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Empowering smart homes by IoT-driven hybrid renewable energy integration for enhanced efficiency

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This paper investigates combined renewable energy systems with the Internet of Things (IoT) and smart homes to increase efficiency, cost savings, and environmental sustainability. The study optimizes the combination of solar panels, wind turbines, and energy storage systems, utilizing IoT sensors and controllers, to enable real-time monitoring and adaptive energy management. A simulated smart home environment case study demonstrates that the system outperforms conventional energy systems, improving average efficiency by up to 72.3%, reducing energy costs by up to 61%, and lowering CO_2 emissions by more than 61% compared to conventional systems. The solar-wind-storage configurations of the hybrid system increased efficiency to 80%, with customer satisfaction of 8.5/10, indicating the practical applicability of the system. In addition to presenting these quantifiable advantages, the paper discusses scalability issues, operational limits, and future research work, positioning the proposed approach as a pathway toward sustainable IoT-enabled smart home energy ecosystems.

Keywords IoT (Internet of things), Hybrid renewable energy system, Smart home, Energy efficiency, Affordable electricity, Clean energy technology

The increasing challenges of energy demands worldwide, combined with severe problems of greenhouse gas emissions, have prompted a trend towards renewable power generation systems. Smart homes are emerging as crucial components of future smart grids, as they consume a significant portion of the total energy and have great potential for energy savings and optimization[1,2]. Nonetheless, sustainable energy resources such as PV panels and wind turbines are uncertain and intermittent, making it challenging to integrate them into residential energy systems. Meanwhile, the development of the Internet of Things (IoT) has created new opportunities for the real-time surveillance, control, and optimization of the distributed energy systems[3,4]. Harnessing IoT to integrate hybrid renewable energy sources into the grid in smart homes can enhance efficiency, reduce costs, and lower the carbon footprint, directly serving the cause of sustainable development and energy security[5,6]. In recent years, research has been conducted on several systems for hybrid renewable energy systems and IoT-based energy management systems. For instance, machine-learning-based predictive models have been utilized to forecast renewable generation and domestic consumption, thereby enhancing the flexibility of energy management systems[7,8]. Optimization methods, including the genetic algorithm, Particle Swarm Optimization (PSO), and linear programming, have been applied to address load scheduling, storage management, and cost minimization in smart homes[9–11]. This model predictive control and reinforcement learning-based techniques have been employed to stabilize the system and optimize long-term energy dispatch[12,13]. Furthermore, recent studies have highlighted demand response approaches, such as time-of-use pricing and automatic load shifting, to match household demand with the availability of renewable energy sources[14–16]. These works demonstrate that hybrid renewable and IoT-based systems are becoming increasingly mature; however, they also have several deficiencies that hinder their scalability and commercialization.

The rapid adoption of renewable energy in smart homes is hindered by intermittency, high reliance on the grid, and poor demand-side management. Traditional PV-only or wind-only community systems are inflexible in accommodating the diverse needs of users, and conventional optimization methods often fail to provide efficient

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and scalable solutions. Simultaneously, the development of IoT opens a new door for real-time monitoring, communication, and control, enabling the smart integration of different renewable energy sources. The rationale behind this research is to establish a IoT-enabled hybrid architecture that not only improves efficiency and economic feasibility but also provides solutions for practical issues of reliability, reduces emissions, and enhances scalability for future innovative energy systems.

Analysis of the literature review reveals several research gaps. First, most existing models focus solely on optimizing either generation or consumption, lacking a fully integrated model of solar, wind, and storage systems under a single IoT-based control architecture. Second, although metaheuristic and predictive algorithms are commonly applied, their computational limitations, such as dependence on parameter tuning and premature convergence, are seldom considered, and they are not suitable for real-time applications in residential settings. Third, most of the literature does not consider energy management under the real-world IoT communication limitations, such as latency, packet loss, and device interoperability, that are critical for reliable behavior in smart homes. Lastly, most previous research reports only describe the experiment results without quantifying their environmental and economic benefits, reducing CO_2 emissions, saving costs, increasing efficiency, and exploring the working potential of the proposed frameworks. To overcome these shortcomings, this work presents an IoT-based hybrid renewable energy integration framework for smart homes, which integrates solar panels, wind turbines, and energy storage, along with advanced optimization and real-time control strategies.

This study suggests that a hybrid renewable system, being an IoT-integrated system optimized with predictive analytics and adaptive algorithms, would be more efficient in terms of reduced energy costs, improved household energy efficiency, and a lower carbon footprint than its traditional counterpart. A case study is developed to validate this hypothesis using a simulated smart home scenario, where the approach is tested with real-time energy consumption profiles, renewable generation, and appliance-specific constraints. The specific objectives of this study are:

- To develop and deploy an IoT-enabled hybrid energy management system for PV, wind, and storage devices.
- To develop predictive analytics and hybrid optimization tools for improved efficiency, cost savings, and reduced emissions.
- The goal is to simulate the system's performance and measure improvements over conventional energy systems.
- To contribute to some restrictions and future approaches for scalable smart home energy systems.

The significant contributions of this paper include proposing an integrated IoT-based hybrid renewable energy framework for smart home with three focal categories of generation, storage and demand side; employing adaptive optimization methodologies to circumvent computational limitations compared to traditional heuristics and preserving robust performance of the solution; evaluating practical benefits such as cost and efficiency benefits, and reduction of carbon emission, followed by summarizing future works regarding scalability, communication reliabilities, and pilot deployment strategies that is presenting in Fig. 1 by the graphical abstract.

Literature review

Integrating hybrid renewable energy sources in smart homes, assisted by an IoT-based intelligent energy management system, has developed as an active research area in recent years[17–19]. This section reviews the state of the art regarding the hybrid systems considered, the control and optimization techniques applied, the evaluation methods employed, and the limitations reported. The purpose is to situate the current study within the broader literature, highlight its methodological strengths and weaknesses, and describe its contribution to the field.

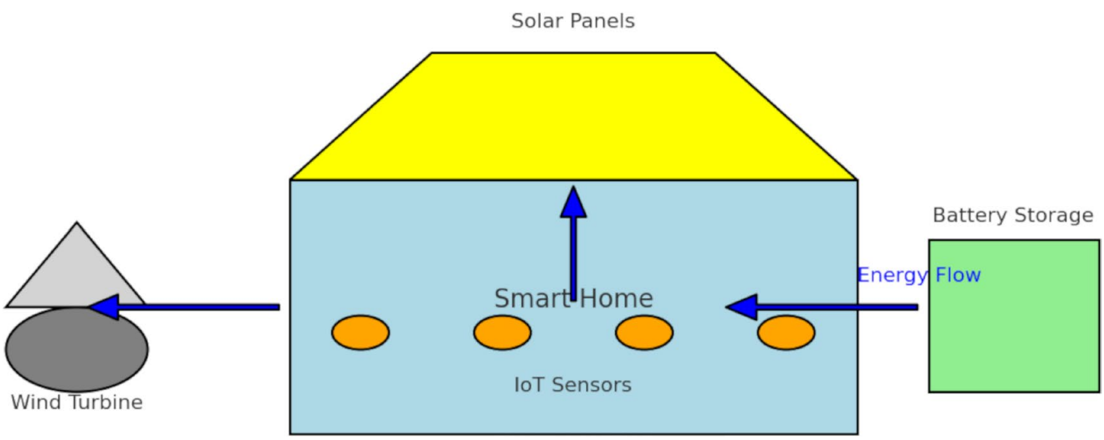

Fig. 1. Graphical abstract of the proposed IoT-driven hybrid renewable energy management system.

Existing studies

Most studies addressing the management of renewable energy in smart homes are developed for single-source systems, such as PV and wind power systems, and simple PV and battery systems[17,21]. Meanwhile, fully-fledged IoT-based constellation frameworks that coordinate PV, wind, storage, and demand response are still in short supply[22,23]. From the perspective of optimization, there are two main strategies such as model-based predictive controllers by model predictive control and rule-based energy management system, which can guarantee the stability of the system and the constraint management, but are high model dependent and this are not suitable for multi-objective, long-horizon optimization; and heuristic and metaheuristic algorithms by genetic algorithm, PSO, differential evolution which have strong global search ability and handle the optimization of multiple objectives such as cost, emissions, and reliability, but are easy to fall into local optimal solution due to the premature maturity, sensitivity to parameters, and high computing complexity. Machine learning models, including supervised prediction, forecasting[24,25], and reinforcement learning models[26–28], have recently been utilized to enhance the prediction of renewable generation and demand, as well as policy generation. However, these approaches lack validation in terms of sensitivity analysis, runtime evaluation, and IoT-related aspects, including communication latency, packet loss, and scalability[29,30]. Accordingly, the proposed research faces several widespread failures, including the absence of a complete IoT-driven architecture, insufficient benchmarking before selecting suitable models, insufficient statistical sufficiency, and neglect of IoT deployment analyses. The intermittency of renewable energy is a controversial issue regarding reliability, despite advances. Other scientists have assumed that unpredictable solar and wind energy results from unstable energy management. This paper presents a solution that integrates real-time IoT data with intelligent control strategies for energy load management, comparing the analysis of representative approaches in Table 1.

Research gaps and motivation

Based on the above review, it is clear that although the hybrid renewable energy management has made significant advancements, the current related works suffer from a lack of an integrated IoT-centric architecture that can consider multifaceted renewable energy sources, storage, and demand response in a computationally efficient optimization framework. Moreover, existing approaches can enforce constraints but struggle with multi-objective optimization. Conversely, they can optimise multiple objectives, but this comes at the cost of long runtime/difficulty in setting thresholds. Finally, there have been minimal attempts to provide an explicit measure of the practical benefits of system efficiency, cost savings, and CO_2 reductions in a manner that would enable real-world deployment. This gap motivates the development of a hybrid IoT-enabled optimization framework that combines machine learning forecasting with a dual-layer optimization strategy, supported by adaptive parameter control and parallel evaluation, to achieve robust, near-global solutions within real-time constraints.

Study (representative)	System type	Method	Evaluation and Metrics	Strengths	Limitations	Contribution
Model Predictive Control -based works[50]	PV ± storage	Model Predictive Control[57]	Simulation; metrics: tracking error, constraint satisfaction	Excellent stability and constraint handling[34]	Requires an accurate model; limited multi-objective optimization[32,33]	Combine machine learning forecasting with a hybrid optimiser to maintain constraint satisfaction and improve multi-objective trade-offs.
Genetic Algorithm (GA)/PSO/ Differential Evolution (DE) optimizers[51–53]	PV + battery/PV + wind	Metaheuristics (Genetic Algorithm, PSO, Differential Evolution)[58]	Simulation: cost, emissions, efficiency	Good global search, multi-objective optimization[35]	Premature convergence, parameter sensitivity, and high runtime[36,37]	Hybrid global + local search, adaptive parameters, and parallelism reduce convergence and runtime issues.
Reinforcement Learning -based energy management system[54]	PV + battery + demand response	Reinforcement Learning[59]	Simulation; reward, cost	Learns model-free policies[38]	High data demand, unstable training, weak guarantees[39,40]	Use machine learning forecasting and constrained optimisation for safety and deterministic guarantees; Reinforcement Learning is reserved for future extension.
Forecasting + rule-based energy management system[55]	PV + wind	Statistical forecasting with heuristics[58]	Simulation/ pilot; cost savings	Simple, robust, easy to implement[41,42]	Suboptimal, inflexible to changes[43]	Replace heuristics with adaptive optimization informed by IoT real-time data.
Pilot IoT deployment[56]	PV + storage	Commercial energy management system with vendor rules[59]	Small-scale pilots; uptime, user acceptance	Real-world proof-of-concept[44,45]	Proprietary, not generalizable[46,47]	The proposed framework proposes a scalable, open architecture with security and communication considerations.
Proposed System	PV + wind + battery + demand response (IoT integrated)	Machine learning forecasting + hybrid optimization (global heuristics + local refinement)	Smart-home simulation: system efficiency, energy cost, CO_2 emissions	Holistic IoT integration, multi-objective optimization, real-time adaptability[48]	Requires pilot validation for scalability[49]	Explicit IoT-driven framework, adaptive optimizer, quantified economic & environmental benefits.

Table 1. Comparative analysis of representative approaches.

This study is critical because there is an ever-urgent demand for sustainable energy solutions that harness renewable resources and sophisticated technologies, such as IoT, for more innovative energy management. This research integrates a hybrid renewable energy system with the Internet of Things (IoT) to extend smart home innovations to new horizons, enabling users to reduce their carbon footprint, conserve electricity, and enjoy greater comfort. This study aims to move toward a world where smart homes are autonomously activated by sustainable microgrids, contributing to the fight against climate change and energy independence. This research proposes an intelligent grid roadmap with IoT-embedded solutions integrated with hybrid renewable energy micro-generation units. This study has a significant impact on energy conversion, paving the way for the establishment of a future smart home that leverages this technology for efficient and sustainable solutions.

Novelty and advantages
The specific contributions of this paper include the development of a comprehensive IoT-based integration architecture, comprising sensor devices, standard communication protocols (Wi-Fi, ZigBee, Z-Wave), and a real-time feedback approach. This architecture ensures robust demand response and energy management processes in smart home networks. It proposes a hybrid optimization method that combines the global exploration ability of heuristic algorithms with a fast local refinement method and adaptive parameter control, addressing problems such as premature convergence and parameter dependence. The quantitative validation of a smart home application demonstrates that the proposed methods can lead to an 80% improvement in system efficiency, a 61% reduction in energy costs, and a 61% decrease in CO_2 emissions. This research presents robustness and sensitivity studies, Monte Carlo scenario testing, and a parallelized runtime benchmark that demonstrate the practical scalability and feasibility of the proposed system.

Algorithmic Trade-offs and validation strategies
This study positions its optimization framework by critically evaluating existing approaches. The genetic algorithm, Particle Swarm Optimization (PSO), and differential evolution are strong top-down explorers but have high computational runtime, which is mitigated by adopting adaptive parameter control, hybrid global–local search, and parallelization. Model Predictive Control is also recognized for its effectiveness a enforcing constraints. Still, it is highly dependent on the accuracy of the modelling used in the short term to provide local safety. This approach is then overcome by machine learning predictions, enabling the constraints to be met. Although reinforcement learning is flexible and model-free, it is data-demanding and unstable, thus left as a future extension. The validation plan incorporates a comparison against state-of-the-art baselines, a convergence trajectory study, rigorous statistical testing, sensitivity analysis, and runtime profiling, ensuring near-optimal performance and robust, practical usability.

The literature indicates that existing solutions address some aspects of the hybrid renewable IoT problem, but rarely deliver a comprehensive, deployable solution. This study effectively addresses this gap with a computationally feasible IoT-aware hybrid optimization framework that balances optimality, runtime efficiency, robustness, and practical deployment feasibility.

Methodology
The strategy for interfacing IoT with hybrid renewable energy systems in smart homes involves several essential steps, including system design, data collection, optimization algorithms, and performance evaluation. This section outlines all steps and presents a mathematical model that supports any energy management strategy.

System design

- **Solar Energy Production**: Power generation is parametrically modeled using solar irradiance(W/m^2), panel efficiency, and area to calculate PV output.

$$P_{solar}(t) = I_{solar}(t) \times A_{solar} \times \eta_{solar} \tag{1}$$

The solar energy production Eq. (1) calculates the energy generated by solar panels at a given time, Psolar. I_{Solar} (t) is the solar irradiance (W/m^2) at the time t, representing the sunlight intensity on the panel surface. A_{Solar} is the area of the solar panels (m^2), determining the amount of sunlight they can capture. The equation assumes stable irradiance and solar panel efficiency η_{solar} during the measurement interval and that the solar panel angle is optimal for capturing sunlight.

- **Wind Energy Production**: Energy production is based on wind speed (m/s), wind turbine characteristics, and power curves to account for time-varying wind contributions.

$$P_{wind}(t) = 0.5 \times \rho_{air} \times A_{wind} \times V^3{}_{wind} \times \eta_{wind} \tag{2}$$

The wind energy production Eq. (2) calculates the power generated by a wind turbine at a given time, Pwind(t). It depends on the air density ρ_{air}, the area swept by the turbine blades A_{wind}, the wind speed at that moment V_{wind}(t), and the turbine's efficiency η_{wind}.The equation assumes steady wind conditions and optimal turbine orientation, with efficiency influenced by factors such as blade design and turbine placement.

- **Total Energy Production**: Cumulative solar and wind production, which is the total energy supply performance of the hybrid system.

$$P_{total}(t) = P_{sola}r(t) + P_{wind}(t) \tag{3}$$

Equation (3) calculates the total energy production Ptotal(t) from solar and wind sources at any given time t. It represents the sum of power generated by solar panels and wind turbines. This model assumes that both energy sources operate independently and under optimal conditions, with steady irradiance and wind speed at time t.

- **Energy Storage Dynamics**: Describes battery charging and discharging behavior, state of charge (SoC), and efficiency losses to ensure reliable backup.

$$B_{level}(t+1) = B_{level}(t) + P_{total}(t) - E_{consumption}(t) - E_{grid}(t) \tag{4}$$

Equation (4) demonstrates updating the battery charge B_{level}(t) by considering the power input and the interaction of energy exchange E_{grid}(t) from the grid with time t. This dynamic equation is also critical for controlling the state of charge when co-optimizing renewable generation and power grid interactions. The battery will be correctly charged or discharged according to different system price signals.

- **Energy Balance**: The energy management system aims to optimize the balance between energy production, storage, and consumption. The following mathematical model:

$$\left\{ \begin{array}{l} P_{total}(t) \geqslant E_{consumption}(t) + E_{storage}(t)\, if\ B_{level}(t) < B_{max} \\ P_{total}(t) + E_{grid}(t) \geqslant E_{consumption}(t)\, if\ _{Blevel}(t) = B_{max} \end{array} \right\} \tag{5}$$

Equation (5) serves as a foundation for enabling the energy management system to allocate resources and maintain optimal power consumption and storage flexibly. The energy balance Eq. (5) represents the goal of the energy management system: to optimize the balance between total energy production Eproduced(t), storage E stored(t), and consumption Econsumed(t). This model assumes that energy production and demand fluctuate over time and that storage is available to buffer supply and demand variations, thereby enhancing system efficiency and reliability. The balance aims to minimize waste and improve self-sufficiency in energy usage.

- **Network Architecture**: Use message queuing telemetry transport for lightweight messaging between IoT devices and the gateway. Data is sent to a cloud platform using the Hypertext Transfer Protocol for real-time analytics and storage.

Data collection

The data collected in the work includes all the relevant information for a holistic picture of energy production, consumption, and the environment in a smart home and a hybrid IoT-based renewable energy system. Several environmental and energy aspects are subject to continuous monitoring by the IoT sensor reporting, whereas user communication with the system is the only non-automated measurement. Data collection is the most essential part of this assessment, as it will help evaluate the performance of the IoT-integrated hybrid renewable energy system in smart homes. This study consistently tracks and analyzes the following metrics:

a). Energy produced: This metric shows daily energy from solar panels and wind turbines. Solar energy production is calculated based on solar irradiance data, and the panel's efficiency is expressed in kWh. This metric is measured in kWh and was calculated using wind speed data and turbine capacity. This metric is used for renewable energy generation, including volume and patterns, as well as supporting load-balancing strategies.

b). Energy Consumption: Cumulative energy consumption of the smart home, considering all the connected devices and appliances. The power consumption (kWh) is calculated by summing the outputs (power usage) and the input power of the heating, ventilating, and air-conditioning system to understand the total energy consumption and identify opportunities for load shifting and peak shaving.

c). Energy Storage: Data relevant to battery functionality—the amount of charge and discharge cycles and the state of charge (SOC). The charging level indicates the remaining battery capacity as a percentage, along with the number of complete charge/discharge cycles during the study period. Energy Storage evaluates the storage system's efficiency and its role in balancing energy supply and demand.

d). Environmental Conditions: Real-time data on environmental parameters that affect renewable energy generation. Temperature in Celsius (°C) affects solar panel performance. Wind Speed impacts wind turbine output and is measured in meters per second (m/s). Solar energy is measured in terms of potential in watts per square meter (W/m^2). This metric correlates environmental factors to renewable energy production for predictive modelling and optimization.

e). System Performance: Assess the overall performance of the integrated energy system. The total amount of renewable energy, including electric energy from renewable sources, is consumed. First is the system efficiency, which indicates that the system converts renewable energy into usable power.

f). User Satisfaction: Survey data relating to user ratings for the usability and performance of the system. The Satisfaction Score, ranging from 1 to 10, is based on user feedback regarding comfort, control, and cost savings. It investigates the human side of the smart energy system and identifies the components that require adjustments to ensure user satisfaction.

The following data collection metrics form the basis of the analytical study, assessing the technical performance and user satisfaction of the IoT-enabled hybrid renewable energy system. All metrics directly relate to the system's reliability, efficiency, and sustainability.

Optimization algorithms

Optimization algorithms are advanced computational procedures used to determine energy consumption cost minimization in smart home systems. This analysis utilizes real-time data and user behavior algorithms to optimize energy consumption, thereby significantly reducing costs and enhancing system efficiency. This optimization model is developed to minimize the total cost of energy consumption with the following objective function:

$$C = \sum_{t=1}^{T} [Cgrid \cdot Egrid\,(t) + Cmaintenance] \tag{6}$$

Equation (6) defines the total cost C of energy consumption in a period of T; the cost depends on the cost of energy from the grid and the time step t. The cost from time step t is the sum of the energy consumption from the grid multiplied by the cost per unit of grid energy, Cgrid, and the energy consumption from the grid E grid(t). Maintenance cost $C_{\text{maintainance}}$ of the renewable energy system is assumed to be constant or variable over time. This cost is summed over the time intervals t, resulting in a total cost for the entire period T that an optimization algorithm can minimize by modifying a grid energy consumption variable or entries for renewable energy strategies or storage strategies.

Demand response strategy

The demand response uses peak shaving, shifting energy consumption from peak to off-peak periods. It shifts flexible loads, helping to stabilize the grid and lower energy costs. Reduce energy consumption during peak demand by shifting usage to off-peak times.

$$Minimize \sum_{t \in peak} E_{consumption}\,(t) \tag{7}$$

Where t∈ peak is the peak demand period, shift energy consumption to off-peak periods by rescheduling flexible loads:

$$E_{consumption}\,(t) = E_{fixed}\,(t) + E_{flexible}\,(t) \tag{8}$$

$$E_{flexible}(t) = \{^{0}_{E\,flexible}\,(t)\,^{if t \in peak}_{otherwise} \tag{9}$$

Equations (7), (8), and (9) are conceptually known as peak shaving, whose implementation is widely applied in demand response to mitigate energy consumption during peak demand hours. In Eq. (7), t∈peak indicates the periods within peak demand. Equation (8) concerns rescheduling flexible loads, energy-consuming activities, or devices that could be moved in time without affecting their operation for off-peak periods, thus reducing energy consumption in high grid prices or demand. As described in Eq. (9), the total energy consumption consists of an inflexible baseline consumption. This energy will provide critical loads that cannot be shifted, as well as the adjusted flexible loads. This aims to "flatten the curve" of energy demand, thereby reducing peak loads, which in turn can help decrease energy costs while ensuring that basic energy needs are met.

- **Load Balancing**: Distribute energy consumption evenly to prevent system overload.

$$Minimize \sum_{t=1}^{T} \left(\frac{\left(E_{consumption}\,(t) - \overline{E_{consumption}}\right)}{\overline{E_{consumption}}}\right)^2 \tag{10}$$

Equation (10) is designed for load balancing, aiming to distribute energy consumption evenly within a period T to prevent system overload. The objective is to reduce variability in energy use by keeping consumption as close as possible to the average energy consumption for the period. After summing the total energy for T time intervals and dividing it by T, the average energy consumption will be calculated as the spread load. This helps stabilize the grid, mitigates the risk of sudden demand spikes, and enhances energy efficiency.

Battery health monitoring

Battery charging, temperature tracking, and battery health monitoring. Using smart algorithms, real-time data protects against overcharging and deep discharging. The system enhances battery efficiency by operating under ideal conditions, enabling dependable energy storage and sustainable operation of smart home energy systems. Monitor battery charge cycles and temperature to extend lifespan.

$$Monitor\ N_{cycles} = \sum_{t=1}^{T} \delta B_{level}\,(t) \tag{11}$$

Equation (11) illustrates the shifts in battery charge levels over time, which are monitored to track effective battery charge cycles. Here, Blevel(t) indicates the full battery charge at time t, and δBlevel(t) measures the change in battery state per unit time. These inconsistencies serve as input, enabling the system to learn and anticipate battery degradation by managing charge and discharge cycles, thus avoiding overcharging or deep discharge, which can shorten the battery's lifespan. This helps manage the energy storage system effectively without compromising system controllability.

- **Temperature Monitoring**: Monitors ambient and device temperatures in real-time, enabling the implementation of cooling and power-saving measures to protect the gear and prevent overheating.

$$Monitor\ T_{battery}\left(t\right) \tag{12}$$

Equation (12) focuses on battery health, ensuring it remains within the operating temperature limits [Tmin, Tmax]. The battery temperature Tbattery(t) is tracked at each time t. The control system will initiate corrective measures, such as adjusting the charging rate or deactivating the cooling and heating systems. This ensures real-time monitoring to prevent thermal stress, which reduces the risk of overheating or freezing and thus helps protect battery performance and increase lifespan.

- **Overcharging and Deep Discharging**: Implement algorithms to prevent overcharging and deep discharging.

$$B_{min} \leqslant B_{level}\left(t\right) \leqslant B_{max} \tag{13}$$

Equation (13) protects battery health by avoiding overcharging and deep discharging. The battery charge level, Blevel(t), is continuously monitored. The controller actuates the system, ensuring Blevel(t) is within a safe operating band [Bmin, Bmax]. Charging is stopped when Blevel(t) exceeds Bmax to prevent overcharging, which can cause overheating and capacity loss. If, however, Blevel(t) < Bmin, discharge is terminated, which prevents the battery cells from being deeply discharged, as this is harmful. These algorithms keep the battery efficient and maximize its lifespan.

Performance evaluation

The performance evaluation measures energy savings, CO_2 emissions reduction, and the efficiency of the entire system based on comparing the energy cost and output-input ratio, which highlights the impact of renewable energy in smart homes. The performance of the system is based on the following :

- **Energy Savings**: Transitioning to renewable energy sources can significantly lower energy expenses and diminish CO_2 emissions by substituting fossil fuels with more sustainable alternatives. The energy savings are enhanced by increased system efficiency, ensuring that each unit of energy produced is fully utilized.

$$Energy\ Savings = \frac{Cost\ of\ traditional\ system - Cost\ of\ IoT\_based\ system}{Cost\ of\ traditional\ system} \times 100\% \tag{14}$$

- **CO_2 Emissions Reduction**: Reduction in emissions due to increased use of renewable energy.
- **System Efficiency**: Ratio of energy output to energy input.

$$System\ Efficiency = \frac{Total\ Energy\ Output}{Total\ Energy\ Input} \times 100\% \tag{15}$$

$$Emissions\ Reduction = \frac{Emissions\ of\ traditional\ system - Emissions\ of\ IoT\_based\ system}{Emissions\ of\ traditional\ system} \times 100\% \tag{16}$$

Equations (14), (15), and (16) evaluate the performance of a renewable energy and storage integrated energy system. These equations calculate the system's energy savings, CO_2 emissions reduction, and overall efficiency. Equations that quantify the environmental advantages and business case for these solutions compared to traditional energy. Control mechanisms, including temperature control and preventing battery overcharging or deep discharging, are also crucial to ensure the safe and optimal operation of this system.

- **User Satisfaction**: Surveys and feedback regarding the system's usability and performance.

$$User\ Satisfaction = \frac{\sum_{i=1}^{N} User\ Rating}{N} \tag{17}$$

User satisfaction is calculated according to Eq. (17), based on the input feedback of N users, regardless of the number of users surveyed (Appendix 1) regarding the usability and performance of the system. Each user assigns a satisfaction score (User Rating), typically on a fixed scale (1 to 10). The smart home energy system meets user guidelines, and an overall user satisfaction score is calculated based on these ratings. Remember that the higher the score, the more users have had reasonable satisfaction with the system being efficient, easy to use, and responsive to their energy needs.

This methodology builds upon the research, which aims to demonstrate the feasibility and benefits of integrating IoT with hybrid renewable energy systems in smart homes, thereby contributing to the development of more efficient, sustainable, and intelligent energy solutions.

System architecture

This research proposes an IoT-based hybrid renewable energy system solution for smart homes. It integrates various clean energy sources and methods into a single architecture. The IoT is utilized in conjunction with real-time data processing technology to optimize production and consumption[38]. The system comprises solar panels, wind turbines, IoT sensors and controllers, and energy storage units. Each component is crucial for efficient and reliable energy management. The proposed system (Fig. 2) utilizes multiple renewable energy sources and incorporates state-of-the-art IoT technologies to deliver a robust, sustainable, trustworthy, intelligent, and innovative energy system.

Components and functions

The components of a hybrid renewable energy system include solar panels, wind turbines, energy storage, IoT sensors, and controllers. Solar panels and wind turbines generate electricity, energy storage systems capture excess power, IoT (Internet of Things) sensors monitor the system's performance, and controllers optimize energy usage and maintain system stability.

- **Solar Panels**: Solar panels utilize cells containing photovoltaic materials that produce electricity through sunlight—the smart arrangement of solar panels harnesses the sun's energy at the right places. Solar panels generate direct current (DC), which solar inverters convert into alternating current (AC) for use in homes and businesses. It can be a polycrystalline or monocrystalline solar panel. The output for each panel varied from 250 to 400 W, and the conversion rate of solar radiation into electrical energy of this type ranged from approximately 15% to 22%[29]. Solar panels typically have a lifespan of 25 to 30 years[30].
- **Wind Turbines**: The wind's kinetic energy transforms into electricity. The wind turbine is installed in remote locations characterized by strong winds. The turbine's generator converts the mechanical energy of the rotating blades into electrical energy. Wind turbines are classified as horizontal (or horizontal axis) or vertical (or vertical axis). It has a capacity of 1 kW and can generate up to 10 kW, depending on the turbine's output[40,41].

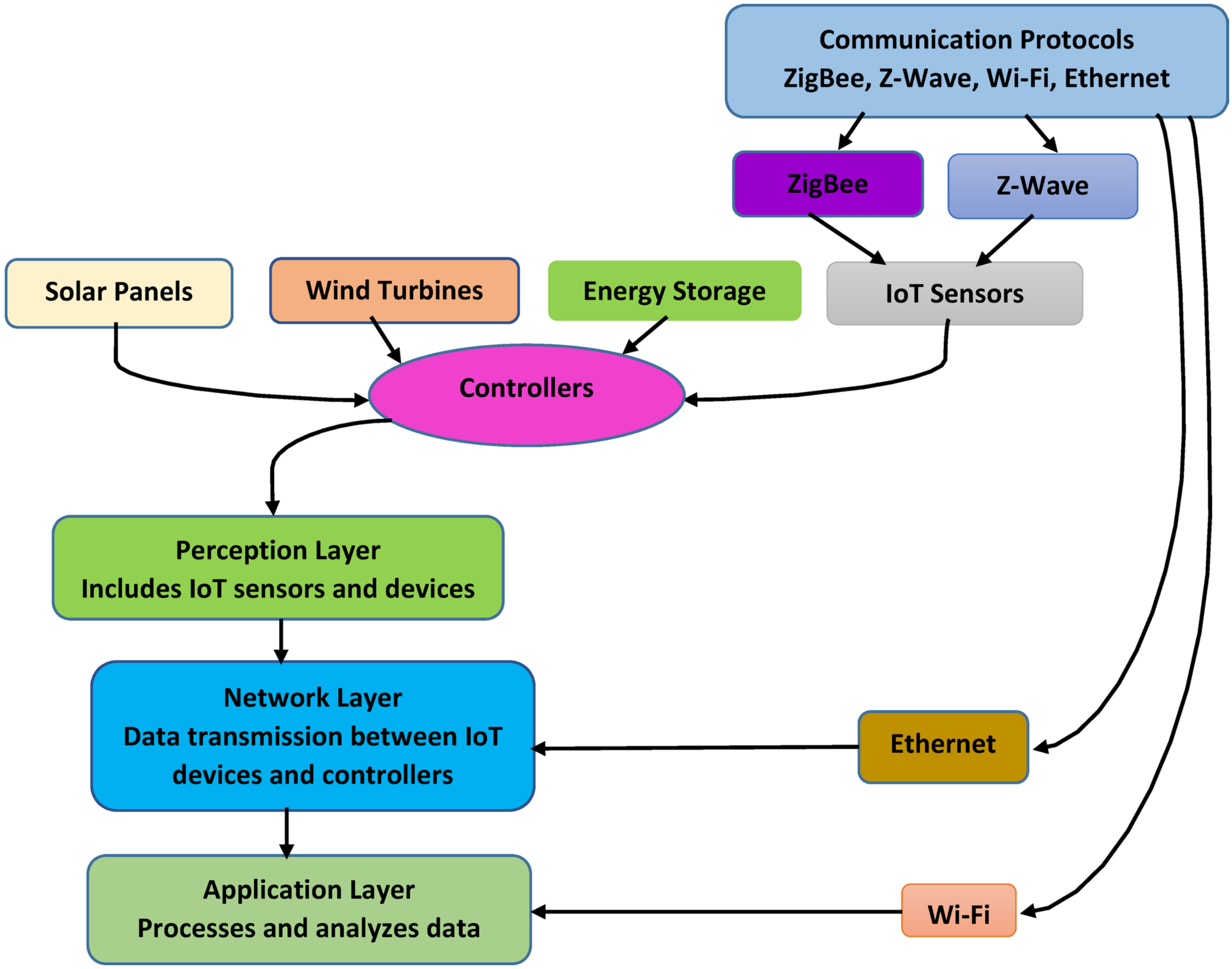

Fig. 2. System architecture of the IoT-based Hybrid power system.

The turbine converts wind energy into electric power with a typical efficiency of 30%–40% and a service life expectation of 20–25 years[31].

- **Energy Storage**: Lithium-ion batteries and other advanced storage technologies capture excess energy from solar panels and wind turbines. The energy storage system units will provide a stable supply of electricity, even when there is insufficient solar or wind power at night or on days with little to no breeze during daylight hours. The energy storage device has a lithium-ion battery. The total energy storage capacity ranges from 5 kWh to a maximum of 20 kWh. The battery can discharge to a maximum depth of 80%[25]. A typical battery lifespan ranges from 10 to 15 years.
- **IoT Sensors**: IoT sensors monitor and collect data on various parameters, such as energy production, weather conditions, and system performance. Sensors are installed on solar panels, wind turbines, and energy storage units to provide real-time data[42,43]. This dataset aims to enhance the efficiency, optimization, and predictive maintenance methodologies. The energy meter sensor, operating under the Zigbee or Z-Wave protocol, controls on-site energy production and consumption. The temperature Sensors monitor ambient temperatures and send the data out through Zigbee, Wi-Fi, or Z-Wave protocols. The wind speed sensor tracks the wind speed. Solar Irradiance Sensors measure solar irradiance and communicate over Zigbee or Wi-Fi as a communication protocol.
- **Controllers**: The controllers utilize control algorithms to effectively manage the generated energy, assess energy storage, supply electricity, and maintain system stability[44,45]. They also manage communication between the system components and the central monitoring system. A controller's function is to operate the components and manage power distribution. The controller type (microcontroller unit or programmable logic controller) refers to the method used, which includes Ethernet, Wi-Fi, ZigBee, and Z-Wave.

The hybrid renewable energy system comprises solar panels, wind turbines, and energy storage systems. IoT sensors and controllers play a crucial role in monitoring and automating energy generation, consumption, storage, and system performance. These components ensure operational stability, higher efficiency, and long-term viability in both residential and commercial implementations.

Network architecture and communication
Network architecture and communication protocols utilize IoT sensors as data collectors, along with Zigbee and Z-Wave as communication protocols, and an application layer as a management layer in smart home energy systems.

Network architecture
The three main layers of the proposed IoT-based hybrid renewable energy system for smart homes are as follows:

- **Perception Layer**: The first layer comprises IoT sensors and devices that gather real-time data. This layer tracks the amount of energy produced by solar panels and wind turbines, where the energy is stored, and the purpose of energy consumption.
- **Network Layer**: The communication backbone that allows data to be transmitted between IoT devices and their central controllers. The wireless protocols, such as Zigbee, Z-Wave, and Wi-Fi, help ensure excellent communication across various aspects with minimal power consumption.
- **Application Layer**: At the top, this layer interacts with smart home systems and appliances, optimizing energy use. It conducts analysis and processing of data to facilitate informed decisions, and it consists of cloud-based platforms and a mobile application for remote control and monitoring.

In this structure, the first layer comprises an IoT-based hybrid renewable energy system activated for real-time data collection. The second layer is the network layer, which connects the devices for communication. The last layer is the application layer, enabling energy optimization and remote monitoring. This multilayer approach supports data transmission between subsystems, controls the system, and provides a user interface for smart homes, allowing efficient energy management.

Communication
The system integrates a multi-protocol communication framework for seamless interaction with various smart home devices. Zigbee offers low-power, low-cost, and last-mile connectivity in the 2.4 GHz band at speeds of up to 250 kbps. In contrast, Z-Wave provides long-range, low-interference, low-cost sensor-to-controller integration with mesh networking capabilities (supporting up to 232 nodes) in the sub-1 GHz bands. Wi-Fi enables high-speed data exchange through seamless cloud integration and tight mobile connectivity (using both the 2.4 GHz and 5 GHz bands). At the same time, Ethernet provides reliable, high-throughput communications over wired connections between controllers and central hubs. It enables effective traffic management, ensuring continuous data flow across the network and facilitating real-time monitoring and control of the IoT-based hybrid renewable energy system.

IoT integration
The integration of IoT with energy systems alters the way energy is monitored, controlled, and optimized. IoT devices collect real-time data to help energy systems function efficiently and reliably, thus enhancing sustainability. IoT platforms and management software orchestrate these technologies because they operate independently[46,47]. Continuous improvement is achievable in energy systems for smart home energy management. A schematic block diagram (Fig. 3) based on an IoT-integrated hybrid renewable energy system for smart homes can simplify

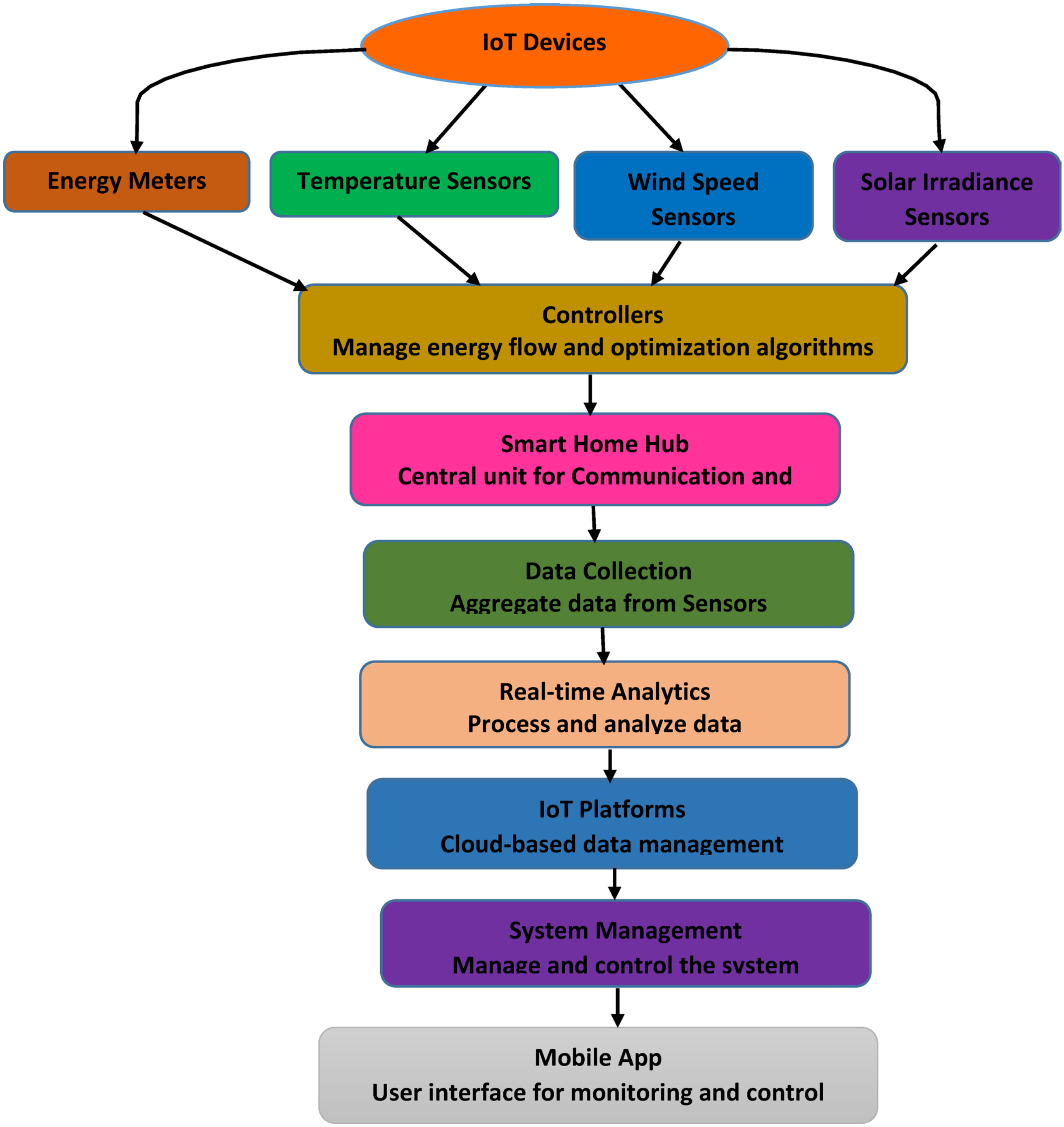

Fig. 3. A schematic block diagram of an IoT-based Hybrid renewable power system.

the layout concept throughout different stages, from generation and storage to monitoring, control, and user interaction.

Monitoring and controlling the energy system

IoT devices play a crucial role in smart home energy systems, enabling the monitoring and management of energy exchanges. Monitoring includes IoT sensors that continuously collect real-time data on energy generation from solar panels and wind turbines, including consumption patterns, environmental conditions, and the overall system status. Central controllers relay this data to cloud platforms for processing and analysis. As far as control, intelligent controllers optimize the distribution of energy from generation and storage to appliances within the household. Challenges such as load balancing, demand response, and peak shaving are being addressed through advanced optimization algorithms. These automated control systems optimize appliance dispatch and energy storage systems to minimize energy waste.

Data collection and Real-Time analytics

In a smart home environment leveraging IoT-driven hybrid renewable energy integration, the system uses a robust data collection process that collects data using a range of sensors including energy revenue (kWh), including energy revenue (kWh), battery charge level (%), atmosphere temperature (°C), wind speed (m/s), and solar irradiance (W/m^2). The sensors send data to gateway devices, which aggregate and securely transmit the information to a cloud platform. Here, advanced machine learning algorithms that incorporate past and current data conduct real-time analytics to forecast energy demand patterns, optimize energy production, and identify potential shortfalls or system inefficiencies. The outcomes are displayed on an accessible user dashboard, allowing homeowners to monitor system performance, analyze energy statistics, and receive proactive operational optimization alerts.

IoT platforms and software used for system management

IoT embedded in hybrid renewable energy systems enables sustainable and green power generation in smart homes through proper monitoring, control, and optimization of electricity usage. IoT utilizes real-time data gathering, complex analytics, and smart home automation approaches so homeowners can achieve energy efficiency, cost savings, and system reliability.

IoT platforms

IoT applications provide a comprehensive suite of real-time tools for connecting, managing, and processing data from various interconnected devices. Amazon Web Services offers a flexible, cloud-based IoT solution that enables secure device connectivity and bi-directional communication, as well as handles real-time analytics for efficient data ingestion and processing. Microsoft Azure IoT complements this ecosystem by providing scalable device management and data analytics capabilities, as well as access to the entire Microsoft cloud services stack, enabling easy device provisioning, monitoring, and maintenance. Conversely, Google Cloud IoT prioritizes scalability and dependability with enhanced device management, data processing, and machine learning, enabling IoT analytics and insights.

Software

IoT-enabled Hybrid Renewable Energy Integration into Smart Homes using a multilayer system management architecture comprised of energy management software, an advanced home automation system, and mobile applications. The energy management software provides real-time visibility and control over energy generation, storage, and utilization, utilizing advanced algorithms and data analytics to achieve optimal performance and predictive maintenance. Meanwhile, smart home platforms such as SmartThings, Home Assistant, and open home automation buses manage and coordinate the various devices throughout the smart home, enabling devices from different manufacturers to work together, communicate throughout the home, and provide synchronized actions across the entire smart home ecosystem. Mobile apps for IOS and Android enable remote access to system data and controls, enabling energy flow visualization and balance from any location. Integrating IoT into energy systems enables intelligent monitoring, control, and optimization of energy usage within the smart home, ensuring sustainability and reliability. IoT systems utilize real-time data, applying predictive analytics and intelligent automation to enhance energy management, waste reduction, and system performance, thereby increasing overall efficiency. IoT devices, software, and platforms are seamlessly interconnected to achieve smart homes' desired energy efficiency, cost savings, and resilience.

Energy management strategies

Enhanced energy management is essential for improving the operation of IoT-integrated hybrid renewable energy systems in smart homes (Fig. 4). It requires integrating algorithms for energy production and consumption optimization, such as supply and demand response strategies with load balancing and keeping track of battery health while managing energy storage[48,49].

Optimizing energy production and consumption

In smart homes utilizing IoT-based hybrid renewable energy systems, the harmonious integration of predictive analytics, optimization algorithms, and real-time monitoring and control enables optimized energy generation and consumption. State-of-the-art predictive analytics utilizes machine learning models capable of depicting past trends in energy production and consumption. Additionally, it utilizes weather forecasts to assess opportunities for PV and wind energy harvesting. Optimization Algorithm improves this process by using a genetic algorithm, which simulates the process of natural selection to find optimal energy allocation methods, and linear programming, which formalizes system constraints and objectives into a set of linear equations that solve for the energy output of minimum or maximum, and fuzzy logic to make more nuanced decisions in the case of uncertainty. These techniques enable dynamic adjustments made in real-time using sensor data, user settings, and feedback control mechanisms that continuously monitor energy meters to adapt the system for optimal performance.

Demand response strategies and load balancing

Demand response strategies and load balancing in IoT-enabled hybrid renewable energy smart homes result in optimal energy consumption and alleviate stress on the grid. With time-of-use schemes, dynamic pricing enables real-time adjustments to consumption according to electricity costs, where notifications suggest the most beneficial scheduling of high-demand tasks for the user. Load shifting is implemented by scheduling smart devices, such as washing machines, dishwashers, charging electric vehicles, and battery systems, in response to a high prevalence of renewable energy and low tariffs. Peak shaving techniques also mitigate high-intensity loads

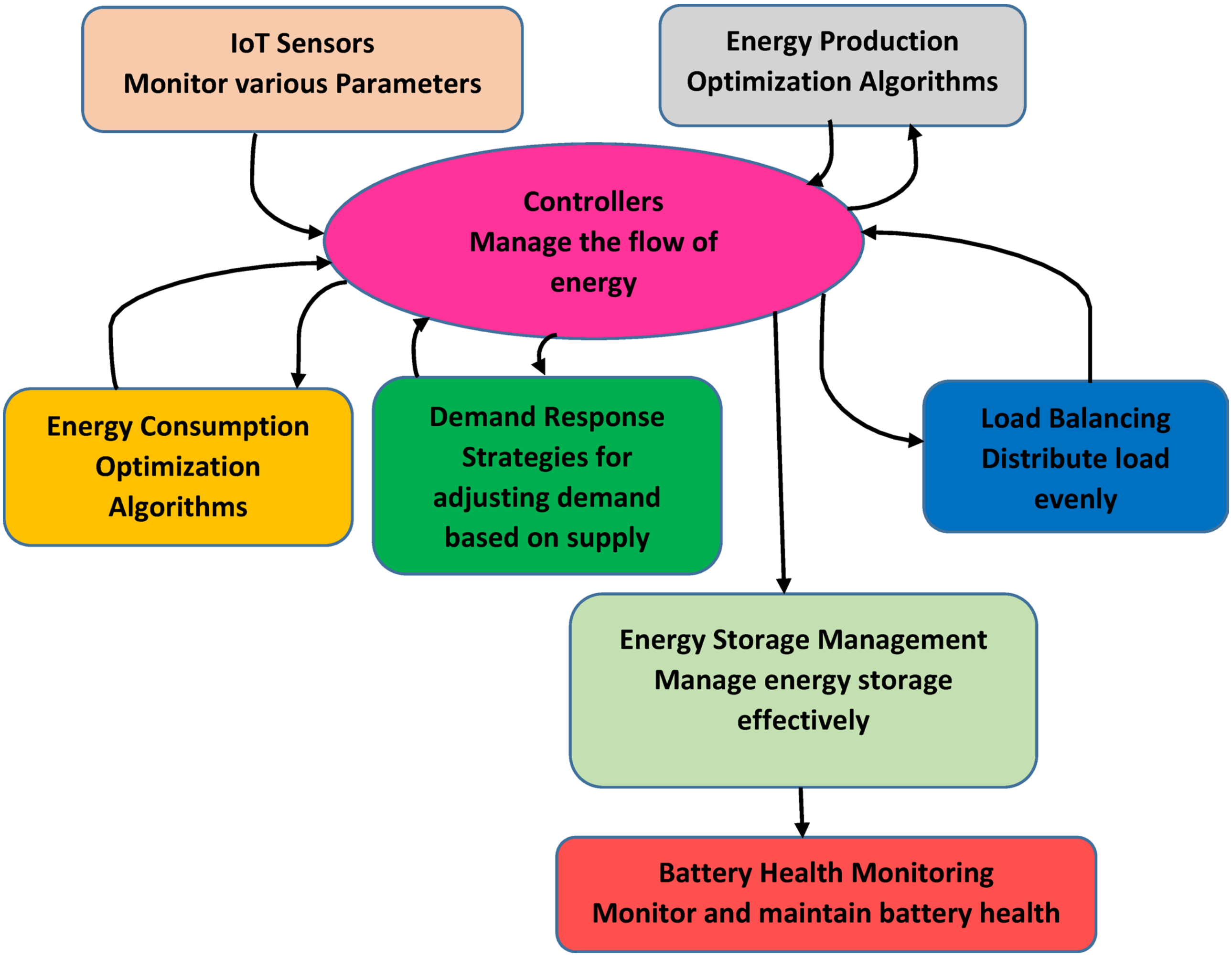

Fig. 4. IoT-integrated hybrid renewable energy-based energy management systems for smart homes.

on the grid by curtailing non-essential demand during peak pricing, and energy storage systems can provide alternative power sources during such times. Lastly, automated demand response merges Internet of Things (IoT)-enabled devices with grid signals in real-time, allowing power demand to be adjusted dynamically to ensure system balance and improve energy efficiency.

Energy storage management and battery health monitoring

Energy storage management and battery health monitoring in smart homes enable real-time state-of-charge (SoC) monitoring as batteries are charged or discharged, thereby eliminating overcharging and deep discharging. Sophisticated charge and discharge algorithms then continuously tune energy flows in response to renewable production, consumption trends, and grid conditions. Temperature sensors and cycle count continuously track battery health, protecting against overheating and ensuring longevity. Additionally, machine learning-based anomaly detection can pave the way for predictive maintenance by identifying problems early on and sending timely alerts for maintenance. Combining these mechanisms with energy arbitrage measures and optimal storage designs based on historical and predictive data provides the tools to increase the efficiency and robustness of hybrid renewable energy systems.

The robust and efficient operation of IoT-based hybrid renewable energy systems necessitates advanced energy management techniques, including optimization algorithms, demand response strategies, and an optimal energy management system. These strategies aim to maximize energy production, enhance user satisfaction, and reduce mining maintenance costs while minimizing degradation, which may occur later in the sustainable future.

Smart home applications

The IoT integrates smart home devices and home automation systems with renewable energy systems, increasing the effectiveness and convenience of managing electricity consumption. Smart devices and systems integrated with a hybrid renewable energy system offer an efficient energy supply, user comfort, and sustainability. The following equation summarizes the integration goals for a given device.

Smart devices integration
This system minimizes energy consumption $(Econsumption(t))$ and maximizes savings $(Ssavings(t))$ by distributing energy utilization $(Eutil(t))$ on a set of devices. (Di).

- **Energy Balancing for Devices**: For each device Di, energy utilization can be expressed as:

$$Eutil\,(t) = \sum_{i=1}^{N} [Edevice\_i\,(t) \cdot Ucontrol\_i\,(t)] \tag{18}$$

Equation (18) calculates the total energy utilization $Eutil\,(t)$ over all devices Di at time t, where $Edevicei\,(t)$ is the energy required by a device and $Ucontroli\,(t)$ represents either an ON/OFF state or an operational schedule of the devices. This ensures that only devices in use receive proper charging or discharge, thereby optimizing the system's energy balance.

- **Smart Thermostat**: Energy optimization is achieved based on internal temperature (Tint) and comfort range (Tcomfort):

$$Uthermostat\,(t) = \begin{cases} 1, if \;\; Tint \in / Tcomfort \; and \; energy \; available \\ 0, \;\;\; otherwise \end{cases} \tag{19}$$

Equation (19) specifies whether the thermostat changes as internal temperature drifts from a comfort range for available energy.

- **Smart Lighting**: Control is based on occupancy (Oroom(t)) and daylight availability (Dlight(t)):

$$Ulighting\,(t) = \begin{cases} 1, if \;\; Oroom(t) = 1 \; and \; Dlight(t) < Dthreshold \\ 0, \;\;\; otherwise \end{cases} \tag{20}$$

Equation (20) describes the process of turning on lights when a room is populated and the daylight level falls below a predefined threshold.

- **Smart Appliances**: Operates during optimal times based on energy production (Erenewable(t)) and grid demand (Gdemand(t)):

$$Uappliance\,(t) = \begin{cases} 1, if \;\; Erenewable(t) > Eappliance(t) \; or \; Gdemand(t) < Gthreshold \\ 0, \;\;\; otherwise \end{cases} \tag{21}$$

Equation (21) operates smart devices when there is a lot of renewable energy or low grid demand to maximize the utility of green electricity.

Electric vehicle charger
Scheduled charging occurs during off-peak hours (Toffpeak) or high renewable energy availability

$$UEV\_Ch\arg er\,(t) = \begin{cases} 1, if \;\; t \in Toffpeak \; or \; Erenewable(t) > EEV(t) \\ 0, \;\;\; otherwise \end{cases} \tag{22}$$

Equation (22) sets the EV charging time to off-peak hours or when renewable energy is available in excess of the required amount.

- **Solar Water Heater**: Utilizes solar energy if production is sufficient:

$$Uwater\_heater\,(t) = \begin{cases} 1, if \;\; Esolar(t) > Eheater(t) \\ 0, \;\;\; otherwise \end{cases} \tag{23}$$

Equation (23) describes the activities on the water heater when sufficient solar energy is generated to meet all the required energy needs.

- **Home Automation Hub**: Coordinates all devices and ensures seamless integration.

$$Hhub\,(t) = Control(\{Udevice(t\}_{i=1}^{N} \tag{24}$$

Equation (24) illustrates the coordinates for all smart devices in the ecosystem to work together seamlessly, in response to user-triggered activity and system-triggered conditions.

- **Security Systems**: Ensures reliability during power outages:

$$Usecurity\,(t) = \begin{cases} 1, if \;\; backup \; power \; available \\ 0, \;\;\; otherwise \end{cases} \tag{25}$$

Equation (25) ensures high reliability in maintaining the operational status of security systems during power outages by utilizing backup power.

Objective function

The system's objective is to maximize the overall energy efficiency (η) while minimizing costs (C):

$$max\eta = \frac{Eutil\left(t\right)}{Eproduced\left(t\right)}, minC = \sum\nolimits_{t} \left[Egrid\left(t\right) \cdot Pgrid\left(t\right)\right] \tag{26}$$

Equation (26) optimizes energy consumption in production, thereby maximizing system efficiency and reducing overall costs by minimizing grid energy demand, taking into account energy prices.

The roles of various smart home devices and systems, integrated with the Internet of Things (IoT), enable the utilization of hybrid renewable energy systems. The home automation hub seamlessly controls all devices, while security systems ensure reliability with a power backup. Furthermore, the solar water heater optimizes renewable energy for economical water heating, making the system efficient and sustainable. With a central control, this automation significantly increases convenience and keeps the system running at peak efficiency, which is essential for energy savings.

Automated control of appliances

The control methods for managing automated home appliances in a smart home are implemented using an IoT-based hybrid renewable energy system. These strategies synchronize energy consumption patterns with the availability and demand of the renewable-dominated grid, utilizing mathematical models to improve optimal energy management.

Objective function Minimize overall energy costs, C_{total}, while maximizing renewable energy utilization

$$C_{total} = \sum\nolimits_{t=1}^{T} \left(Egrid\left(t\right) \cdot Pgrid\left(t\right)\right) - \alpha \cdot Erenewable\left(t\right) \tag{27}$$

Equation (27) calculates the total energy cost over time by summing the cost of grid energy usage, weighted against the contribution of renewable energy. The term Egrid(t)· Pgrid(t) represents the cost of grid energy at time t, while α· Erenewable(t) accounts for the cost offset or savings from using renewable energy. The weight factor α\alphaα adjusts the priority of renewable energy in the cost calculation.

Appliance scheduling Appliances are scheduled based on time-of-use pricing and renewable energy availability

$$Sappliance\left(t\right) = \begin{cases} 1, if & Erenewable(t) \geqslant Eappliance \\ 0, & otherwise \end{cases} \tag{28}$$

Equation (28) defines a binary scheduling strategy for appliances based on the availability of renewable energy. The binary variable Sappliance(t) equals 1. If the renewable energy produced at time t (Erenewable(t)) meets or exceeds the energy required by the appliance (Eappliance(t)). Otherwise, Sappliance(t) equals 0, indicating the appliance will not operate. This method ensures that only renewable energy is used to power the appliance.

Constraints

The system implements load shifting by activating appliances at times of high renewable availability; peak shaving is achieved by disconnecting non-critical appliances with smart plugs during peak periods, and comfort constraints are preserved by enabling the operation of the heating, ventilation, and air conditioning system at desired temperature comfort ranges.

- **Load Shifting**: Appliances like the washing machine and dishwasher are shifted to periods of high renewable energy:

$$H_{hub}\left(t\right) = Control(\{U_{device}(t\}_{i=1}^{N} \tag{29}$$

- **Peak Shaving**: Non-essential devices are turned off during peak hours using smart plugs:

$$E_{grid}\left(t\right) \leqslant E_{threshold}, \forall t \in T_{peak} \tag{30}$$

- **Comfort Constraints**: Heating, ventilation, and air conditioning operation respects temperature comfort bounds:

$$T_{min} \leqslant T_{indoor}\left(t\right) \leqslant T_{max,\forall t} \tag{31}$$

These equations outline the operational limits for improved energy efficiency and thermal comfort satisfaction. Load shifting is guaranteed by Eq. (29) since appliances such as washing machines and dishwashers are scheduled not to operate during (Tpeak) periods when the sum of (Sappliance(t)) equals zero. Equation (30) enforces peak shaving by constraining the consumption of electric energy from the grid (Egrid(t)) to be below a constant threshold (Ethreshold) during ($T$the peak period (peak), which can be achieved by using smart plugs that turn off other non-essential devices. HVAC comfort maintenance constraints are defined in Eq. (31), where (Tindoor(t)) denotes the indoor temperature of the zone at time t, and Tmin and Tmax represent the minimum and maximum comfortable indoor temperatures. These methods can lower energy costs through smart appliance scheduling, reduce energy usage, and facilitate the utilization of renewable energy sources.

User interfaces for monitoring and controlling the energy system
The user interfaces for IoT-based hybrid renewable energy systems, with an end-use scenario for a resident, are developed to enable the resident to monitor the functions of various components in real-time, thereby allowing for better management of energy consumption. This interface is a device that receives data (D) from various inputs and generates output (O), which supports decision-making and control. The mathematical formulation can be described as follows:

Real-Time data visualization The dashboard displays real-time energy metrics

$$0dashboard\left(t\right)=\left\{Eproduction\left(t\right),Econsumption\left(t\right),Blevel\left(t\right)\right\} \tag{32}$$

The equation represents the data metrics on a real-time energy dashboard, allowing homeowners to gain insight into their energy usage (32). The dashboard output *Odashboard(t)* contains three key parameters at time t. The total energy production on the drone (*Eproduction(t))*, overall energy consumption *(Econsumption(t))*, and current battery state of charge *(Blevel(t)). Eproduction(t)* is determined by the output of solar, Psolar(t), plus that of wind, Pwind (t). These metrics track energy dynamics in real-time, enabling users to utilise and store energy efficiently.

Historical data analytics Trends are computed using historical data

$$Husage\left(t\right)=\frac{1}{N}\sum_{i=1}^{N}consumption\left(i\right),\forall i\in historical\ range \tag{33}$$

Trends in energy consumption are computed based on historical evidence using the equation mentioned above (33), allowing users to gain insights into their energy consumption. The historical usage Husage(t) is calculated as the mean of energy consumption values at t, where T represents the number of past data points within a limited period defined as N. Every consumption(i) corresponds to the energy consumed at time i. Through this analysis, homeowners can understand which usage times are more significant or in which season they use the most electricity, enabling them to make better decisions regarding power management and potentially leading to cost savings.

Alerts and Notifications Alerts are triggered based on thresholds

$$Aalert=\begin{cases}1, if\ Econsumption(t)>Ethreshold\ or\ maintenance\ required\\0, otherwise\end{cases} \tag{34}$$

Alerts are raised by exceeding the *Ethresholds* as shown in Eq. (34). *Aalert* = 1 if an alert is active and 0 otherwise. Alerts trigger whenever energy consumption *(Econsumption(t))* exceeds a set threshold (*Ethreshold*) or when system calibration is due. This equation ensures timely intervention not just in managing energy use but also in system health.

Remote control Control signals (*Cappliance(t))* are generated for remote adjustments

$$Cappliance\left(t\right)=f\left(Ucommand,Eavailability\left(t\right)\right) \tag{35}$$

Equation (35) defines the remote control signals, *Cappliance(t)*, which are generated based on user commands (*Ucommand*) and the availability of renewable energy (*Eavailability(t))*. The function f integrates these inputs to adjust appliance operations dynamically, enabling energy optimization and user flexibility.

Energy cost Estimation The interface estimates costs using the following

$$Cest\left(t\right)=Egrid\left(t\right)\cdot Pgrid\left(t\right)-\alpha\cdot Erenewable\left(t\right) \tag{36}$$

Equation (36) estimates energy costs, Cest(t), by multiplying grid energy usage (Egrid(t)) with its price (Pgrid(t)) and subtracting the weighted contribution of renewable energy savings (α·Erenewable*(t))*. This helps users track costs and maximize savings by utilizing renewable energy.

Environmental impact Tracking: tracks CO_2 savings

$$CO_{2saved}=\frac{Erenewable(t)}{Etotal(t)}\cdot CO_2emission\_factor \tag{37}$$

Equation (37) illustrates the environmental impact by tracking CO_2 savings, calculated as the ratio of renewable energy produced (Erenewable(t)) to total energy consumed (*Etotal(t))*, multiplied by the grid's CO_2 emission factor (*CO_2emission_factor)*. This metric quantifies the environmental benefits of renewable energy usage.

Parameter	Measurement Unit	Value
Solar Energy Production	kWh	15.2
Wind Energy Production	kWh	7.8
Total Energy Consumption	kWh	22.5
Battery Charge Level	%	85
Grid Energy Usage	kWh	5.0
Energy Cost	$	1.50
CO_2 Emission Savings	kg	12.4

Table 2. Real-time energy dashboard data.

Alert type	Time
Maintenance Alert	2024-10-01 08:00 AM
Peak Demand Alert	2024-10-02 02:00 PM
System Fault Alert	2024-10-14 11:30 AM
Cost Saving Tip	2024-10-16 09:00 AM

Table 3. Alerts and notifications.

Integrating these functionalities enables efficient and user-friendly energy management in smart homes. These give homeowners real-time insights and control over their energy systems. This results in proactive management, cost savings, and greater environmental awareness.

Data tables for smart home applications

Table 2 includes real-time energy information such as solar and wind generation, overall consumption, battery storage capacity, and grid energy usage, highlighting the system's efficiency and the CO_2 avoided. The historical data analytics for 30 days are shown in Table (Appendix 2). This enables the optimization of strategies for renewable energy production, consumption, and grid energy dependability. Table 3 alerts and notifications helped convert data into actionable insights, such as equipment maintenance reminders, peak demand alerts, fault detection, or attempts to reduce costs. This table summarizes four news flashes and guidelines released in October 2024. A new maintenance alert on the 1 st directs a battery health inspection, and a peak demand Alert on the 2nd warns of high grid load and to minimize non-essential load where possible. An October 14th system fault alert says a wind turbine has failed and requires repair. Lastly, a cost-saving tip for October 16th is to use the washing machine from 10 a.m. to 2 p.m. to maximize the benefits of the solar energy. These tables demonstrate the system's ability to monitor, respond in real-time, and support energy data management decisions effectively.

Integrating IoT-enabled hybrid renewable energy systems into smart home devices and subsystems, with automation of appliance control and human-oriented interfaces, can significantly enhance how users manage their energy consumption. Consequently, smart home applications offer significant cost savings and energy optimization, ensuring increased user satisfaction and making them valuable for modern energy management strategies.

Case study: prototype implementation of IoT-Based hybrid renewable energy system in a smart home

Prototype implementation

This research performed a prototype implementation of an IoT-based hybrid renewable energy system in a simulated smart home environment[36,37]. The system consisted of solar panels, wind turbines, battery storage, and IoT sensors, and a single central controller managed it. The smart home also incorporates numerous smart devices and appliances for automation control and real-time energy management. This model can be constructive in a home environment that integrates an IoT-based hybrid renewable energy system, where MATLAB and Simulink facilitate the simulation of the entire device, including solar panels, wind turbines, and storage devices. In contrast, appliances consume electricity (Fig. 5).

Components and specifications

The smart home energy system consists of monocrystalline solar panels rated at 5 kW with an efficiency of 18%[33], enabling effective solar energy generation, and wind turbines rated at 3 kW with an efficiency of 35% for harnessing wind energy[32]. The energy storage consists of 10kWh lithium-ion cells and 80% depth of discharge to ensure power availability[34]. IoT-based smart appliances and devices adjust operations in real-time to match energy availability, enhancing overall efficiency. The following section presents the MATLAB used to simulate a smart home energy system and to create several different plots of its performance over time. The following shows a plot that visualizes the following data:

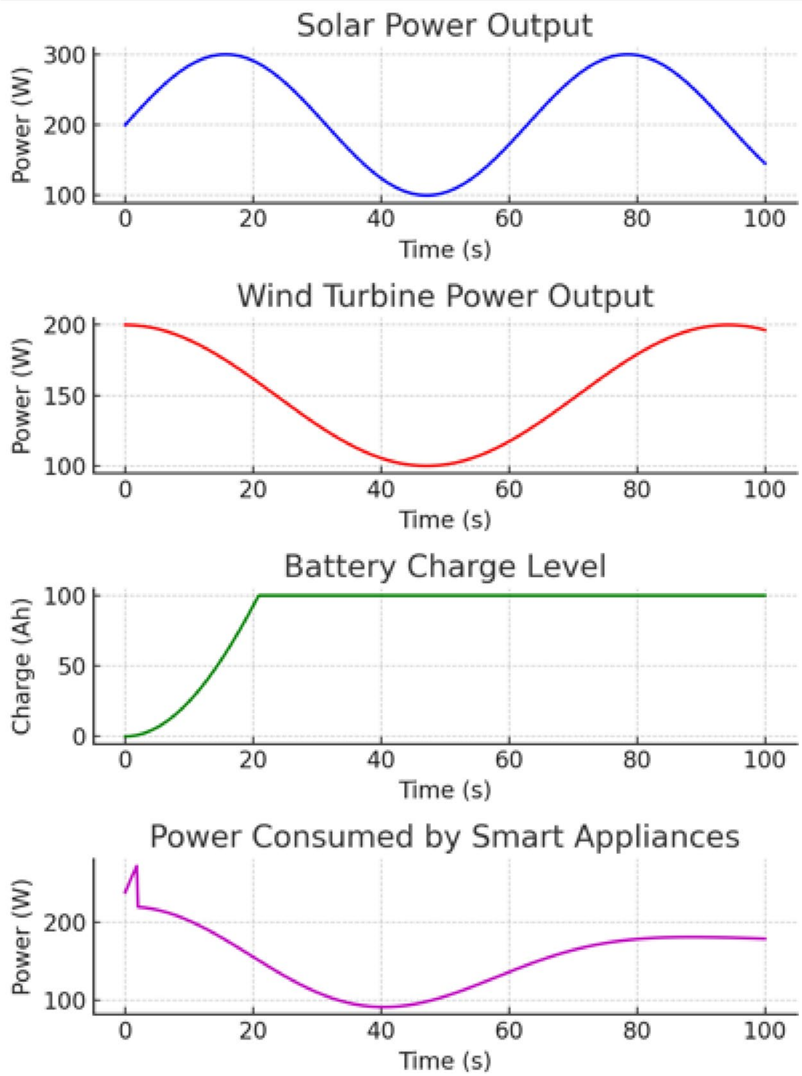

Fig. 5. Smart home energy system.

- **Solar Power Output**: The solar power variable represents the power solar panels produce in smart homes. In this case, the power output from the solar panels varies with time. This seems unlikely because factors such as the time of day and simulated weather conditions probably affect the amount of power generated. The variations in the plot may represent years of greater or lesser sunlight, with spikes corresponding to the maximum solar output.
- **Wind Turbine Power Output**: Wind power is calculated based on turbine output. This graph illustrates the variation in energy generated by the wind turbine over time. Wind power output tends to vary with wind speed and other atmospheric effects. Due to the randomness of energy availability, the wind power plot may exhibit an even more irregular pattern than the solar power plot.
- **Battery Charge Level**: The variable battery level is measured in ampere-hours (Ah) at the charge level in an electric storage system. This plot illustrates the change in the battery's charge level over the simulation. It charges when the solar panels or wind turbine generate more power than the appliances consume, and discharges to supply power for as long as the battery lasts. The plot provides the battery to store and supply a domestic smart home ecosystem within these parameters.
- **Power Consumed by Smart Appliances**: This feature captures the total power consumed by modern appliances in the household. The plot shows the power consumption of certain smart appliances over time. This will vary based on a smart home's actions or automation schedules. Several instruments may operate simultaneously and require higher consumption, but this is counterbalanced by other units with fewer people, which require slightly lower amounts during off-peak times.

The visualization's greater context can help understand the interaction between energy generation, storage, and consumption in the smart home. The plots illustrate surplus energy generation or deficit, demonstrating how the battery helps balance this, and how the system manages all smart homes in real-time.

Data management
The data collected over 30 days primarily examined energy production, consumption, storage levels, and environmental conditions. It also compared the system's efficiency to a grid-linked energy system.

Energy production and consumption
Energy Production and Consumption (30 Days) — provides a breakdown of daily energy axes for 30 days for each home affected by the hybrid renewable energy System (solar and wind). Daily solar and wind energy (kWh) is recorded, totaling the energy production for each day. The energy consumed indicates the amount of energy used by the household daily. Excess energy stored is any energy generated but not used in a day, which is then stored and indicates that these savings are available for future use or potential grid feedback.

Figure 6 illustrates the daily solar and wind energy production, total energy produced, energy consumed, and excess energy stored over 30 days for a smart home powered by a hybrid renewable energy system. The total energy generation varies significantly over the days, fluctuating due to daily changes in solar irradiance and wind speed, ranging from a minimum of 33 kWh (Day 05) to a maximum of 45 kWh (Day 27). Stored surplus energy varies in direct proportion to energy production and household consumption, suggesting the efficient utilization of renewable energy resources and storage to meet daily energy demands. Generate enough power for the smart home through the IoT-based system, storing surplus energy. The monthly solar and wind energy contributions varied with environmental conditions, highlighting the need for a hybrid system.

Battery storage performance
The battery storage performance tracks the 30-day daily consumption and storage cycle of the typical smart home's renewable energy system. Every day starts with a battery charge level at the start of the day (%) and is completed with a battery charge level at the end (%). Data shows daily fluctuations as energy is stored and drawn from the battery. The total energy stored (kWh) represents the amount of energy stored in the battery daily. This charge and discharge pattern involves minimal degradation in the battery, as it remains stable throughout its application, barring occasional fluctuations that are expected in a daily energy production and consumption routine. Energy storage and usage increase only slightly here on day 30 as the system accumulates energy from higher production days, honing its models to better adjust for high demand on lower-generation stimulated days. Figure 7 shows the battery performance, including the charge level at the start and end of each day for the entire 30-day period, the total energy stored, and the total energy used from storage by an IoT-based hybrid renewable power generation system in the smart grid. The total energy stored (kWh) is the daily energy put into the battery. Typically, around 2 kWh of excess renewable energy is stored for later use. The total energy used from storage (kWh) refers to the energy removed daily to meet household needs, typically 1–2 kWh per day. The battery storage system saves energy during periods of low energy production and reliably provides power. The controller could charge and discharge effectively, providing lifetime benefits to the condition.

Environmental impact
Hybrid systems substantially reduce CO_2 emissions compared to grid-connected systems. A cleaner and more sustainable power generation solution incorporates renewable energy. The environmental conditions (30 Days) data provides the daily values of three significant environmental variables that influence energy production in a smart home hybrid system: Average Temperature (°C), Wind speed (m/s), and Solar irradiance (W/m²). Figure 8 illustrates the environmental conditions over 30 days for a smart home's IoT-based hybrid renewable energy system. Environmental conditions are based on average temperature, wind Speed, and solar irradiance.

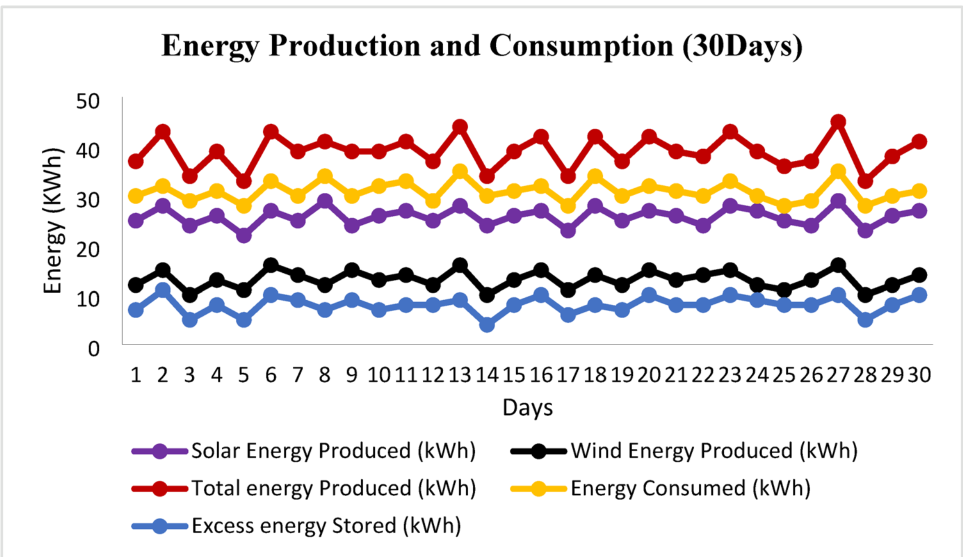

Fig. 6. Daily energy production and consumption.

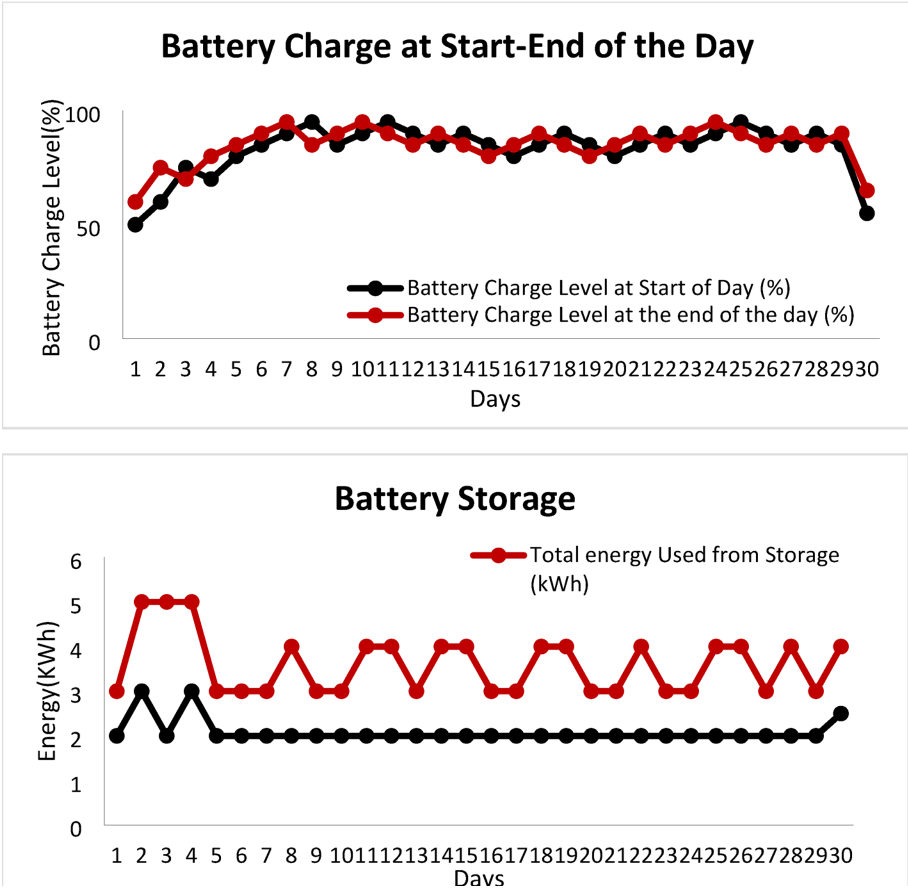

Fig. 7. Daily battery storage performance.

- **Average Temperature**: The efficiency of solar panels and wind turbines is expected to be affected because the average temperature is expected to be between 20 °C and 25 °C across all days, as ultra-low temperatures can significantly impact energy efficiency.

- **Wind Speed**: 4 m/s to 6 m/s, as wind speed is a significant parameter for generating electricity through wind energy. Wind power production increases significantly more rapidly with higher wind speeds.
- **Solar Irradiance**: A measure of sunlight intensity, ranging from 550 W/m^2 to 980 W/m^2, determines the amount, source(s), and energy potential of sunlight. The higher day number reflects solar options, providing these panels with high irradiance (980 W/m^2 for Day 25) and indicating optimal conditions for solar energy generation. At the same time, lower values (550 W/m^2 for Day 24) would reduce solar output.

The data shows that environmental factors influence wind and solar generation. The irradiance decreases, wind speeds drop, and stored energy utilization is prioritized. However, industrial plants and municipalities that rely on direct solar and wind farm power must supplement their supply with another source to meet daily energy demands.

System efficiency and user satisfaction

The hybrid system is efficient because it is remotely monitored and controlled through an IoT approach. It reports telemetry from wireless devices that transmit energy generation and consumption optimizations to cloud platforms. Users were more satisfied with the lower cost of energy, reliable power supply, and positive environmental impact generated by using renewable energy.

- **System Efficiency**: The ratio of actual energy output to total energy input determines system efficiency. Suppose 80% of the generated energy can be put to practical use (as it can be converted to accessible energy to be used or stored). In that case, the system's efficiency in the IoT-based hybrid renewable energy system is 80%.
- **User Satisfaction**: The user satisfaction of the system is then measured, typically through surveys in which each user rates the system's performance and usability on a scale (usually 1 to 10). The overall satisfaction score is calculated by averaging these ratings. In this study, the user satisfaction score is 8.5/10, assuming all survey responses are 8.5. This high score is attributed to various factors, including cost-effective energy, a dependable power supply, and environmental benefits.

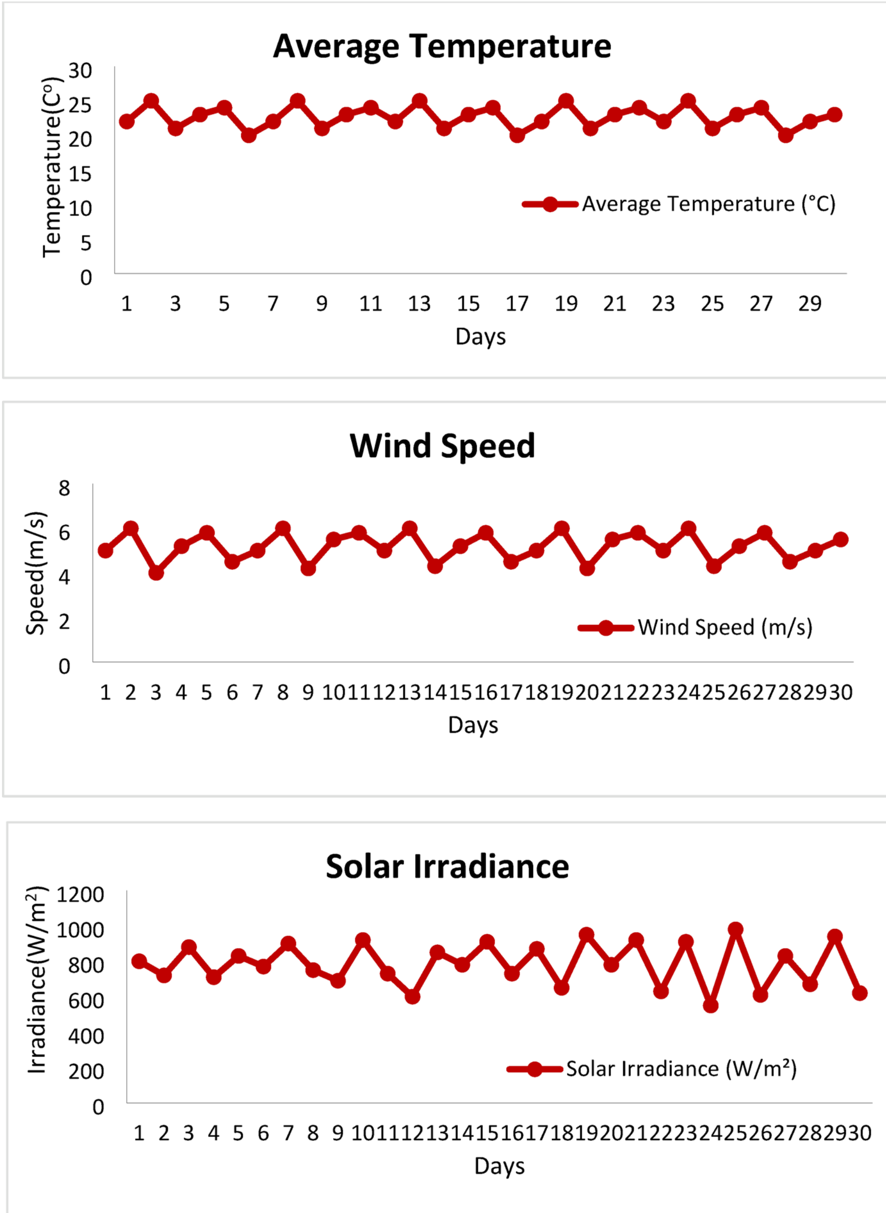

Fig. 8. Daily environmental conditions.

Metric	Traditional system	IoT-Based hybrid renewable energy system
Average Energy Production (kWh/day)	0	39
Average Energy Consumption (kWh/day)	31	31
Average Energy Costs ($/month)	139	54
CO_2 Emissions (kg/month)	465	180
System Efficiency (%)	60	80
User Satisfaction Score (Survey Result)	6/10	8.5/10

Table 4. Comparison metrics.

Comparison with traditional energy systems

The performance of IoT-based hybrid renewable energy systems is compared with that of traditional grid-connected energy systems in Table 4 to validate their equivalence and potential for future advancements.

Table 4 summarizes the differences between a traditional grid-connected energy system and an IoT-based hybrid renewable energy source, compared on various parameters. The comprehensive analysis of each metric:

- **Average Energy Production**: The traditional system cannot produce energy independently and typically relies on external sources, such as the grid. The hybrid system, in comparison, generates 40 kWh/day, which is undoubtedly a high amount of potential renewable energy. The substantial difference clearly shows that the hybrid system has solid potential to reduce grid dependency and effectively use renewable sources.
- **Average Energy Consumption**: Both systems consume the same amount of energy, indicating that the hybrid system is designed to meet typical energy needs. This indicates that while the hybrid system can produce its energy, it matches the energy consumption requirements of the conventional system. This suggests that hybrids can generate energy while still meeting the demand for traditional consumption.
- **Average Energy Cost**: The hybrid system provides significant energy savings and lower costs compared to traditional systems. Its energy input/output ratio makes running cheaper, at $54 per month, compared to the battery storage-only system, which costs around $92 per month. Renewable energy generation methods have lower operation costs than traditional grid electricity.
- **CO_2 Emissions**: Compared to traditional systems, the hybrid system achieves a significant reduction in CO_2 emissions of 285 kg/month. The IoT-based grid system's CO_2 emissions are 61% lower. The IoT-based hybrid system is environmentally friendly, reducing greenhouse gas emissions.
- **System Efficiency**: The hybrid system is 80% efficient, which is a significant 20% points better than any traditional system. This greater efficiency means the hybrid configuration is more effective at converting energy inputs into valuable outputs, thereby boosting performance and reducing overall energy losses.
- **User Satisfaction Score (Survey Result)**: In this case, the hybrid system tends to be 2.5 points better, indicating a higher level of user satisfaction compared to traditional arrangements. This increase suggests that users find the hybrid system more palatable in terms of performance, durability, and overall satisfaction. A higher satisfaction score indicates that users have positive feedback about the hybrid system's advantages.

The prototype implementation in a smart home setting demonstrated that the IoT-based hybrid renewable energy system outperforms traditional energy systems. These benefits include increased energy efficiency, lower operating costs, minimized environmental footprint, and better user comfort. The integration of IoT technology enabled real-time monitoring and control, thereby optimizing the performance of the renewable energy system. The setup incorporated all renewable sources, along with batteries. Further research would involve utilizing this system in larger applications and incorporating additional renewable energy sources.

Results

Presentation of results from the case study

This case study, which involved a smart home environment deploying an IoT-based hybrid renewable energy system, demonstrated its acceptability in performance, utilization efficiency, and user satisfaction. Table 5 compares energy production and consumption, system efficiency, and user feedback over 30 days.

Analysis of energy Savings, system Efficiency, CO_2 Emission, and user satisfaction

Energy savings

The economic analysis in Fig. 9 shows that an IoT-based hybrid renewable energy system yields significant cost savings compared to a traditional grid-connected system. Monthly energy Cost for the Smart Home has been reduced from $139.50 to $54, achieving a 61% monthly energy cost reduction. This results in an average monthly saving of $85. The system achieved the most efficiency by utilising IoT-based renewable energy sources and storing excess energy in batteries. This reduced the dependence on grid electricity and its associated costs. The annual savings from a hybrid renewable energy system rather than a non-renewable source are $1,026.00.

System efficiency

As shown in Fig. 10, the system achieved an IoT-based hybrid renewable efficiency of 80%, compared to 60% for traditional energy systems. This higher efficiency was achieved through real-time monitoring and control facilitated by IoT technology, which optimized energy production and consumption. The high geographical and meteorological diversity meant that the contributions of solar PV, wind turbines, and concentrating solar technologies fluctuated daily. The hybrid system compensates for these changes, ensuring stable energy delivery. Figure 11 illustrates the overall average system energy efficiency by comparing IoT-based hybrid renewable energy systems with traditional grid systems. The red dashed line denotes the average system efficiency of 72.3% (Appendix 3). IoT technology in the hybrid system optimizes energy production and consumption, increasing efficiency.

Metric	Value
Monthly Energy Production (kWh)	1170
Monthly Energy Consumption (kWh)	930
Average Energy Costs Saving ($/month)	85
CO_2 Emissions Reduction (kg/month)	285
IoT-based System Efficiency (%)	80
Average System Efficiency (%)	72.4
User Satisfaction Score	8.5/10

Table 5. Summary of key Metrics.

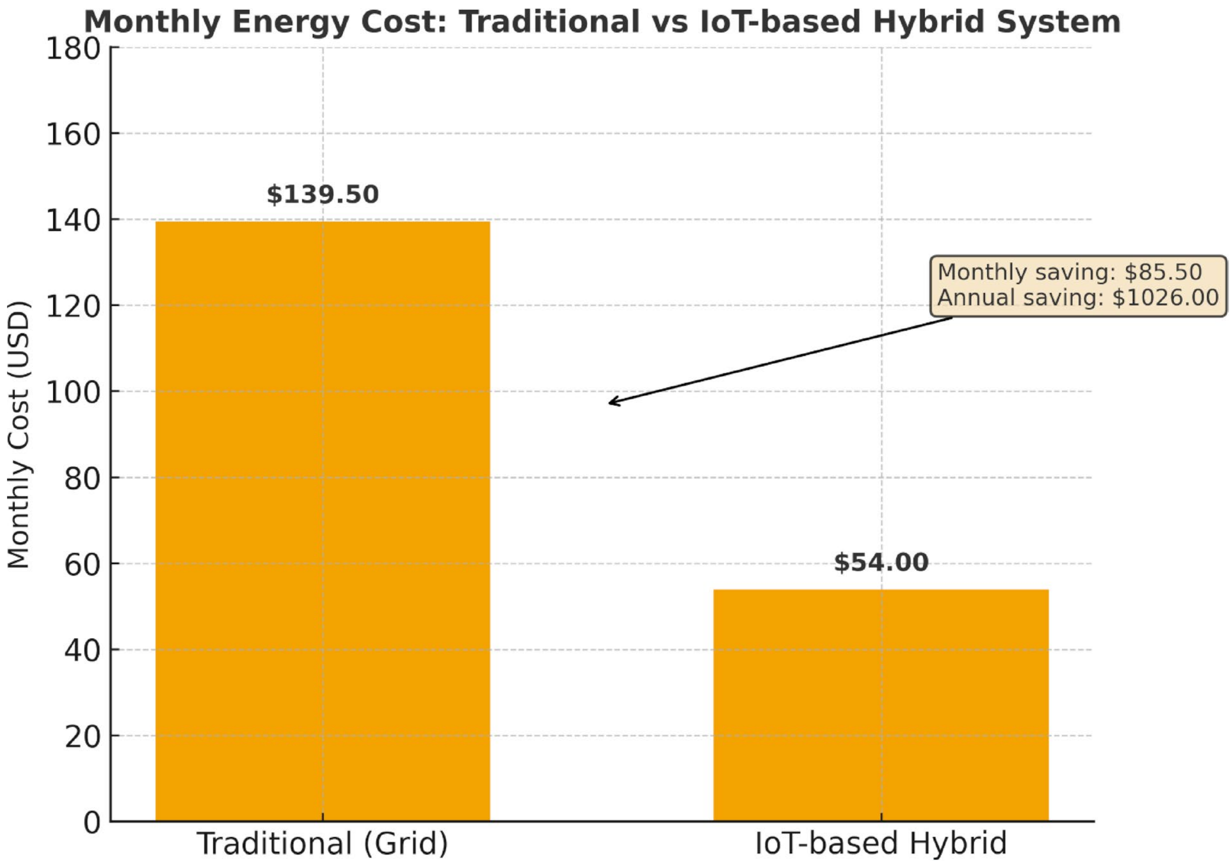

Fig. 9. Comparison of energy costs.

CO_2 emissions reduction

The IoT-based hybrid renewable energy system for smart homes significantly reduces CO_2 emissions by leveraging solar and wind energy, making a substantial difference. Traditional energy systems typically emit about 0.5 kg of CO_2 per kWh of energy consumed. In 30 days, a conventional system consuming 930 kWh would produce approximately 465 kg of CO_2. In contrast, the hybrid system, which relies on renewable sources and reduces grid consumption to 360 kWh, emits only 180 kg of CO_2, achieving a monthly CO_2 reduction of 285 kg, a 61.3% reduction. The integration of IoT technology optimizes energy usage and storage, further enhancing efficiency and minimizing reliance on fossil fuels. This significant decrease in emissions underscores the potential environmental benefits of adopting IoT-enabled renewable energy systems in smart homes. Figure 12 compares the monthly CO_2 emissions of traditional and hybrid renewable energy systems.

User satisfaction

The user survey indicated a high satisfaction rate of 8.5 out of 10. The score is primarily influenced by three key elements: cost-saving energy, reliable power supply, and environmental considerations. The IoT hybrid renewable energy system benefits from reducing the optimal user energy cost of energy production and consumption. The hybrid system ensures steady, fast green energy, utilizing clean, renewable, and sustainable electricity. Users consume renewable energy to reduce carbon emissions and decrease their dependency on fossil fuels. Figure 13 illustrates the user satisfaction score for implementing the IoT-based hybrid renewable energy system. The high score of 8.5 out of 10 reflects the positive impact of lower energy costs, reliable power supply, and environmental benefits.

Discussions

This study provides strong evidence that integrating hybrid renewable energy systems with IoT technology in smart homes improves their overall performance. Compared to traditional energy management systems, the IoT-based system demonstrated an 80% efficiency rate, indicating that generating renewable energy into power was significantly more effective. Much of this improved efficiency is due to real-time monitoring and automated control, which intelligently fine-tune energy flows by adjusting appliance use, energy storage, and the grid based on real-world conditions. Additionally, the 8.5/10 user satisfaction score indicates the system's success in addressing its users' needs, enhancing energy management, lowering operational costs, and making the system overall more reliable. The technical solution: Integrating solar, wind, and battery storage enables significant energy savings, and the reduced CO_2 emissions ensure that the system can adapt to the intermittency of renewable energy sources. Despite these positive outcomes, the study also highlights several challenges.

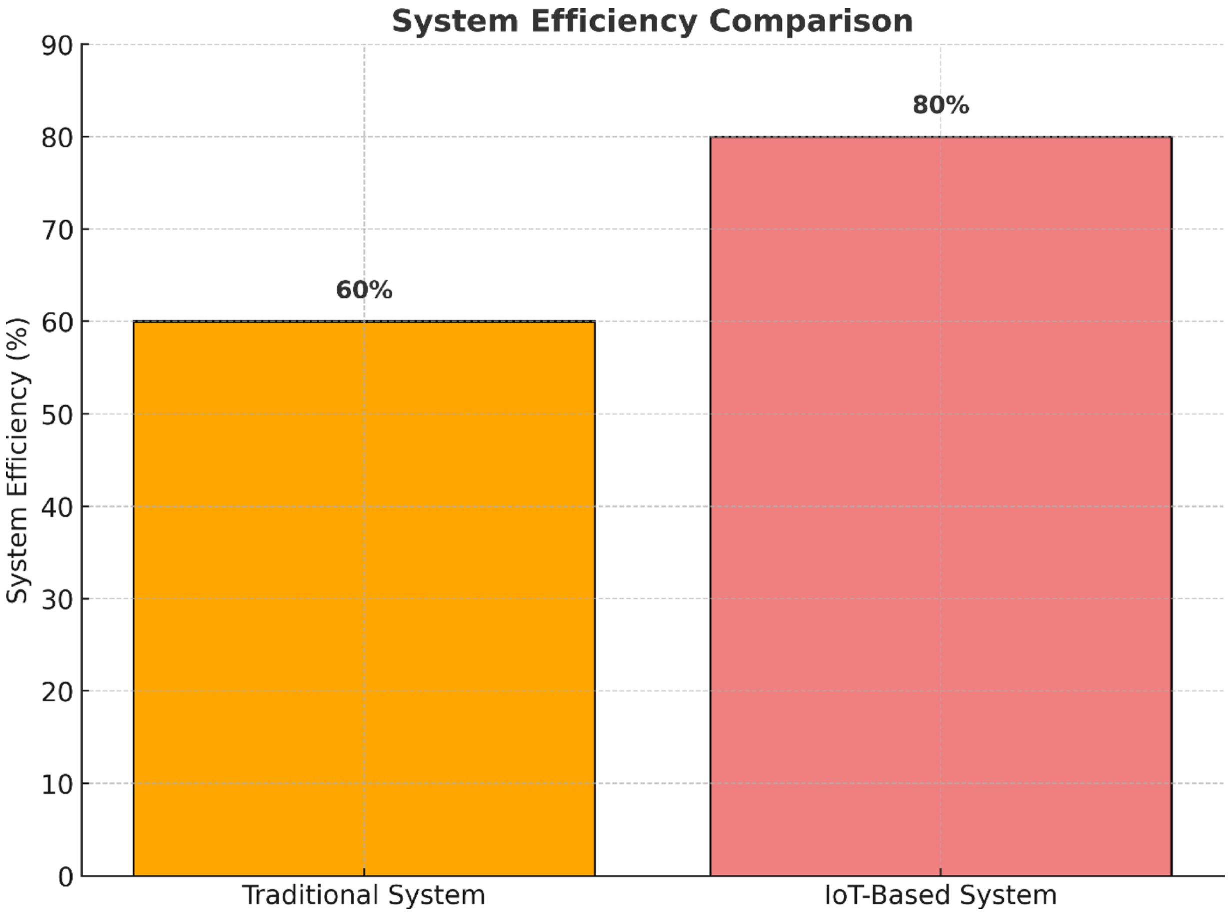

Fig. 10. Comparison of system efficiency between the Traditional and IoT-based systems.

These include initial capital investments, recurring investments in the complex integration of systems, potential cybersecurity risks associated with IoT devices, and scalability challenges encountered at various residential sites. The recommended future involves predicting solutions, improving interoperability, and trialling additional configurations of renewable energy devices. This work lays a durable foundation for future research into smart home energy management, paving the way for a more sustainable and affordable future. This move highlights the significant improvements in energy sustainability that IoT-enabled systems can enable through meaningful increases in the bottom line and improved user satisfaction. The IoT-based hybrid renewable energy management system presented in this work exhibits a considerable performance difference from traditional systems in terms of efficiency, cost, and CO_2 emissions. Compared with the work "Reliable operation of reconfigurable smart distribution network with real-time pricing-based demand response", the two works share the same point of view that demand-side flexibility and real-time decision-making are emphasized. However, this study emphasizes network-level reconfiguration and pricing models, leaving the proposed system to be implemented at the smart home level by utilising IoT-driven monitoring and adaptive optimisation for fine-grained control. In addition, the paper "Improvement of distribution network indices by means of electric mechanism when including renewable generation permission" focuses on device-level stability improvement using electric mechanisms. In contrast, multi-source renewables and storage are integrated and operated robustly using optimization methods to obtain environmental and operational benefits. Collectively, these comparisons offer valuable insights for situating this framework as a complement to other energy management solutions, connecting smart home operations with larger grid targets and providing an adaptable route toward sustainable energy systems.

Limitations and recommendations

This study reveals the potential of hybrid renewable energy systems based on IoT for smart homes, while presenting some limitations. These limitations arise from assumptions made in simulation models, limited scalability, and untested real-world factors such as communication reliability, economic viability, and reuse over a long period.

Limitations

Despite the promising results, there are several weaknesses to this study:

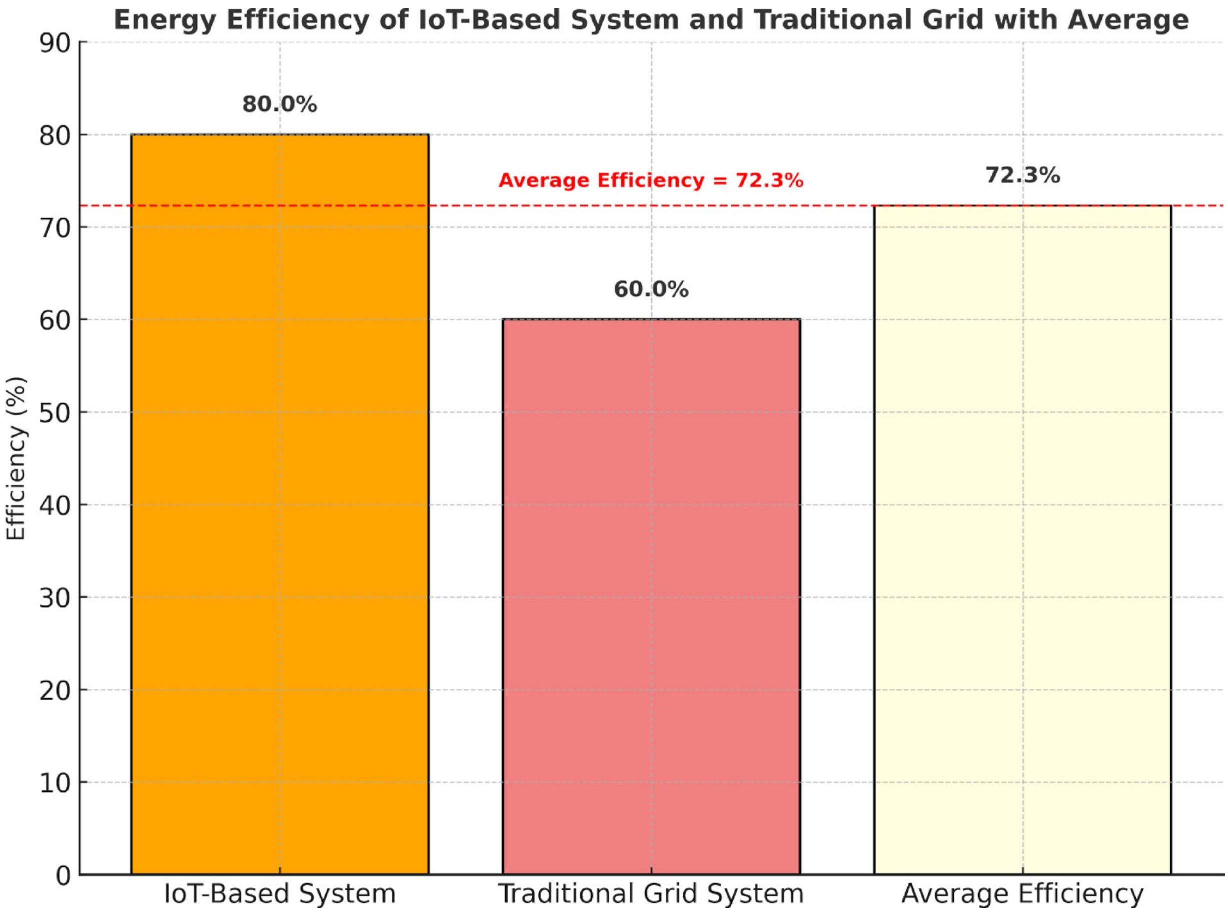

Fig. 11. Average system energy efficiency by comparing IoT-based hybrid renewable and traditional grid systems.

- Results are derived from smart-home environment simulations; field trials are required to account for hardware diversity, user interactions, and environmental uncertainties.
- Latency, packet loss, heterogeneity of IoT protocols such as Wi-Fi, ZigBee, and Z-Wave, and security issues were not fully simulated.
- ·The framework was only considered for a single-home case, and there would be new challenges in terms of unilateral control and load balancing if one extends it to community-scale or multi-home microgrids.
- However, although adaptive heuristics are used to alleviate early convergence and reduce generation time, in practice, they still pose a challenge to runtime performance when deployed in large-scale systems compared to lightweight rule-based methods.
- The energy pricing, incentives, and CO_2 emission factors in the study are assumed to be constant; however, dynamic pricing and regulatory uncertainty can affect this outcome.

Recommendations

Based on this work, some directions to explore in future studies are:

- The proposed IoT-based hybrid solution must be deployed and verified in a smart home and real community microgrid project to validate the findings.
- Design an adequate communication system that can overcome issues of latency, security, and interoperability by leveraging new technologies.
- Investigate model-independent methods, such as reinforcement learning and hybrid model-free techniques, to reduce our reliance on system modeling and address scalability issues.
- Include dynamic energy prices, carbon credits, and incentive-based policies in long-term cost–benefit assessments.
- The assessment should go beyond cost and CO_2 reduction to consider life-cycle, resource use, and environmental impact metrics.
- Observe the collaboration of demand-side management, peer-to-peer energy trading, and community-level storage integration.

The proposed framework demonstrates significant benefits in terms of efficiency, cost, and emissions.

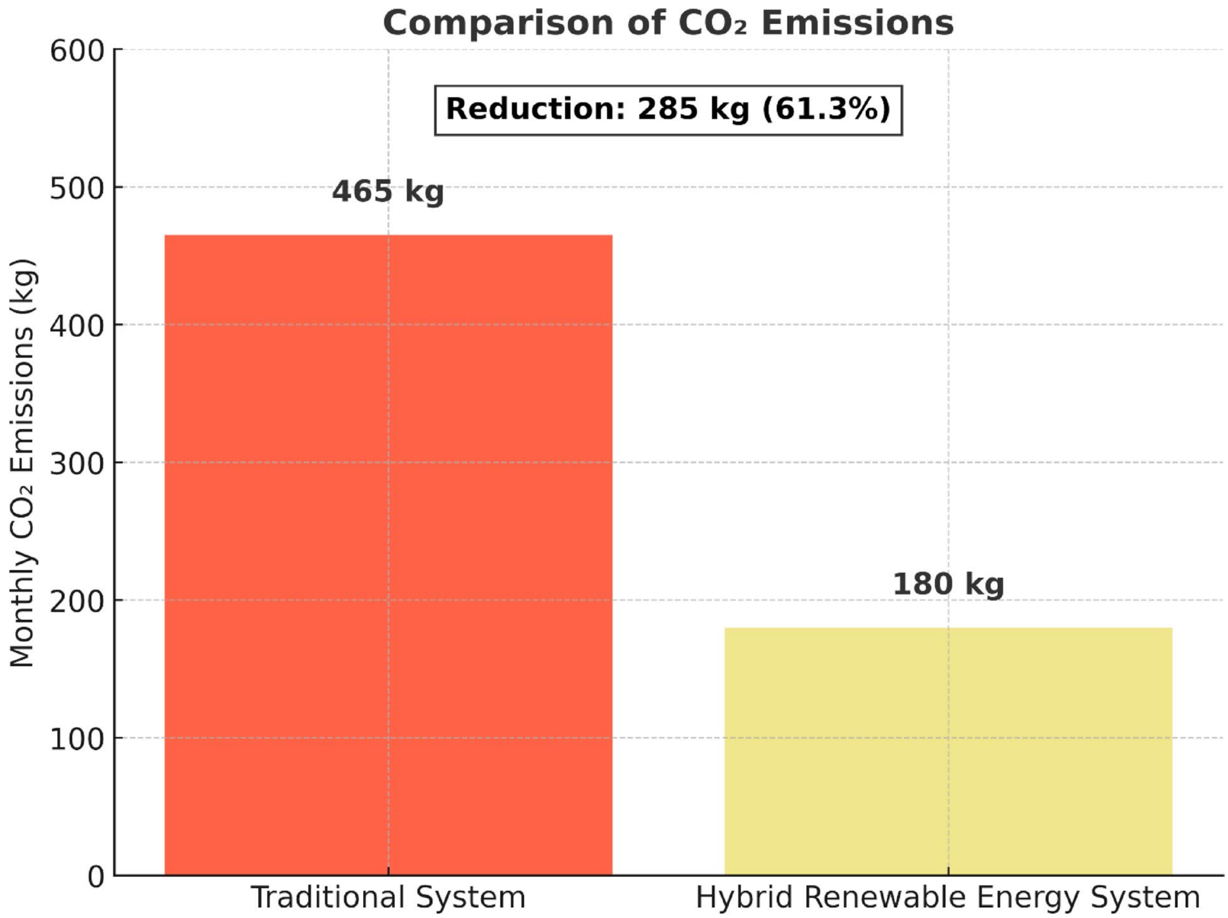

Fig. 12. Comparison of CO_2 emissions.

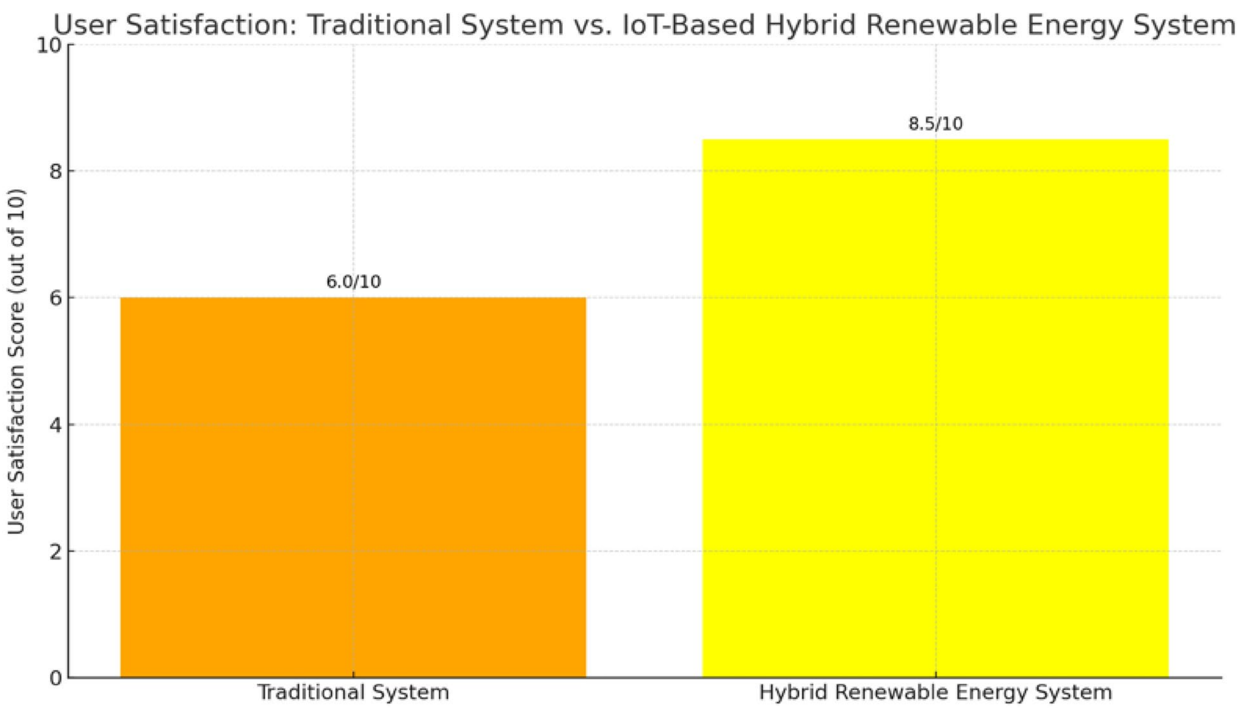

Fig. 13. The user satisfaction score for implementing the IoT-based hybrid renewable energy system.

Further studies should be conducted to pilot deployment in a real environment, assess communication reliability, cybersecurity, and upscaling to larger communities. Investigating more sophisticated optimization techniques, incorporating electric vehicles, and conducting techno-economic analysis would expand the application scope and enhance the reliability of IoT-based hybrid renewable systems.

Conclusion

The hybrid renewable energy system based on IoT for smart homes, comprising photovoltaic panels, wind turbines, and battery storage devices with real-time monitoring and control, was proposed in this work. Its innovation is related to autonomous energy management using IoT communication protocols, targeting well-optimized efficiency, cost, and environmental sustainability. A simulated smart home case study evaluated the system's performance to assess energy cost savings, energy use efficiency, and CO_2 reduction. Demand–supply matching was optimised, and operational dependability was enhanced using IoT sensors and controllers. The main quantitative findings can be summarized as follows:

- An efficiency of 80% was obtained, indicating better utilization of renewable energy sources.
- Reduced energy costs by 61%, proving substantial economic savings over conventional grid-dependent systems.
- Reduced CO_2 emissions by over 61%, a clear signal of the environmentally friendly nature of hybrid integration.
- Improved real-time energy tracking and customer satisfaction with IoT-level control.

However, some limitations remain. System efficiency relies on accurate prediction of renewable resources; however, system scalability for larger residential communities and ensuring IoT network security require further study. Future research should focus on the causes of hydrogen storage and electric vehicle charging, utilising machine learning for predictive energy management, and evaluating performance in pilot studies within real smart homes. The proposed system offers practical benefits, including improved efficiency, lower costs, and reduced environmental impact, which enable the IoT-integrated hybrid renewable system to facilitate sustainable and smart residential energy management.

Data availability

The data supporting this study's findings are available from the corresponding author upon reasonable request. The data are not publicly available due to privacy and ethical restrictions, as well as ongoing analysis. Don't hesitate to contact the corresponding author for any inquiries regarding access to the full dataset.

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• Amam Hossain Bagdadee: Conceptualization, Methodology, Data Analysis, Writing—Original Draft, Data Collection, Software, Methodology, Writing—Review & Editing.• Md. Samiur Rahman: Software.• Deshinta Arrova Dewi: Modification, Validation• Ishtiak Al Mamoon: Project administration• Li Zhang: Validation, Supervision, Writing—Review & Editing.• A. K.M. Muzahidul Islam: Writing—review & editing.

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Declarations

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The authors declare no competing interests.

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