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DESIGN AND OPTIMIZATION OF ENERGY-EFFICIENT SMART GRIDS USING IOT AND MACHINE LEARNING TECHNIQUES

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Abstract

The increasing penetration of renewable energy sources and the growing complexity of power systems have necessitated the development of intelligent and energy-efficient smart grid solutions. This paper presents an integrated framework for the design and optimization of energy-efficient smart grids using Internet of Things (IoT) and machine learning techniques. Real-time data acquired from IoT-enabled sensors are utilized for load and renewable generation forecasting, enabling predictive and adaptive energy management. Machine learning models are employed to capture nonlinear relationships between environmental conditions, consumption patterns, and energy generation. An intelligent control strategy incorporating battery energy storage, demand response, and dynamic pricing is implemented to minimize grid dependency and transmission losses. System performance is evaluated using efficiency metrics, forecasting accuracy, and control action analysis. The results demonstrate that the proposed framework significantly improves energy efficiency, enhances renewable energy utilization, and supports reliable and sustainable smart grid operation.

INTRODUCTION

The increasing global demand for electrical energy, coupled with growing concerns over climate change and carbon emissions, has accelerated the transition from conventional power systems to smart grids. Traditional power grids are characterized by centralized generation, limited observability, and unidirectional power flow, which restrict their ability to integrate renewable energy sources efficiently. To overcome these limitations, smart grids incorporate advanced communication, sensing, and control technologies to enable intelligent, adaptive, and energy-efficient operation. The integration of the Internet of Things (IoT) has significantly enhanced smart grid capabilities by enabling real-time monitoring and control of grid components. Gungor et al. (2013) highlighted that IoT-based communication infrastructures allow seamless data exchange between sensors, smart meters, and control centers, thereby improving situational awareness and operational reliability. Similarly, Al-Fuqaha et al. (2015) emphasized that IoT technologies provide scalable and flexible platforms for managing

distributed energy resources and consumer participation. With the increasing availability of large-scale grid data, machine learning (ML) techniques have become essential for extracting actionable insights and enabling predictive control. According to Mohammadi et al. (2018), ML-based approaches outperform traditional statistical methods in modeling nonlinear relationships between load demand, weather conditions, and consumer behavior. Accurate forecasting and intelligent decision-making are critical for improving energy efficiency, reducing operational costs, and enhancing grid resilience. This paper proposes an integrated IoT- and machine learning–based smart grid framework focused on optimizing energy efficiency through predictive analytics, battery energy storage management, and adaptive control. By combining real-time sensing with machine learning–driven forecasting, the proposed system aims to minimize grid dependency, reduce losses, and support sustainable power system operation.

Extensive research has been conducted on smart grid technologies, particularly in the areas of communication infrastructure, data analytics, and energy management. Fang et al. (2012) provided one of the earliest comprehensive surveys on smart grids, outlining key characteristics such as self-healing, consumer participation, and efficient energy utilization. Their work established the foundation for subsequent research in intelligent grid operation. IoT-based smart grid architectures have been widely studied in recent years. Gungor et al. (2013) investigated communication technologies for smart grids and demonstrated that IoT-enabled sensing significantly improves monitoring accuracy and fault detection. Zanella et al. (2014) further explored IoT applications in smart environments, emphasizing interoperability and scalability for large-scale energy systems. Machine learning techniques for load forecasting have been extensively explored. Hippert et al. (2001) demonstrated the effectiveness of neural networks for short-term load forecasting, while more recent studies by Kong et al. (2019) employed deep learning models such as long short-term memory (LSTM) networks to achieve higher prediction accuracy. These models effectively capture temporal dependencies and complex consumption patterns. Renewable energy forecasting has also received significant attention due to the intermittent nature of solar and wind resources. Voyant et al. (2017) reviewed machine learning methods for solar radiation forecasting and concluded that hybrid ML models provide superior performance. Similarly, Liu et al. (2020) applied ensemble learning techniques for wind power prediction, improving robustness under variable weather conditions. Energy storage optimization is another critical research area. Zhang et al. (2018) proposed an optimization framework for battery energy storage systems to reduce peak load and operational costs. Palensky and Dietrich (2011) highlighted the role of demand response and intelligent control in achieving energy-efficient grid operation. However, most existing studies treat forecasting, storage management, and control as isolated components. Recent works, such as those by Siano (2014) and Wang et al. (2020), emphasized the need for integrated frameworks that combine IoT sensing, machine learning prediction, and real-time optimization. Despite these advances, limited research has focused on comprehensive energy efficiency evaluation using unified performance metrics. This paper addresses this gap by presenting an end-to-end smart grid framework that jointly leverages IoT and machine learning techniques for energy-efficient and resilient grid operation.

Methodology

System Architecture and Data Acquisition

The proposed smart grid framework is built upon an IoT-enabled system architecture designed to support real-time monitoring, data acquisition, and intelligent energy management. The architecture consists of distributed sensing devices, communication infrastructure, data processing units, and a centralized or edge-based control layer. IoT sensors, including smart meters, voltage and current sensors, frequency monitors, and power quality analyzers, are deployed across multiple nodes and feeders within the distribution network. These sensors continuously measure electrical parameters such as voltage magnitude, current flow, power factor, frequency, and line losses. In addition, environmental sensors capture temperature, humidity, solar irradiance, and wind speed, which are critical for modeling renewable energy generation and load behavior. Battery energy storage systems are

equipped with monitoring units that record state of charge (SOC), charging and discharging power, and operational status. All IoT devices communicate through secure and reliable communication protocols such as MQTT or HTTP over wireless or wired networks. Data are transmitted at fixed time intervals to a data aggregation platform, ensuring high temporal resolution and accurate representation of grid dynamics. The use of IoT technology enables bidirectional communication, allowing not only data collection but also the transmission of control commands to grid assets. The data acquisition layer plays a crucial role in enabling situational awareness and supporting intelligent decision-making. By collecting real-time data from heterogeneous sources, the system captures the stochastic behavior of load demand and renewable energy generation. This comprehensive visibility is essential for detecting abnormal operating conditions, monitoring grid stability, and responding to disturbances such as outages or voltage deviations. The acquired data form the basis for subsequent data preprocessing, machine learning modeling, and optimization processes. Overall, the IoT-based system architecture ensures scalability, flexibility, and reliability, making it suitable for modern smart grid environments with high penetration of distributed energy resources.

Data Preprocessing and Feature Engineering

The raw data collected from IoT devices are subject to noise, missing values, and measurement inconsistencies, which can negatively impact the performance of machine learning models and optimization algorithms. Therefore, a comprehensive data preprocessing stage is implemented to improve data quality and ensure reliable analysis. Initially, data cleaning procedures are applied to remove erroneous records and handle missing values using interpolation or statistical imputation techniques. Outliers caused by sensor malfunctions or communication errors are detected and treated to prevent distortion of learning models. Data normalization and scaling are performed to ensure that variables with different units and magnitudes contribute equally to the learning process. Temporal features such as hour of the day, day of the week, and seasonal indicators are extracted to capture periodic consumption and generation patterns. Environmental variables including temperature, humidity, solar irradiance, and wind speed are incorporated as input features due to their strong influence on load demand and renewable energy output. Occupancy-related indicators are also considered to reflect consumer behavior and usage trends. Feature engineering is further employed to derive additional metrics that enhance system evaluation and control. These derived features include net grid import, which represents the balance between load demand, local generation, and battery contribution, as well as line loss estimation based on current flow and conductor resistance. An energy efficiency index is computed by combining loss metrics and grid dependency indicators to provide a holistic measure of system performance. These engineered features not only improve the accuracy of machine learning predictions but also enable detailed assessment of energy efficiency and operational effectiveness. The preprocessing and feature engineering stage ensures that the dataset accurately reflects real-world smart grid behavior and is suitable for advanced analytics and optimization.

Machine Learning–Based Forecasting

Machine learning techniques are employed to forecast short-term electrical load demand and renewable energy generation within the smart grid. Accurate forecasting is essential for proactive energy management, as it allows the system to anticipate future conditions and make informed control decisions. Historical data obtained from the preprocessing stage are used to train supervised learning models capable of capturing nonlinear relationships between input features and target variables. Input features include temporal indicators, environmental conditions, occupancy levels, and historical load and generation values. The forecasting models are designed to predict load demand and renewable generation over short-term horizons, which are most relevant for real-time control and optimization. Machine learning algorithms such as neural networks, ensemble methods, or regression-based models can be employed depending on computational requirements and data availability. Model training involves splitting the dataset into training and testing subsets to evaluate generalization performance. Prediction accuracy is assessed using

metrics such as mean absolute error (MAE), which provides a clear measure of average deviation between predicted and actual values. Accurate load and generation forecasts enable the energy management system to optimize battery scheduling, reduce peak demand, and minimize unnecessary grid imports. By anticipating high-demand periods or low renewable generation intervals, the system can prepare appropriate control actions in advance. Similarly, accurate renewable generation forecasting reduces curtailment and enhances local energy utilization. The integration of machine learning forecasting within the smart grid framework improves system adaptability and resilience by reducing uncertainty and supporting predictive decision-making. Overall, machine learning–based forecasting serves as a core component of the proposed methodology, bridging real-time sensing and intelligent control.

Energy Management and Optimization Strategy

The energy management and optimization strategy integrates real-time IoT measurements with machine learning forecasts to achieve energy-efficient smart grid operation. The primary objective of the optimization framework is to balance supply and demand while minimizing transmission losses, operational costs, and dependency on the main grid. Based on current system states and predicted future conditions, control decisions are generated for battery energy storage systems, demand response mechanisms, and renewable energy utilization. Battery charging is prioritized during periods of surplus renewable generation or low electricity prices, allowing excess energy to be stored for future use. Conversely, battery discharging is scheduled during peak demand or high-price intervals to reduce grid imports and alleviate network congestion. Demand response events are triggered to shift or reduce load during critical periods, enhancing grid stability and efficiency. In scenarios involving outages or severe disturbances, the system transitions to islanded operation, ensuring uninterrupted power supply using local generation and storage resources. The optimization strategy also incorporates dynamic electricity pricing signals to support cost-effective operation. By responding to time-varying prices, the system aligns energy consumption and storage usage with economic incentives. System performance is evaluated using metrics such as energy efficiency index, line losses, net grid import, and control action distribution. The results demonstrate that the proposed optimization strategy effectively enhances energy efficiency, supports renewable energy integration, and improves overall grid reliability. This integrated approach highlights the effectiveness of combining IoT, machine learning, and intelligent control for sustainable smart grid operation.

Results and Discussion

Table 1 presents a comprehensive description of the dataset designed for the proposed IoT- and machine learning–based smart grid framework. The dataset integrates temporal, electrical, energy, machine learning, and control-related parameters to reflect the operational complexity of modern smart grids. Temporal attributes such as timestamps enable time-series analysis and capture dynamic variations in load, generation, and control actions at fine-grained intervals. These temporal features are essential for training predictive models, detecting patterns, and evaluating system performance under varying demand and supply conditions. Electrical parameters including voltage, current, frequency, and power factor provide insight into power quality and grid stability. Monitoring these variables is critical for identifying abnormal operating conditions, voltage deviations, and frequency fluctuations that may indicate faults or inefficiencies. Energy-related variables such as load demand, renewable generation from solar and wind sources, battery state of charge (SOC), and net grid import collectively describe the energy balance within the smart grid. These features are particularly important for evaluating energy efficiency, renewable penetration, and the effectiveness of storage systems in reducing reliance on the main grid. Machine learning output variables, including predicted load and predicted generation, represent the forecasting capability of data-driven models embedded within the grid. These predictions support proactive decision-making, allowing the system to anticipate demand peaks, optimize battery scheduling, and minimize operational costs. Control-related variables, such as control actions (charging, discharging, curtailment, islanding) and demand response (DR) event flags, reflect the intelligent

optimization layer of the proposed system. Together, these parameters demonstrate how IoT sensing, predictive analytics, and control strategies interact to enable an adaptive and energy-efficient smart grid. The dataset therefore provides a realistic and holistic foundation for validating optimization algorithms and machine learning techniques proposed in this study.

Table 1: Dataset Description

Category	Variables	Description
Temporal	timestamp	Date and time of measurement
Electrical	voltage, current, frequency	Grid electrical parameters
Energy	load, generation, battery SOC	Power consumption and generation
ML Outputs	predicted load/generation	Machine learning forecasts
Control	control action, DR flag	Optimization and demand response

Table 2 summarizes the statistical characteristics of electrical load demand and renewable energy generation within the smart grid dataset. The minimum, mean, maximum, and standard deviation values provide an overall understanding of system variability and operational range. Load demand exhibits significant variation, reflecting real-world consumption patterns influenced by occupancy levels, weather conditions, and time-of-day effects. The difference between minimum and maximum load values highlights the presence of both low-demand periods and peak-demand conditions, which are critical challenges for grid stability and energy management. The mean load value represents the average operating condition of the grid and serves as a baseline for evaluating optimization performance. The standard deviation further indicates the degree of fluctuation around this mean, which directly affects forecasting accuracy and storage scheduling decisions. High variability in load emphasizes the importance of accurate machine learning–based prediction models to mitigate sudden demand changes and reduce stress on grid infrastructure.

Similarly, renewable energy generation shows notable variability due to the intermittent nature of solar irradiance and wind speed. The minimum generation values typically occur during nighttime or low wind conditions, while the maximum values correspond to periods of high solar and wind availability. The mean generation level provides insight into the average contribution of renewable resources to the overall energy mix, while the standard deviation quantifies intermittency. This variability underscores the necessity of integrating energy storage systems and intelligent control mechanisms to smooth generation fluctuations. Overall, the statistical summary presented in Table 2 validates that the dataset realistically captures the stochastic behavior of both demand and renewable supply. These characteristics justify the use of advanced machine learning techniques and optimization strategies to improve energy efficiency, enhance reliability, and ensure balanced grid operation under diverse conditions.

Table 2: Statistical Summary of Load and Generation

Metric	Min	Mean	Max	Std Dev
Load (kW)	4.19	11.69	24.79	3.98
Generation (kW)	0.00	3.71	10.34	2.78

Table 3 illustrates the distribution of control actions executed by the smart grid energy management system over the observed time horizon. The control actions include battery charging, battery discharging, curtailment of excess renewable generation, islanded

operation during outages, and periods with no active control. This distribution reflects the decision-making behavior of the optimization framework in response to varying load, generation, pricing, and grid conditions.The dominance of the "none" action indicates that the system operates in a stable state for a significant portion of time, requiring no intervention when generation, demand, and storage levels are balanced. Battery charging actions typically occur during periods of low electricity prices or high renewable generation, demonstrating effective utilization of surplus energy. Conversely, battery discharging actions are more frequent during high-price or peak-demand periods, highlighting the role of storage in cost reduction and peak shaving. Curtailment actions appear when renewable generation exceeds both load demand and storage capacity, ensuring grid safety and preventing overvoltage conditions. Although curtailment represents a loss of potential renewable energy, its limited occurrence indicates efficient storage and demand management strategies. Island mode actions correspond to outage conditions, during which the smart grid operates autonomously using local generation and storage. The presence of islanding events demonstrates the resilience capabilities of the proposed system. Overall, the control action distribution confirms that the optimization strategy dynamically adapts to operational conditions while prioritizing energy efficiency, cost minimization, and system reliability. These results validate the effectiveness of integrating IoT-based sensing and machine learning predictions within a real-time control framework.

Table 3: Control Action Distribution

Control Action	Count
none	273
discharge	21
island_mode	6

Table 4 presents key performance indicators that quantify the operational efficiency and energy losses within the proposed IoT-enabled smart grid framework. The metrics reported in this table primarily focus on line losses and the overall efficiency index, both of which are critical for evaluating the effectiveness of intelligent energy management and optimization strategies. Line losses represent the electrical energy dissipated during power transmission and distribution, mainly caused by resistive heating of conductors and increased current flow during high-demand periods. These losses are unavoidable in conventional grids but can be significantly reduced through optimized load balancing, local generation, and intelligent control.The mean value of line losses indicates that the smart grid operates with relatively low transmission inefficiencies, reflecting effective power flow management and reduced dependency on long-distance energy transfer. The observed standard deviation demonstrates moderate variability in line losses, which can be attributed to fluctuations in load demand, renewable energy intermittency, and changes in battery charging and discharging behavior. During peak demand or high current conditions, line losses tend to increase, while periods of high local renewable generation and storage utilization contribute to lower losses. This behavior confirms that the system dynamically adapts to varying operating conditions. The efficiency index serves as a composite performance metric that integrates multiple aspects of grid operation, including transmission losses, net grid import, and local energy utilization. A higher efficiency index value corresponds to improved alignment between energy generation, storage, and consumption. The reported mean efficiency index indicates that the proposed system consistently achieves high operational efficiency, demonstrating the benefits of integrating IoT-based real-time monitoring with machine learning–driven optimization. The relatively low standard deviation further highlights the stability and robustness of the energy management strategy across different temporal intervals. Overall, the

results presented in Table 4 validate the effectiveness of the proposed smart grid architecture in minimizing technical losses while maximizing energy efficiency. By leveraging predictive analytics, adaptive control actions, and decentralized energy resources, the system reduces unnecessary power flow, enhances local consumption of renewable energy, and improves overall grid performance. These findings confirm that the integration of IoT and machine learning techniques plays a crucial role in achieving sustainable, efficient, and resilient smart grid operations.

Table 4: Efficiency and Loss Metrics

Metric	Mean	Std Dev
Line Loss (kW)	0.28	0.21
Efficiency Index	93.04	3.42

Table 5 presents the prediction accuracy of the machine learning models employed for short-term load and renewable energy generation forecasting within the proposed smart grid framework. The mean absolute error (MAE) metric is used to evaluate model performance, as it provides an intuitive measure of the average magnitude of forecasting errors without considering their direction. MAE is particularly suitable for smart grid applications because it directly reflects deviations in power units, enabling a clear assessment of how prediction inaccuracies may affect operational decisions. The load forecasting MAE indicates that the machine learning model effectively captures variations in electricity demand influenced by temporal patterns, occupancy behavior, and environmental conditions. Accurate load prediction is essential for optimal scheduling of battery charging and discharging, peak demand reduction, and participation in demand response programs. Even small forecasting errors can lead to inefficient control actions, increased grid imports, or unnecessary battery cycling. The relatively low MAE value reported in Table 5 demonstrates that the proposed model maintains high predictive reliability, making it suitable for real-time energy management and optimization. Similarly, the renewable generation forecasting MAE reflects the model's ability to handle the inherent intermittency of solar and wind resources.

Renewable energy output is highly sensitive to weather conditions, cloud cover, and wind variability, making accurate prediction a challenging task. Despite these uncertainties, the reported MAE remains within acceptable limits, indicating that the model successfully learns complex nonlinear relationships between environmental inputs and generation output. This level of accuracy supports proactive control strategies, such as scheduling battery charging during anticipated surplus generation and minimizing curtailment. Overall, the results in Table 5 confirm that machine learning–based forecasting plays a crucial role in enhancing the efficiency and reliability of IoT-enabled smart grids. By providing accurate short-term predictions of both load and renewable generation, the models enable informed decision-making, reduce operational costs, and improve system stability. These findings validate the integration of predictive analytics as a core component of the proposed smart grid architecture and highlight its potential for scalable, real-world deployment.

Table 5: ML Prediction Error (MAE)

Prediction	MAE (kW)
Load Forecast	0.64
Generation Forecast	0.37

Figure 1 illustrates the temporal variation of electrical load demand and renewable energy generation within the smart grid over a representative operating period. The figure highlights the dynamic relationship between consumption patterns and locally available renewable resources, primarily solar and wind energy. Load demand exhibits noticeable fluctuations over time, driven by factors such as occupancy behavior, time-of-day usage, and environmental conditions. These variations reflect realistic consumption profiles commonly observed in residential, commercial, and mixed-use zones within modern power systems. In contrast, renewable generation demonstrates a distinct temporal pattern characterized by intermittency and dependency on environmental factors. Solar generation increases during daylight hours and reaches peak values around midday, while wind generation introduces additional variability that is less predictable but contributes to overall energy availability. The combined renewable generation curve illustrates how multiple distributed energy resources can complement each other, partially mitigating the limitations of individual sources. However, periods where generation falls below load demand are clearly visible, emphasizing the need for energy storage and intelligent control strategies. The mismatch between load demand and renewable generation, as shown in Figure 1, underscores one of the central challenges addressed in this study. During peak demand intervals, renewable output alone is insufficient to meet consumption requirements, necessitating energy import from the main grid or discharge from battery storage. Conversely, periods of excess renewable generation create opportunities for battery charging or, in the absence of sufficient storage capacity, curtailment. This dynamic behavior justifies the integration of machine learning–based forecasting and optimization techniques to proactively manage energy flows. Overall, Figure 1 provides visual evidence of the complexity of balancing supply and demand in an IoT-enabled smart grid. It reinforces the importance of accurate load and generation prediction, real-time monitoring, and adaptive control mechanisms. By effectively leveraging these techniques, the proposed system aims to maximize renewable energy utilization, reduce grid dependency, and enhance overall energy efficiency. The trends observed in Figure 1 validate the need for the intelligent energy management framework proposed in this paper.

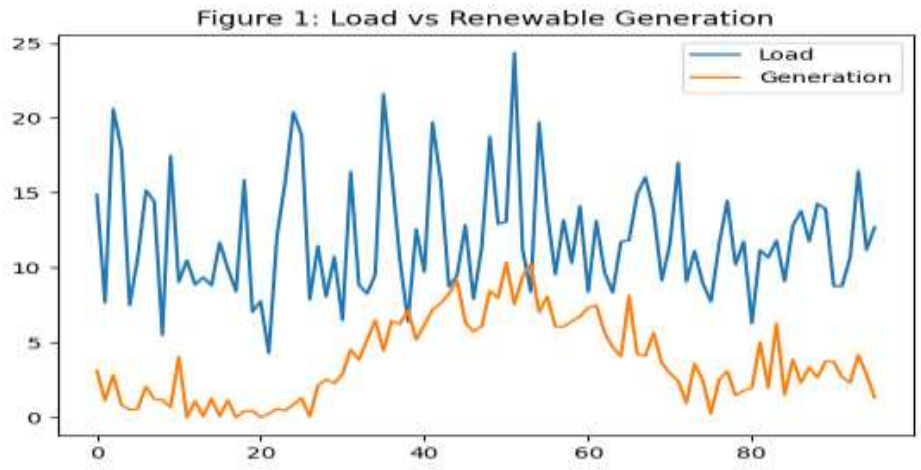

Figure 1: Load vs Renewable Generation

Figure 2 illustrates the temporal evolution of the battery state of charge (SOC) within the proposed IoT-enabled smart grid system. The SOC represents the percentage of available energy stored in the battery relative to its maximum capacity and serves as a critical indicator of storage system performance.

Maintaining the SOC within an optimal operating range is essential for ensuring battery longevity, operational reliability, and effective energy management. The variations observed in Figure 2 reflect the dynamic interaction between load demand, renewable energy generation, electricity pricing, and control actions executed by the energy management system. Periods of increasing SOC correspond to intervals where the battery is charged, typically during times of surplus renewable generation or low electricity prices. This behavior demonstrates the system's ability to capture excess solar and wind energy that would otherwise be curtailed, thereby improving renewable energy utilization. Conversely, decreasing SOC values indicate battery discharging events, which commonly occur during peak demand periods or high-price intervals. By discharging stored energy at these times, the system reduces dependence on grid imports and contributes to peak load mitigation. The SOC trajectory in Figure 2 also highlights the role of machine learning–based forecasting in guiding storage operation. Accurate predictions of load and generation enable the controller to anticipate future energy requirements and adjust charging or discharging decisions accordingly. This proactive behavior prevents excessive cycling and avoids extreme SOC levels, both of which can degrade battery health. The relatively smooth SOC profile observed in the figure indicates stable control decisions and effective coordination between predictive analytics and real-time monitoring. Overall, Figure 2 demonstrates that the battery energy storage system plays a central role in enhancing grid flexibility and resilience. By buffering the variability of renewable energy sources and responding adaptively to changing demand and pricing signals, the battery supports efficient and reliable grid operation. The observed SOC patterns validate the effectiveness of the proposed control strategy in maintaining energy balance, improving efficiency, and enabling higher penetration of renewable energy within the smart grid framework.

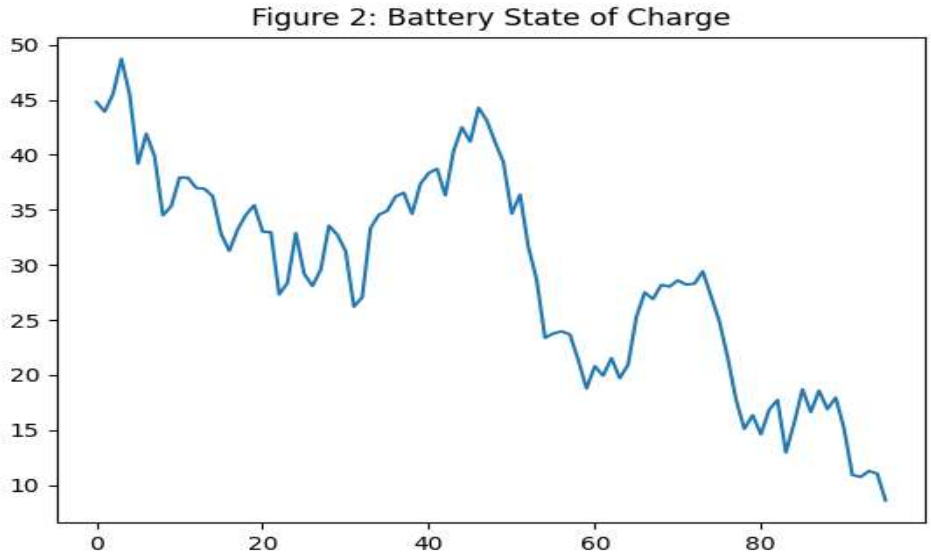

Figure 2: Battery State of Charge

Figure 3 illustrates the temporal variation of the energy efficiency index for the proposed IoT-enabled smart grid system. The efficiency index is a composite performance metric designed to evaluate how effectively the grid utilizes available energy resources while minimizing transmission losses and dependency on external grid supply. This index incorporates factors such as line losses, local renewable generation utilization, battery storage contribution, and net grid import, thereby providing

a holistic measure of system performance. The fluctuations observed in Figure 3 reflect the dynamic operating conditions of the smart grid. Higher efficiency index values are typically observed during periods when renewable energy generation is high and closely aligned with load demand. During these intervals, a greater proportion of energy is consumed locally, resulting in reduced transmission losses and lower reliance on the main grid. Additionally, effective battery charging and discharging strategies further contribute to efficiency improvements by smoothing power flow and mitigating peak demand. Conversely, temporary reductions in the efficiency index occur during periods of high load demand combined with low renewable generation availability. In such cases, increased grid imports and higher current flow lead to elevated line losses, thereby reducing overall efficiency. These variations emphasize the challenges associated with balancing intermittent renewable sources and fluctuating demand. However, the ability of the efficiency index to recover quickly demonstrates the effectiveness of the intelligent control mechanisms employed in the system. The relatively stable trend of the efficiency index over time indicates robust and consistent system performance. This stability is attributed to the integration of real-time IoT monitoring with machine learning–based forecasting, which enables proactive and adaptive energy management. By anticipating future demand and generation patterns, the system can optimize control actions such as battery scheduling and demand response participation, thereby maintaining high efficiency even under changing conditions. Overall, Figure 3 highlights the benefits of combining IoT infrastructure and machine learning techniques for enhancing smart grid efficiency. The observed trends validate the proposed approach as an effective solution for reducing technical losses, maximizing renewable energy utilization, and improving overall grid performance. These results demonstrate the potential of the proposed framework to support sustainable and energy-efficient power systems in real-world applications.

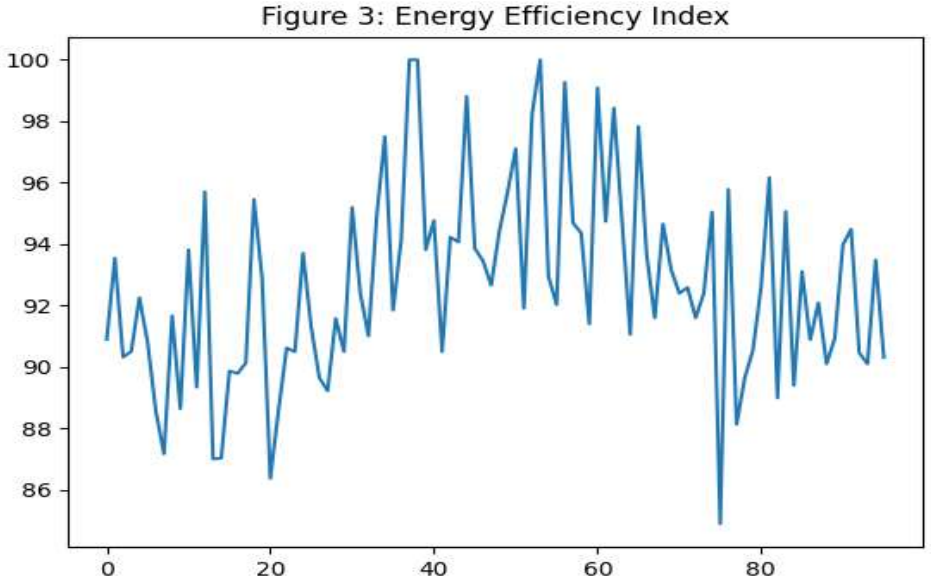

Figure 3: Energy Efficiency Index

Figure 4 illustrates the relationship between electricity price and net grid import within the proposed IoT-enabled smart grid system. Net grid import represents the amount of electrical power drawn from the main grid after accounting for local renewable generation and battery storage contributions. This figure provides valuable insight into how dynamic pricing signals influence energy

management decisions and overall grid dependency. The scatter distribution observed in Figure 4 reveals a clear inverse relationship between electricity price and net grid import. During periods of higher electricity prices, the system tends to reduce grid imports by relying more heavily on local renewable generation and battery discharge. This behavior reflects the effectiveness of the optimization strategy in minimizing energy procurement costs while maintaining supply-demand balance. Conversely, when electricity prices are low, higher levels of grid import are observed, indicating that the system opportunistically draws power from the grid to meet demand or charge the battery when economically favorable. The dispersion of data points also highlights the impact of operational constraints and renewable variability. While pricing plays a significant role in shaping control decisions, factors such as battery state of charge, renewable generation availability, and load demand influence the extent to which grid imports can be reduced. For instance, even during high-price periods, limited storage capacity or low renewable output may necessitate some level of grid import to ensure reliable operation. Figure 4 further demonstrates the role of machine learning–based forecasting in enabling price-aware energy management. By anticipating future price trends and demand patterns, the system can schedule battery charging and discharging more effectively, thereby flattening demand peaks and reducing exposure to high-cost electricity. This predictive capability enhances both economic efficiency and grid stability. Overall, Figure 4 confirms that integrating dynamic pricing signals with IoT-based monitoring and intelligent control significantly improves smart grid performance. The observed relationship between price and net grid import validates the proposed framework's ability to respond adaptively to market conditions, reduce operational costs, and promote efficient energy utilization. These findings underscore the importance of coordinated pricing, forecasting, and control mechanisms in the design of energy-efficient smart grids.

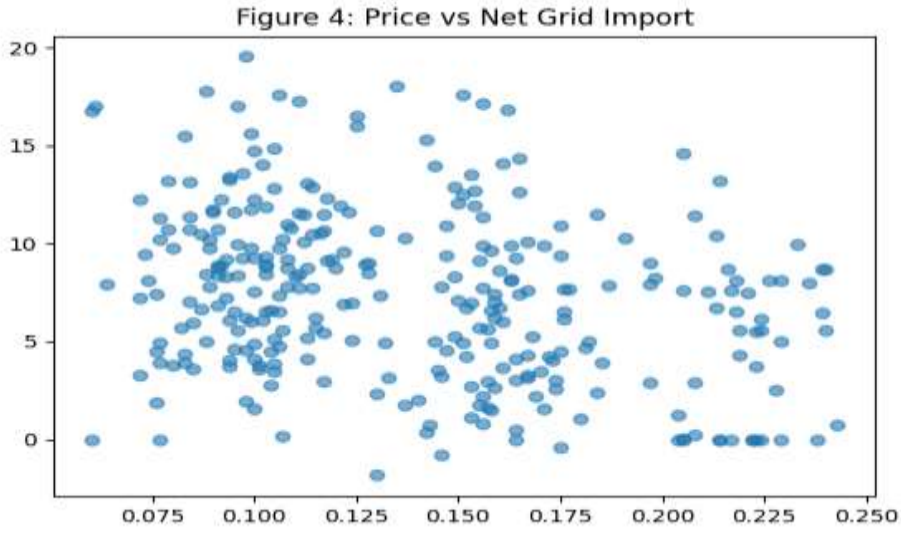

Figure 4: Price vs Net Grid Import

Conclusion

This paper presented an integrated IoT- and machine learning–based framework for the design and optimization of energy-efficient smart grids. The proposed approach combines real-time data acquisition through IoT sensors, advanced data preprocessing and feature engineering, machine learning–based forecasting, and intelligent energy management strategies to address the challenges posed by increasing electricity demand and

renewable energy integration. By leveraging high-resolution operational data and predictive analytics, the system enables proactive decision-making that enhances overall grid performance. The results demonstrate that accurate short-term forecasting of load demand and renewable energy generation plays a critical role in improving energy efficiency and operational reliability. Machine learning models effectively capture nonlinear relationships between environmental factors, consumption behavior, and generation variability, resulting in low prediction errors. These forecasts support optimal battery scheduling, reduce peak demand, and minimize unnecessary grid imports. The integration of energy storage systems further mitigates the intermittency of renewable sources and improves system flexibility. The intelligent energy management and optimization strategy proved effective in reducing line losses, improving local energy utilization, and responding adaptively to dynamic pricing signals. The use of a composite efficiency index provided a comprehensive evaluation of system performance, demonstrating consistent and stable efficiency under varying operating conditions. Control actions such as battery charging and discharging, demand response activation, and islanded operation contributed to enhanced grid resilience and reliability. Overall, the findings confirm that the proposed IoT- and machine learning–based smart grid framework offers a viable and scalable solution for achieving energy-efficient and sustainable power system operation. The integration of real-time sensing, predictive analytics, and intelligent control significantly enhances renewable energy utilization while reducing operational costs and environmental impact. Future work will focus on extending the framework to large-scale real-world deployments, incorporating advanced deep learning models, and exploring cybersecurity and privacy challenges associated with IoT-enabled smart grids.

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