Smart Energy Management and Load Optimization in Electrical Systems Using IoT and Hybrid Renewable Sources

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ABSTRACT

Smart energy management and load optimization aim to enhance efficiency and sustainability by dynamically regulating energy consumption and distribution. Internet of Things (IoT) devices enable the collection of real-time data on energy usage, environmental conditions, and system performance. This information is utilized to optimize energy flow from hybrid renewable sources—such as solar and wind—alongside traditional power grids. IoT-based control systems facilitate real-time load adjustments, thereby reducing energy waste and dependence on non-renewable resources. Predictive analytics are employed to forecast renewable energy (RE) generation, enabling proactive load balancing. Integrating IoT with hybrid RE sources enhances operational efficiency, lowers energy costs, and accelerates the transition to sustainable energy systems. This approach is adaptable across residential, commercial, and industrial applications, contributing to a cleaner, more reliable, and future-ready energy infrastructure.

Keywords: Energy Management, Hybrid Renewable Energy Sources, Internet of Things, Load Optimization, Predictive Analytics

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INTRODUCTION

A nation's economic growth is heavily dependent on its energy supply. In emerging economies, the energy sector plays a critical role, with escalating demand necessitating substantial investment (Wang et al., 2022). The primary objective of energy management is to produce goods and deliver services at minimal cost while reducing environmental impact. Energy management can be defined as the efficient and targeted use of energy to enhance competitiveness and maximize profits through cost minimization. Another definition describes it as the systematic modification and optimization of energy-related processes to reduce energy requirements per unit of output while maintaining or lowering the total production cost (Sarker et al., 2019).

Effective energy management involves structured decision-making, often beginning with an energy audit to determine total energy inputs and identify energy streams within a facility (Wang et al., 2019). As global demand for energy increases and carbon reduction becomes urgent, innovative energy management systems are required. Hybrid Renewable Energy Systems (HRES), which integrate wind, solar, and other renewable sources, present a viable pathway toward sustainable energy production (Bloess, 2020). However, these systems require advanced management tools to ensure optimal energy generation and load distribution.

The Internet of Things (IoT) has transformed energy management by enabling real-time monitoring and control of electrical systems. Through interconnected devices, sensors, and control units, IoT facilitates predictive analysis and adaptive decision-making (Shao et al., 2021a). IoT-based systems can minimize energy waste, optimize load distribution, and seamlessly integrate RE sources. Nevertheless, practical constraints such as financial limitations and technological challenges must be addressed to ensure the effective deployment of RE solutions (Le et al., 2023). Technical and financial feasibility studies, along with assessments of environmental and societal benefits, should inform the design and operation of Renewable Energy Systems (RES).

RES can be divided into five subsystems: production, transmission and distribution, consumption, storage, and resource planning (Moradi-Sepahvand et al., 2023). Each presents unique decision-making challenges, such as optimizing biomass feedstock supply or determining the most efficient site for installations. The production subsystem, for example, requires strategies for heat supply, electricity generation, and hydrogen synthesis to improve performance and system integration (Kayalvizhi et al., 2024). The transmission subsystem must address line design, cable configuration, and grid balancing to match supply and demand (Bakare et al., 2023).

Recent advancements in IoT-based energy management have enabled predictive maintenance and fault detection in RE systems, ensuring uninterrupted power supply (Sayal et al., 2024). Real-time energy data processing supports demand-side management by adjusting consumption patterns during peak and off-peak hours, thus enhancing grid stability. However, challenges such as inefficient storage and weather unpredictability persist in HRES. Advanced control techniques, including AI-driven predictive strategies, have demonstrated potential in mitigating these issues and improving reliability.

This study proposes an intelligent Energy Management System (EMS) that integrates HRES with IoT-based monitoring and control. The framework aims to maximize RE utilization, maintain grid stability, and improve system efficiency through innovative control methodologies.

LITERATURE REVIEW

Integration of the Internet of Things (IoT) with Renewable Energy (RE) systems has been extensively studied to enhance energy management efficiency. Zia et al. (2020) emphasised the importance of real-time data acquisition for effective load balancing in IoT-based Energy Management Systems (EMS) for solar–wind hybrid configurations. Their research demonstrated that IoT can optimise energy storage by accurately predicting consumption patterns and employing maintenance prediction strategies to ensure system reliability. These measures significantly reduced maintenance costs and downtime. Given their high energy generation potential, RE sources such as wind and photovoltaics are increasingly promoted to reduce greenhouse gas emissions and electrify remote areas (Eltamaly et al., 2021). Hybrid systems can operate in both autonomous and grid-connected modes using diverse RE combinations, although their intermittent nature presents integration challenges.

Communication networks play a crucial role in integrating Distributed Energy Resources (DERs) into smart grids, enabling bidirectional energy and data exchange. HRES can deliver multiple services, including demand response and consumption-side optimisation, enhancing reliability and resilience (Tazay et al., 2020). Eltamaly et al. (2021) proposed a novel sizing methodology for HRES comprising loads, diesel engines, batteries, wind turbines, and photovoltaic systems, optimised using algorithms such as Bat Algorithm (BA), Social Mimic Optimisation, and Particle Swarm Optimisation (PSO). Their case study in rural Saudi Arabia incorporated actual load data for accurate system sizing.

Feasibility assessments by Tazay et al. (2020) demonstrated the viability of hybrid RE configurations—comprising PV, wind turbines (WT), fuel cells (FC), and battery storage systems (BSS)—for university campus applications. Kermani et al. (2020) implemented a microgrid at Sapienza University, with Supervisory Control and Data Acquisition (SCADA) systems demonstrating effective energy management. Similarly, Abidi et al. (2019) developed a strategy for optimising source capacity and distribution in microgrids, validated through a case study on a Tunisian petroleum platform. Sawle et al. (2021) confirmed HRES viability for remote Indian towns, employing HOMER software to assess economic and environmental performance across multiple configurations.

Plazas-Niño et al. (2022) identified gaps in optimisation studies for RE systems, noting a lack of comprehensive frameworks addressing the entire generation-to-utilisation cycle. Existing literature often focuses on specific stages, with limited integration of scenario analysis, optimisation models, and long-term energy planning tools such as LEAP and MARKAL. This review highlights the necessity for holistic approaches that address technical, economic, and environmental dimensions to enhance RE adoption.

RESEARCH METHODOLOGY

This study adopts a systematic methodology to design and evaluate an IoT-enabled smart energy management and load optimisation framework for HRES. The process begins with developing an IoT-integrated architecture capable of real-time data acquisition from energy consumption points, environmental sensors, and system performance monitors (Kayalvizhi et al., 2024). The data is processed using predictive analytics to forecast renewable energy generation, enabling proactive load balancing.

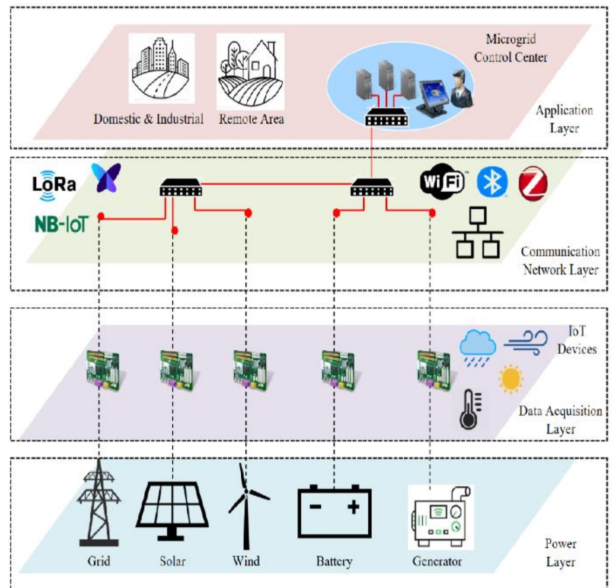


Figure 1 IoT-driven design for smart hybrid energy systems

Hybrid energy sources—such as photovoltaic arrays, wind turbines, and conventional grid power—are modelled within a simulation environment. Optimisation algorithms, particularly PSO, are implemented to dynamically allocate loads, minimise waste, and reduce dependence on fossil fuels (Eltamaly et al., 2021). Key performance indicators (KPIs) include system efficiency, cost savings, and carbon reduction potential.

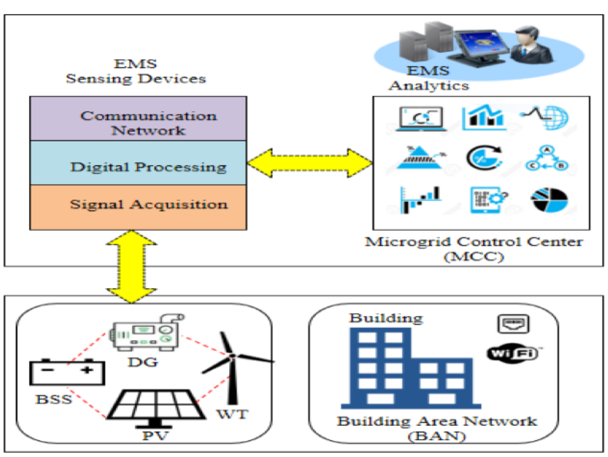
Modelling of Hybrid RE System

The purpose of HRES is to produce electricity through a variety of power generation technologies, including photovoltaic systems, diesel-powered generators, and small-scale wind turbines. These systems may supply electricity to a single house or building or a large system, such an island or town. Depending on how the system is attached to the main grid, it can be classified as either independent or grid-linked. To meet the required power need in the separate mode, HRES should be constructed. The configuration of the HRES can be either AC, DC, or hybrid AC/DC, based on the voltage source of the main bus that connects each asset.

Energy sources, which include wind turbines, electric grids, diesel generators and photovoltaic, energy storage systems, and loads are the primary HRES elements in this work. Due to the high cost of energy generation in remote places, such as hilly, village, and arid regions, as well as several obstacles, including low population density and challenging travel to remote locations, the choice of HRES components is predicated on the Saudi Arabian context. Thus, HRES production would lessen reliance on fossil fuels and aid such remote places. IEC 61400-25, IEC 61850-7-420and IEC 61850 are among the standards that have been considered for the HRES data format.

In order to express the data model for the device itself that must be transferred with other gadgets as well as systems, the logical node idea is used. The fundamental components of the hybrid energy system's EMS are depicted in figure 2. The two primary components of it are EMS analytics and EMS detectors. Table 1 shows the monitoring scope of HRES

Figure 2 EMS for a HRES



Level	Coverage	Monitoring Scope	Control Decision	Technology
local control	LAN, BAN	HRES subsystem including solar, wind, battery, generator, grid	local	ZigBee, Wi-Fi, Ethernet, etc.
area control	NAN	groups of HRES	local, distributed	Wi-Fi, Ethernet, etc.
central control	WAN	large scale HRES	central	LoRa, NB-IoT, 4G, LTE, etc.

Table 1 Monitoring scope of HRES.

IoT Based load management

An IoT based approach the suggested smart load management system uses sensors and analysis of data to efficiently track and manage power use, particularly in industrial settings. The system can precisely identify any irregularities or variations in power consumption by employing a network of sensors, quickly warning the consumer or operator of possible problems. Besides anomaly detection, the system provides insightful analysis and helpful suggestions for optimising power consumption. In the end, this improves energy management and lowers expenses by empowering users to adopt energy-efficient behaviours and make well-informed decisions. With its sophisticated features, the suggested system seeks to improve sustainability and operational effectiveness in industrial environments by offering proactive alarms, real-time monitoring, and practical suggestions for power usage optimisation. Figure 3 illustrates the block diagram of IoT Based smart load management.

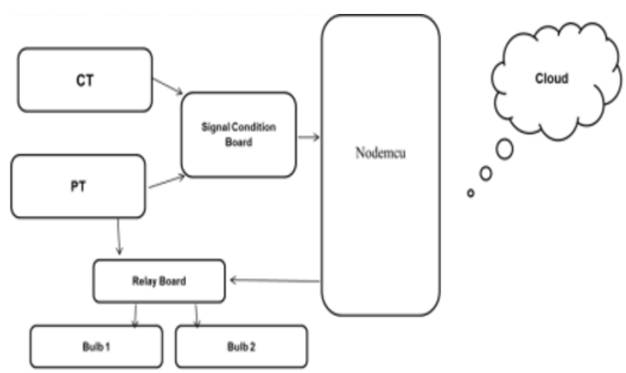


Figure 3 Block Diagram of IOT Based smart load management

A simulation-based evaluation is conducted using case studies from residential and industrial applications to validate the framework's scalability and adaptability. The methodology incorporates constraints related to battery State of Charge (SOC), generator ramp rates, and energy storage capacities to ensure operational stability (Bakare et al., 2023). Data-driven decision rules are embedded into the EMS to optimise energy flow and reduce peak demand stress on the grid.

Load management, control, and energy balance

The system calculates the energy balance at each stage by subtracting the load and energy demand, from the total DC power generated by the wind and solar sources. The final outcome determines whether the amount of generation is sufficient or excessive. In the case of additional generation, the battery stores additional energy. If there is insufficient generating, electricity is supplied by the battery. By ensuring that the energy generated and spent are equal, this mechanism preserves equilibrium. In accordance with the energy balance, the algorithm's battery State of Charge (SOC) control component keeps track of the battery's SOC. The battery is fully charged in the event of surplus production. Battery discharge occurs when there is not enough generation, but it does not go below a minimal SOC. By maximising energy utilisation, this control system extends battery life and guarantees that power will be available whenever required. After taking into consideration the battery and the total DC power, a diesel engine is employed in the load control stage when there remains a load. To satisfy the remaining load while staying within the generator's capacity and minimal load, the diesel generator's output is managed. This guarantees that the load is consistently satisfied. In order to determine whether the diesel generator is necessary, it was incorporated into the algorithm.

In order to prevent abrupt variations in the diesel generator's output, the control regulates its operation. Limiting the ramp rate—the generation shift from just one step to the next—is how this is accomplished. Rapid variations in load can be avoided by using this control technique to protect the generator.

The following procedures are used to accomplish energy balance, control, and load management:

1. Determine the overall DC power: The sum of the power produced from the PV and WT panels is used to compute this.

2. Determine the energy balance (E_b) by deducting the entire DC power from the load profile, or the demand for energy at time i.

3. Modify the battery's (SOC): The battery's SOC is modified in accordance with the energy balance. The battery stores energy if there is surplus generation (Energy_balance > 0). The battery capacity and charging efficiency set a limit on how much energy can be stored. Additionally, the SOC is constrained by the battery's capacity. The battery is used to supply energy if there is not enough generating (Energy_balance < 0). The power rating and discharge efficiency of the battery set a limit on the quantity of energy that can be extracted. Additionally, the SOC is constrained to a minimal SOC. The battery SOC doesn't change if the energy balance is 0.

4. Determine the remaining load: This is done by deducting the overall DC power and the battery change.

5. Possible functioning of the diesel generator: The diesel generator is employed if there is still a load. The generator's minimum load capacity as well as limit the quantity of generation. In order to minimise the generation, change from one time step to the next, the generator's ramp rate is also considered.

Implementation of Particle Swarm Optimization Algorithm

The social behaviour of fish schools and flocks of birds served as the inspiration for PSO, a population-based optimisation algorithm. Iteratively improving potential solutions using the idea of particles travelling through the solution space allows it to optimise a problem.

The velocity as well as position of every particle in the space relate to a set of decision variables, and each particle indicates a possible solution. Mathematically, the position of the i-th particle at iteration t is denoted as $x_i(t)$, and its velocity as $v_i(t)$. A swarm of particles with arbitrary coordinates and velocities is initialised at the beginning of the PSO algorithm. Each particle maintains a record of its best position found so far, called $pbest_i$, and the best position found by any particle in the swarm, called $gbest$. The objective is to minimize (or maximize) a fitness function *f(x),* which is problem-dependent, such as minimizing cost or error. The velocity of every particle is changed at each iteration using the following equation:

$$v_i(t+1) = w\,.\,v_i(t) + c_1\,.\,r_1\,.\left(pbest_i - x_i(t)\right) + c_2 . r_2 .\ (gbest - x_i(t))$$

where:

- $v_i(t)$ is the velocity of the particle at time step t,
- w is the inertia weight that controls the influence of the previous velocity,
- c_1 and c_2 are acceleration constants,
- r_1 and r_2 are random values between 0 and 1 that introduce stochastic behavior,
- $pbest_i$ is the best position of the particle,
- $gbest$ is the best position found by any particle in the swarm.

The position of each particle is then updated using the equation:

$x_i(t+1) = x_i(t) + v_i(t+1)$

The procedure is carried out repeatedly until the convergence requirements are satisfied or for a predetermined number of iterations, such as when the change in fitness values becomes insignificant. The algorithm terminates when the global best position $gbest$ represents the optimal solution to the problem. For non-differentiable, chaotic, or multifunctional objective processes, PSO is appropriate as it doesn't need gradient information. It is widely used in solving optimization problems in engineering, control systems, and machine learning due to its simplicity and efficiency.

The research design ensures robustness by integrating financial feasibility and environmental impact assessments, in line with recommendations from Moradi-Sepahvand et al. (2023). Outcomes from the simulation are compared against baseline scenarios to quantify improvements in energy efficiency, system reliability, and cost-effectiveness.

RESULT AND DISCUSSION

The optimised configuration identified through PSO consists of 31 batteries, 154 solar panels, three wind turbines, and 136 inverters. Annual electricity generation reached 42.17 MWh, with 41.974 MWh from solar photovoltaics and 196.59 kWh from wind turbines. The total economic cost (TEC) was minimised to USD 476,731, with an annualised cost of USD 301,947. The Levelised Cost of Energy (LCOE) was calculated at USD 0.011/kWh, with additional TEC-related expenses amounting to USD 174,784. Capital cost analysis revealed that 30% was allocated to wind turbines, 30% to photovoltaic systems, 25% to battery banks, and 8% to inverters. High capital costs limited the number of wind turbines to three, confirming solar PV and wind as the primary contributors to autonomous HRES in the study region.

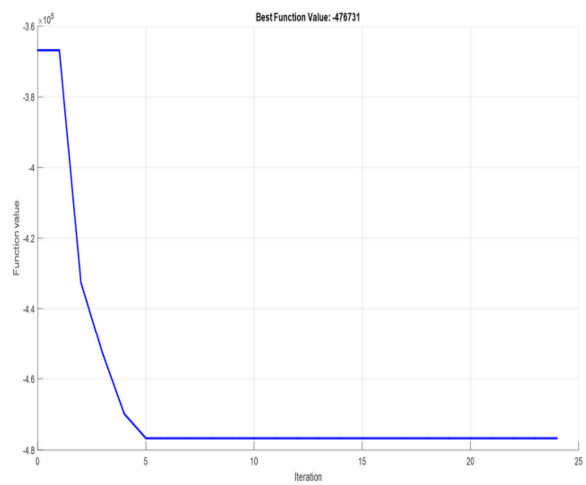


Figure 4 Optimized fitness function from PSO

Operational and maintenance costs were recorded at USD 219,772, with replacement costs at USD 446,300 and capital costs at USD 341,630. The PSO algorithm effectively balanced capital investment against operational efficiency, with the optimised fitness function demonstrating rapid convergence toward cost-effective configurations. System resilience was maintained by employing battery storage for excess generation and diesel generation during deficits, regulated to avoid sudden output fluctuations.

The results underscore the cost-effectiveness of integrating IoT-based control with HRES. Predictive load management reduced reliance on diesel generation, extended battery life through optimised SOC control, and ensured grid stability. These findings align with earlier research by Tazay et al. (2020) and Abidi et al. (2019), confirming that hybrid configurations optimised through advanced algorithms can deliver substantial economic and environmental benefits.

The study's results also reinforce the importance of intelligent communication networks in facilitating seamless data exchange for real-time decision-making (Wu et al., 2020). Furthermore, the scalability of the proposed system suggests applicability across diverse geographical and operational contexts. Challenges remain in storage efficiency, interoperability, and weather-related unpredictability; however, ongoing advancements in AI-based predictive control hold promise for further performance gains (Sayal et al., 2024).

CONCLUSION

This research presents an IoT-based smart energy management framework for optimising load distribution in Hybrid Renewable Energy Systems (HRES) incorporating solar, wind, and conventional power grids. By leveraging predictive analytics and advanced control strategies, the framework enhances energy efficiency, reduces operational costs, and supports the transition to sustainable energy solutions. The integration of Particle Swarm Optimisation (PSO) algorithms further improves energy flow by minimising waste and maintaining grid stability.

The study demonstrates that intelligently integrated IoT and HRES can offer significant benefits for both residential and industrial applications, providing a scalable and adaptable solution. While challenges such as storage inefficiency, interoperability, and environmental unpredictability persist, these can be mitigated through advancements in AI-based control and predictive maintenance strategies.

Overall, this research contributes valuable insights into the role of IoT in transforming energy management practices and lays the groundwork for future enhancements aimed at achieving cleaner, more resilient, and economically viable energy infrastructures.

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