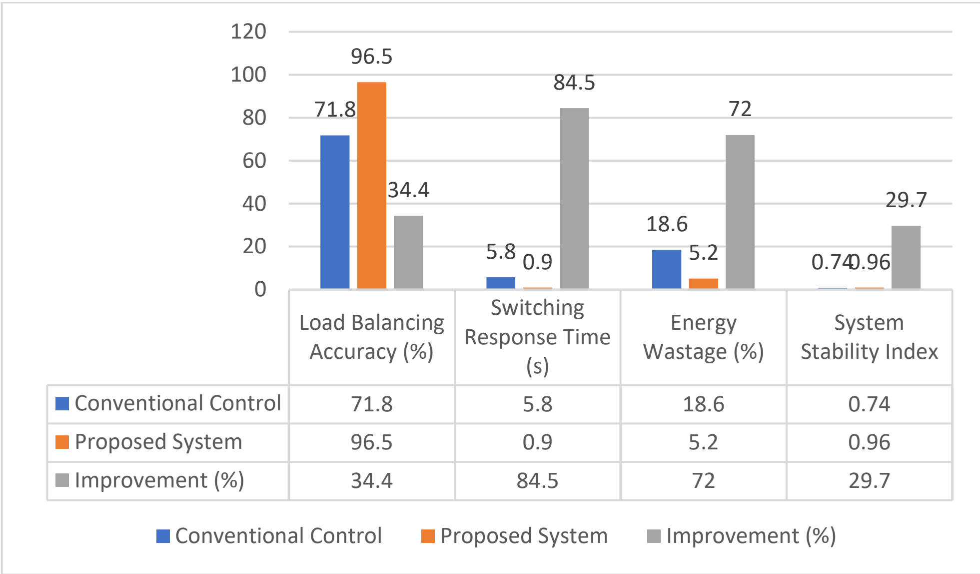

Figure 4: Comparative Performance of Load Balancing, Source Switching, Energy Wastage and System Stability Test of Hypotheses

The null hypotheses were tested at the 5% level of significance ($\alpha = 0.05$). The mean and standard deviation values obtained from experimental evaluation were used to evaluate differences between the conventional system and the proposed SEMS. For the summary statistics comparison, an independent-samples t-test was performed using the reported mean ± standard deviation values and a sample size of $n = 20$ observations per group. Cohen's d effect size was used to express the magnitude of the observed difference: an effect size of 0.20 was considered small, 0.50 moderate and ≥0.80 large.

The t-test statistic was computed as follows:

$t = (\bar{X}_1 - \bar{X}_2) / \sqrt{[(s_1^2/n_1) + (s_2^2/n_2)]}$

Where $\bar{X}_1$ and $\bar{X}_2$ are the group means, s_1 and s_2 are the corresponding standard deviations, and n_1 and n_2 are the sample sizes. The pooled standard deviation for use in Cohen's d calculation was calculated as:

$S_p = \sqrt{\{[(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2] / (n_1 + n_2 - 2)\}}$

Cohen's effect size was calculated using the formula:

$d = (\bar{X}_1 - \bar{X}_2) / s_p$

A p-value of <0.05 (p < 0.05) was considered statistically significant

Hypothesis One

H_{01}: There is no significant difference in the performance of the conventional grid-dependent system and the proposed SEMS in terms of energy availability, power continuity, grid dependency and system reliability.

Table 5: Hypothesis Testing – Solar PV–Battery–Grid System Performance

Performance Variable	Group	N	Mean ± SD	t-value	p-value	Cohen's d
Energy Availability (%)	Conventional	20	62.4 ± 5.1	-25.74	<0.001	8.14 (Large)
	Proposed SEMS	20	94.6 ± 2.3			
Power Continuity (hrs/day)	Conventional	20	14.8 ± 3.2	-10.97	<0.001	3.47 (Large)
	Proposed SEMS	20	23.1 ± 1.1			
Grid Dependency (%)	Conventional	20	100.0	59.79	<0.001	18.91 (Large)
	Proposed SEMS	20	38.5 ± 4.6			
System Reliability (%)	Conventional	20	68.7 ± 6.0	-18.74	<0.001	5.93 (Large)

Source: Experimental Data, June 2025–May 2026

The results in Table 5 clearly show that there were significant differences between the conventional grid-dependent system and the proposed SEMS. The energy availability increased from 62.4 ± 5.1% to 94.6 ± 2.3%, the power continuity increased from 14.8 ± 3.2 hours/day to 23.1 ± 1.1 hours/day; the grid dependency decreased from 100.0% to 38.5 ± 4.6%, while the system reliability increased from 68.7 ± 6.0% to 95.2 ± 2.0%.

All the tested performance variables yielded $p < 0.001$ which implies that there were significant differences based on the comparison of summary-statistics. The calculated Cohen's d values were higher than 0.80 indicating large effect sizes.

Decision: The null hypothesis (H_0) is rejected. The results showed that there was a significant difference between the conventional grid-dependent system and the proposed SEMS in terms of energy availability, power continuity, grid dependency and system reliability.

Hypothesis Two

H_{02}: There is no significant difference between conventional metering and the proposed IoT-based monitoring system in terms of data accuracy, monitoring delay and fault-detection capability.

Table 6: Hypothesis Testing – IoT-Based Energy Monitoring Performance

Performance Variable	Group	N	Mean ± SD	t-value	p-value	Cohen's d
Data Accuracy (%)	Conventional Metering	20	78.5 ± 4.3	-18.95	<0.001	5.99 (Large)
	IoT-Based System	20	97.8 ± 1.5			
Monitoring Delay (s)	Conventional Metering	20	12.4 ± 2.8	16.40	<0.001	5.19 (Large)
	IoT-Based System	20	1.9 ± 0.6			
Fault-Detection Capability (%)	Conventional Metering	20	55.2 ± 6.7	-22.68	<0.001	7.17 (Large)
	IoT-Based System	20	91.3 ± 2.4			

Source: Experimental Data, June 2025–May 2026

A comparison of the results presented in Table 6 indicates that the application of an IoT-based monitoring system resulted in significantly improved performance compared with conventional metering. Specifically, data accuracy improved from 78.5 ± 4.3% to 97.8 ± 1.5%, and monitoring delay was reduced from 12.4 ± 2.8 seconds to 1.9 ± 0.6 seconds. The ability to detect faults also increased from 55.2 ± 6.7% to 91.3 ± 2.4%.

A statistical comparison yielded $p < 0.001$ for all three-performance metrics. Accordingly, Cohen's d effect sizes were large for all three variables, which suggests that the differences between the two techniques being compared were highly significant.

Decision: The null hypothesis (H_0) is rejected as the results indicate a significant difference between the conventional metering technique and the IoT-based monitoring system being proposed.

Hypothesis Three

H_0: There is no significant difference between the baseline forecasting model and the proposed machine-learning model in terms of prediction accuracy, energy-optimization efficiency and forecast response time.

Table 7: Hypothesis Testing – Machine-Learning-Based Energy Forecasting Performance

Performance Variable	Group	N	Mean ± SD	t-value	p-value	Cohen's d
Prediction Accuracy (%)	Baseline Model	20	72.6 ± 5.8	-15.08	<0.001	4.77 (Large)
	Proposed ML Model	20	93.4 ± 2.1			
Energy-Optimization Efficiency (%)	Baseline Model	20	70.3 ± 4.9	-17.40	<0.001	5.50 (Large)
	Proposed ML Model	20	91.7 ± 2.5			
Forecast Response Time (s)	Baseline Model	20	8.6 ± 1.7	15.90	<0.001	5.03 (Large)
	Proposed ML Model	20	2.3 ± 0.5			

Source: Experimental Data, June 2025–May 2026

Table 7 demonstrates that the suggested machine-learning model was significantly superior to the baseline model. Specifically, the accuracy of prediction increased by 28.6% (from 72.6 ± 5.8% to 93.4 ± 2.1%). In addition, the efficiency of the energy-optimization process improved by 30.4% (from 70.3 ± 4.9% to 91.7 ± 2.5%). Finally, the time needed to produce a forecast was reduced by 73.2% (from 8.6 ± 1.7 seconds to 2.3 ± 0.5 seconds).

Statistical analysis yielded $p < 0.001$ effects for all three variables, with all Cohen's d exceeding 0.80.

Decision: The null hypothesis (H_0) is rejected. The results provide evidence of the statistically significant improvement of the proposed model over the baseline in terms of prediction accuracy, efficiency of energy optimization. Forecasting response time.

Hypothesis Four

H_{04}: There is no significant difference between conventional energy control and the proposed intelligent energy control system in terms of load-balancing accuracy, switching response time and energy wastage.

Table 8: Hypothesis Testing – Intelligent Energy Control System Performance

Performance Variable	Group	N	Mean ± SD	t-value	p-value	Cohen's d
Load-Balancing Accuracy (%)	Conventional Control	20	71.8 ± 5.4	-19.41	<0.001	6.14 (Large)
	Proposed SEMS	20	96.5 ± 1.8			
Switching Response Time (s)	Conventional Control	20	5.8 ± 1.2	17.72	<0.001	5.60 (Large)
	Proposed SEMS	20	0.9 ± 0.3			
Energy Wastage (%)	Conventional Control	20	18.6 ± 3.1	17.62	<0.001	5.57 (Large)
	Proposed SEMS	20	5.2 ± 1.4			

Source: Experimental Data, June 2025–May 2026

Table 8 shows significant differences between the conventional energy control and the proposed intelligent control system. The load balancing accuracy was significantly improved from 71.8 ± 5.4% to 96.5 ± 1.8%. The switching response time was significantly reduced from 5.8 ± 1.2 seconds to 0.9 ± 0.3 seconds and energy wastage was significantly decreased from 18.6 ± 3.1% to 5.2 ± 1.4%.

All three comparisons yielded $p < 0.001$, with large Cohen's d. Therefore, it can be concluded that there is a significant difference in the performance between the proposed intelligent control system and the conventional control system.

Decision: The null hypothesis (H_0) is rejected. It is evident that the proposed intelligent control system had a significant improvement in the load balancing while reducing the switching response time and energy wastage.

DISCUSSION

The results of the study were obtained, showing that the proposed Smart Energy Management System (SEMS) significantly improved the performance of the solar-powered energy management system compared to the conventional grid-dependent system. In particular, the results showed that energy availability, power continuity, and system reliability increased while the grid dependency was reduced. Specifically, energy availability increased from 62.4% in the conventional system to 94.6% in the proposed SEMS (a 51.6% improvement). Similarly, power continuity improved from 14.8 to 23.1 hours per day and system reliability increased from 68.7% to 95.2%. Additionally, grid dependency decreased from 100% to 38.5%. The results suggest that integrating solar PV, battery, and automated control of energy sources could provide better electricity supply to institutional buildings. The lower standard deviations for the proposed system also suggest stable performance during the study period.

The results also revealed that using the IoT-based monitoring component improved the ability to monitor the energy system. Specifically, data accuracy improved from 78.5% to 97.8%, monitoring delay decreased from 12.4 to 1.9 seconds, and fault detection improved from 55.2% to 91.3%. The results suggest that real-time digital monitoring could provide better information on energy system performance than conventional monitoring. The reduction in monitoring delay is particularly useful, allowing faster response to emerging problems.

The results also showed that implementing the machine learning component improved energy-demand prediction accuracy and consequently energy management efficiency. Specifically, prediction accuracy increased from 72.6% in the baseline system to 93.4% for the proposed SEMS. Additionally, mean absolute error decreased from 0.84 to 0.29, and energy optimization increased from 70.3% to 91.7%. Finally, forecast response time decreased from 8.6 to 2.3 seconds. The results suggest that integrating the predictive analytics component improves the energy management system's ability to predict energy demand and take timely action. The lower standard deviation for the proposed model indicates more consistent performance throughout the research period.

The results also showed that implementing the intelligent control component improved energy system performance. Specifically, load balancing accuracy improved from 71.8% to 96.5%. Switching response time decreased from 5.8 to 0.9 seconds, and energy wastage decreased from 18.6% to 5.2%. The results further showed that system stability improved from 0.74 to 0.96. The results suggest that effective utilization of available energy could be achieved by integrating intelligent load control. As with the monitoring and prediction component, the proposed model's consistent performance was confirmed by the lower standard deviation of its performance parameters.

As shown by the hypothesis tests, there was a significant difference between the performance of the conventional and proposed SEMS. Specifically, all performance parameters showed p-values less than 0.001 and Cohen’s d above 0.8, suggesting a large effect size. Therefore, the null hypotheses were rejected. Overall, the results suggest that SEMS provides a better energy management solution than the conventional system.

CONCLUSION

An SEMS was evaluated for the solar-powered institutional buildings at the University of Delta, Agbor, Delta State, Nigeria. The performance of the system was compared with the conventional grid-based energy operation with respect to energy availability, power continuity, grid dependency, system reliability, monitoring, demand forecasting, and intelligent control. The results revealed that the proposed system had a significant performance gain across all the selected criteria.

In particular, the results showed that the proposed system, integrating photovoltaic generation, battery storage, and grid supply, increased energy availability from 62.4% to 94.6%, power continuity from 14.8 to 23.1 h/day, and system reliability from 68.7% to 95.2%, while reducing grid dependency from 100% to 38.5%. These findings indicate that integrating renewable energy sources and battery storage can reduce dependence on grid electricity while improving the overall energy performance of institutional buildings.

In addition, the study revealed that the IoT-based monitoring component improved data accuracy from 78.5% to 97.8%, reduced monitoring delay from 12.4 s to 1.9 s, and increased fault-detection capability from 55.2% to 91.3%. These results indicate that IoT-based monitoring can contribute to a more accurate, reliable, and responsive energy monitoring system for institutional buildings.

The results also revealed that the machine-learning component improved prediction accuracy from 72.6% to 93.4%, reduced the mean absolute error from 0.84 to 0.29, increased energy-optimization efficiency from 70.3% to 91.7%, and reduced forecast response time from 8.6 s to 2.3 s. This finding indicates that the proposed machine-learning-based forecasting model can provide more accurate and timely predictions of energy demand, thereby supporting improved energy-management decisions.

Moreover, the intelligent control component enhanced overall system performance by increasing load-balancing accuracy from 71.8% to 96.5%, reducing switching response time from 5.8 s to 0.9 s, decreasing energy wastage from 18.6% to 5.2%, and increasing the system stability index from 0.74 to 0.96. These results demonstrate that intelligent load prioritisation and automated energy-source management can improve energy utilisation and operational stability in institutional buildings.

The hypothesis tests further revealed statistically significant differences between the conventional and proposed systems, with p-values less than 0.001 and large Cohen's d effect sizes across the tested performance variables. The null hypotheses were therefore rejected. Overall, the findings demonstrate that the proposed SEMS provides an effective approach to improving energy availability, monitoring accuracy, forecasting performance, load management, reliability, and energy utilisation in solar-powered institutional buildings.

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