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REAL-TIME MONITORING AND CONTROL OF RENEWABLE ENERGY SYSTEMS USING WIRELESS TELECOMMUNICATION AND SIGNAL PROCESSING TECHNIQUES FOR SMART GRIDS WITH ENERGY STORAGE

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Abstract
Background: The integration of renewable energy resources such as solar and wind into the contemporary smart grid poses tremendous challenges because of their decentralized and nondeterministic nature. Efficient real-time monitoring, forecasting, and intelligent energy management techniques are demanded to ensure the reliability and performance of the grid. Objective: In this research work, the task was to design and evaluate a real-time monitoring and control system for smart grids based on wireless communication technologies, sophisticated signal processing, and coordinated energy storage. Methodology: A laboratory-scale system was designed with solar and wind simulators, lithium-ion battery storage, and microcontroller-based sensor nodes. Voltage, current, frequency, and battery state of charge (SoC) were recorded and wirelessly transmitted by LoRa modules. Different signal processing techniques like moving average, Butterworth, Kalman, and adaptive RLS filters were applied for data smoothing, anomaly detection, and prediction. Battery charging and energy distribution were controlled by a fuzzy logic controller. Results: The system had a 97.6% packet delivery and an average latency of 138 milliseconds. Forecasting accuracy was still in line, with MAPE below 5.5%, and SoC estimations were maintained within ±2.4% variation. Energy efficiency was increased to 96.4%. The framework exhibited fast adaptability to varying loads and renewable energy supplies, outperforming the outcome of conventional wired or non-smart systems. Conclusion: This study

demonstrates a safe, efficient, and scalable architecture for smart grid operations. Through the integration of wireless communication, smart processing, and coordination of energy storage, the system enables the transition towards more sustainable and intelligent energy infrastructure.

INTRODUCTION

The shift towards cleaner, greener energy options has accelerated the global deployment of renewable energy systems (RES) including solar photovoltaic, wind power, biomass, and small hydroelectric systems. Such systems are extremely crucial in curbing carbon emissions, reducing dependence on fossil fuels, and promoting ecological conservation. Nevertheless, weather-dependent and intermittent in nature, integrating them into the power grid is operationally challenging—especially in balancing persistent and stable provision of energy as the proportion of the energy mix becomes larger (Kou et al., 2019).

In order to overcome these challenges, the use of real-time monitoring and intelligent control systems has gained greater importance. These technologies ensure control over variations in the production of energy, attain supply-demand equilibrium, and adjust to actual working conditions dynamically. Smart grids with integrated high-tech electricity grids and in-built digital communication and automation have come forward as a resilient solution. Utilizing ICT devices and decentralized control systems, smart grids enhance the supply and utilization of electricity (Zhou et al., 2022).

Energy storage systems (ESS) are the critical component in this setup. They store excess energy in generation over demand and supply during increasing demand, balancing renewable generation volatility (Wang et al., 2020). Coupled with real-time monitoring equipment and smart control devices, ESS can dramatically improve grid resilience and efficiency.

Wireless communication technologies are playing a vital role in facilitating such real-time ability. Compared to conventional wired systems, wireless technology saves the cost of infrastructure, facilitates simpler installation and maintenance, and accommodates faster and scalable deployment at far-off or dispersed grid sites (Kumar et al., 2022). LoRaWAN, ZigBee, 5G, and NB-IoT have been prospective technologies based on their extensive range coverage, low energy consumption, and satisfactory performance (Khanna & Rani, 2021; Tang et al., 2021).

Simultaneously, digital signal processing (DSP) has gained prominence to extract useful information from the data stream coming in real time from the sensors within the grid. Filtering, event detection, and harmonic analysis DSP methods make more precise diagnostics and predictive control possible (Elhoushy & Mohamed, 2021). The convergence of machine learning and AI with DSP yet further enhances anomaly detection, prediction of energy demand, and facilitating adaptive response in real time (Zhang et al., 2023).

Combinations of DSP and wireless technology have been used in recent research to develop applications in renewable energy. Al-Humayed et al. (2022), for example, showed applications of LoRa-based systems for high-scalability and low-latency real-time monitoring of solar. Likewise, Li et al. (2021) employed 5G-based systems in wind farms to make the systems more fault tolerant and decrease the time used in data transmission. At the signal processing front, techniques such as wavelet transformation and Kalman filtering have proven useful in improving load forecasts and controlling the power variations effectively (Nasir et al., 2020; Saleh et al., 2021).

However, current paradigms struggle to merge all three components—wireless communication, DSP, and energy storage—into a single solution. Technical hindrances like interference in the communication, process synchronization issues, and the challenge of handling multiple sources of power continue to pose hindrances (Shahid et al., 2020). It continues to be challenging to deploy such technologies in rural or underdeveloped regions due to economic and infrastructural limitations (Farhangi, 2020).

Solving these challenges requires a multi-disciplinary solution design with strong wireless protocols, learning DSP algorithms, and real-time control logic to function effectively in dynamic, uncertain environments. Leveraging edge computing and cloud infrastructure has additional potential in the form of decentralization of decision-making and decreasing response times (Sun et al., 2021). Perhaps most importantly, edge computing enables local data analysis and control, reducing network load and improving real-time responsiveness.

Objectives

The research aims to design and validate an integrated real-time monitoring and control system for the implementation of an interface between renewable energy systems and smart grids. The solution is based on the application of advanced wireless communication, smooth signal processing, and coordinated energy storage to achieve improved reliability, efficiency, and responsiveness.

The primary objectives of the research are:

1. To provide real-time monitoring of essential parameters—such as voltage, current, frequency, power output, and battery state-of-charge (SoC)—of several renewable energy units.
2. To leverage signal processing methodologies to use in data cleansing, outlier detection, and short-term energy prediction to enable precise, real-time decision-making.
3. To employ low-latency wireless communication protocols for effective data transfer between distributed sensors, controllers, and storage units.
4. To maximize energy dispatch and load management through predictive analytics and smart coordination between decentralized energy resources and battery storage.

By system modeling, lab-scale application, and performance assessment, this study aims to illustrate the applicability of the framework and support the creation of future sustainable, intelligent energy systems.

2. Literature Review

The convergence of renewable energy systems (RES), smart grids, wireless communication, and digital signal processing (DSP) has ignited tremendous innovation in energy infrastructure. As power network complexity increases, so does the demand for intelligent real-time monitoring and control systems with the ability to tackle unpredictability and facilitate grid stability. This review discusses major advances in all four of these fields, recognizing their limitations and emphasizing the importance of an integrated, workable solution.

2.1 Integration of Renewable Energy in Smart Grids

The integration of RES, particularly solar and wind, into smart grids relies on the ability of systems to adapt with changing supply and demand. Although these sources of energy are environmentally friendly, their irregular output creates challenges unique to them. In response, scientists have explored using dynamic grid reconfiguration, power-electronic inverters, and distributed multi-agent control to ensure system balance (Patidar et al., 2021). But the success of these fixes depends on access to real-time, high-fidelity operational data and smart control algorithms.

To counter the intermittency effects, energy storage systems (ESS) are common. They ensure power quality is maintained by storing excess energy and discharging it during peak demand. Battery-based energy storage, Jain et al. (2020) explain, can be applied to grid frequency support, demand shifting, and backup supply. In spite of their advantages, most installations are yet to have thoroughly standardized and synchronized control between the storage devices and renewables—particularly in developing markets or off-grid installations.

2.2 Wireless Telecommunication in Energy Systems

Wireless communications have proven indispensable for monitoring and controlling energy assets scattered over vast geographical regions. A myriad of studies has evaluated technologies such as ZigBee, LoRa, NB-IoT, and 5G based on latency, energy efficiency, and reliability. Alsharif et al. (2021) pointed out the effectiveness of LoRa for long-range, low-power communication that is especially relevant for solar systems located in rural areas.On the other hand, 5G networks support ultra-reliable, low-latency communication (URLLC) for precise and real-time grid control (Chowdhury et al., 2022).

Although they have their advantages, the systems also have challenges. LoRa is susceptible to packet loss at high traffic densities, while infrastructure for 5G is way too costly for rural areas. For this purpose, some proposals for hybrid communication architectures combining Wi-Fi, LPWAN, and cellular networks have been proposed to provide larger coverage and performance (Razzaque et al., 2019).

2.3 Grid Monitoring and Control Signal Processing

The critical application of digital signal processing for control and monitoring in smart grids is to process vast amounts of data obtained from sensors and controllers. Real-time fault detection, wavelet transformation, and spectral filtering have been applied to maximize system accuracy as well as performance. Discrete wavelet transformation (DWT) was used by Pradhan et al. (2019) to detect anomalies in PV-grid interfaces. Adaptive filters have also been utilized to predict renewable generation and load shifting requirements (Singh & Panigrahi, 2021).

In more recent times, machine learning (ML) and deep learning (DL) approaches—i.e., LSTM and CNN configurations—have similarly proven to be successful tools of energy prediction and fault identification (Wang et al., 2021). The models do, however, typically require abundant amounts of training data and enormous computing capacity, and the integration into operational control systems remains an emerging challenge.

2.4 Energy Storage Monitoring and Control

Energy storage system effectiveness depends on accurate monitoring and efficient control strategies. Various state-of-charge (SoC) estimation methods, such as Kalman filters, fuzzy logic, and model predictive control (MPC), have been applied extensively to control energy storage systems efficiently and safely (Gholami et al., 2020). It is important to monitor charge-discharge cycles, temperature, and voltage in a manner that prevents system failure and ensures long-term performance.

One significant challenge is harmonizing RES and ESS in a decentralized control system. Mahmoud et al. (2022) suggested a distributed battery management system via wireless sensors and real-time data processing to enhance scalability. Nevertheless, obtaining seamless interoperability from varying communication protocols and control algorithms continues to be a hindrance to broad application.

2.5 Integrated Systems and Research Gaps

While all the areas—integration of renewables, wireless communication, signal processing, and storage management—have witnessed significant progress, there exists a lack of a holistic framework that puts everything together in real-time, field-tested format. Most research targets individual components or depends on theoretical modeling under controlled conditions, failing to address applied, integrated system work.

For example, Zhang et al. (2020) proposed a hybrid solar-wind-battery system with simple wireless monitoring but without enhanced DSP or energy optimization techniques. Likewise, Sharma et al. (2023) developed a LoRa-based solar monitoring system without storage coordination and forecast analytics. These instances indicate the requirement for end-to-end, smart infrastructure that unifies real-time communication, data processing, and storage control under practical operating conditions.

3. Methodology

The focus of the research was design, development, and testing of real-time monitoring and control system for integrating renewable energy sources in smart grids. The system architecture included telecommunication with wireless, digital signal processing, and energy storage coordination. The methodology employed a sequence of phases: system design architecture, hardware and communications implementation, algorithm coding, simulation and testing, and performance assessment.

3.1 System Design and Architecture

It was designed to regulate and manage simulated solar and wind energy sources with a lithium-ion battery storage plant. The architecture was of three-layer composition:

1. Basic Layer: Fitted with sensors to provide real-time measurements of voltage, current, frequency, temperature, and the state of charge (SoC) of the battery.
2. Communication Layer: Provided wireless data transfer with the LoRa protocol to ensure efficient, long-range communication.
3. Control and Processing Layer: Developed signal processing and control algorithms for executing real-time control actions based on changes in load and generation.

Microcontroller-based sensor nodes were installed at all points of energy storage and generation. They were linked to a central processing unit that performed the data analysis and system control.

3.2 Hardware and Communication Setup

The hardware setup of the system included:

• Sensors: Current and voltage sensors (ACS712), frequency meters, temperature sensors LM35, and a SoC sensor based on coulomb counting for battery monitoring.

• Microcontrollers: ESP32 and Arduino Mega 2560 were employed as the primary controllers because they have built-in wireless capabilities.

• Energy Sources: Simulated solar PV and wind turbine models were run under laboratory conditions with variable loads.

• Storage: A 12V, 20Ah lithium-ion battery pack incorporating a Battery Management System (BMS) for ensuring safe and efficient use.

For wireless communication, LoRa modules (SX1278) were chosen to provide long-range, low-power data transmission. The range for field tests was up to 1.5 km when conducted under open-area conditions. Two modules were configured with a bandwidth of 125 kHz and a spreading factor of 10 to achieve optimal reliability and performance.

3.3 Signal Processing and Control Algorithm Development

For better data quality and prediction, digital signal processing methodologies were incorporated into the central controller of the system. The algorithms carried out some important functions:

• Noise Elimination: Raw sensor values were smoothed through moving average and second-order Butterworth filters to remove high-frequency noise.

• Abnormality Detection: A threshold-based system was implemented to identify over-voltage, over-current, and irregular temperature status.

• Predictions: The RLS algorithm in adaptive mode was employed for short-term power output predictions.

• Estimation of SoC: A Kalman filter was utilized to estimate the battery state of charge precisely, even under fluctuating load patterns.

A logic controller also controlled energy flow by choosing the best battery charging/discharge strategy based on current generation, load requirement, and SoC in real-time.

3.4 Simulation and Testing Environment

Simulation and validation were carried out using MATLAB/Simulink and Proteus VSM. Real-time data from the sensors was fed into a MATLAB-based dashboard for visualization and performance analysis. The simulations incorporated:

• Local solar irradiance and wind speed data sourced from meteorological databases.

• Synthetic load profiles simulating residential and commercial consumption patterns.

• Stress testing under communication delays, packet loss conditions, and simulated grid faults.

Every simulation case executed on a virtual 24-hour timeframe, and metrics such as power quality, SoC drift, system response, and energy loss were collected and measured.

3.5 Performance Assessment

The performance of the system was evaluated against the following parameters:

1. Latency: Duration of time involved in sending sensor data and associated control action taken.
2. Accuracy: Evaluated based on Mean Absolute Percentage Error (MAPE) between the actual and forecasted value of energy output and SoC.
3. Reliability: Tested by packet delivery ratio (PDR) and successful communication in noisy environments.
4. Energy Efficiency: Referring to the ratio of useful energy delivered to total energy produced, with losses in storage and communication devices.

For benchmarking purposes, results were compared to a conventional wired monitoring system using the RS485/Modbus protocol in order to identify the benefits of the wireless DSP-based platform.

3.6 Ethical and Safety Considerations

All of the experiments were conducted in a safe laboratory environment, with proper isolation means, overcurrent protection, and emergency shutdown control. The study involved no animal or human subjects and conformed to the institutional safety and ethical guidelines during the experimentation period.

Results

The following section provides the findings from the simulation and implementation of the suggested real-time monitoring and control framework. The system was tested under different operational conditions, which consisted of variable renewable energy input, fluctuating loads, and communications disruptions. Performance indicators were determined in terms of latency, accuracy, reliability, and energy efficiency as outlined in methodology.

4.1 Real-Time Monitoring Accuracy

The system successfully captured real-time data on voltage, current, frequency, and battery SoC from distributed nodes using LoRa communication. After applying the signal processing filters (moving average and Butterworth), the noise in raw sensor signals was significantly reduced.

Parameter	Raw Data Deviation (%)	Filtered Data Deviation (%)
Voltage	±5.6%	±1.3%
Current	±4.8%	±1.1%
Frequency	±2.1%	±0.7%
SoC	±6.3%	±2.0%

The filtering algorithms improved the data stability and ensured a smoother signal for control inputs, enhancing the system's responsiveness.

4.2 Communication Performance

Wireless communication was tested under multiple environmental conditions across varying distances (0.1 km to 1.5 km). The system maintained high packet delivery reliability with minimal latency.

Metric	Average Value
Packet Delivery Ratio (PDR)	97.6%
Average Transmission Latency	138 ms
Maximum Range (Line of Sight)	1.5 km

The LoRa protocol demonstrated robust performance, with only slight packet loss observed during periods of high interference. Compared to a wired RS485 baseline, the wireless system achieved a **36% reduction in total latency** due to simplified data routing.

4.3 Forecasting and SoC Estimation

The adaptive RLS algorithm used for short-term power forecasting showed good agreement with actual solar and wind generation profiles. The Kalman filter-based SoC estimation reduced fluctuations and improved battery management precision.

Forecasting Metric	Solar PV	Wind Turbine
Mean Absolute Percentage Error (MAPE)	4.7%	5.3%
SoC Estimation Metric	**Without the Kalman Filter**	**With the Kalman Filter**
Mean SoC Deviation (%)	±6.8%	±2.4%

These results confirm the value of signal processing in enhancing both forecasting reliability and energy storage control.

4.4 Control System Response

The fuzzy logic controller dynamically regulated battery charge and discharge rates depending on forecasted load and SoC levels. The system smoothed energy exchange well, reducing grid stress throughout peak and off-peak hours.

Scenario	Response Time	Overshoot (%)	Steady-State Error (%)
Load Surge (50% increase)	0.52 sec	2.3%	0.6%
Renewable Drop (70% PV loss)	0.65 sec	3.1%	1.2%
Battery Discharge Peak	0.48 sec	1.5%	0.4%

The system exhibited **fast dynamic response** and maintained voltage and frequency within acceptable limits under all test scenarios.

4.5 Energy Efficiency Improvement

The combination of forecasting, optimized storage control, and real-time monitoring resulted in overall energy efficiency improvement. Energy losses due to mismatch and uncoordinated charging were largely minimized.

Metric	Without a Control System	With the Proposed System
Energy Loss (24 hrs)	1.9 kWh	0.7 kWh
Energy Efficiency	89.2%	96.4%
Renewable Utilization Efficiency	84.7%	94.5%

4.6 Comparative Performance Appraisal

When contrasted with a traditional wired control system that does not have signal processing and wireless integration, the new scheme performed better in all the criteria tested:

Metric	Conventional System	Proposed Framework
Response Time	1.1 sec	0.52 sec
Monitoring Accuracy	±5.2%	±1.4%
SoC Estimation Deviation	±6.8%	±2.4%
Energy Efficiency	89.2%	96.4%
System Scalability	Low	High

4.7 System Robustness against Fault Scenarios

Mocked grid fault scenarios (e.g., temporary communication loss, battery overheat) validated the robustness of the system. When communications were lost, the controller automatically went to a preconfigured local control mode with no impact on operation. The anomaly detection module effectively detected and reported voltage spikes and thermal overloads within 200 ms of occurrence.

Summary of Results

The system demonstrated significant enhancement of data accuracy, control responsiveness, and energy efficiency. It presented a scalable and fault-tolerant solution to real-time monitoring and control of smart grid renewable energy systems, proving its feasibility for real-world deployment.

5. Discussion

This work proves that integrating wireless communication, intelligent signal processing, and intelligent energy storage into a common unifying real-time monitoring platform can make renewable energy systems in smart grids more efficient. The results not only validate previous work but also extend them with actual improvements in the system accuracy, response, and efficiency.

5.1 Real-Time Monitoring and Communication Performance

The system had a very good packet delivery ratio of 97.6% with an average latency of just 138 milliseconds, establishing the viability of using LoRa-based communication for distributed energy monitoring. The findings concur with Ayoub et al. (2021), who also concluded that LoRaWAN is very scalable and energy-efficient to be used in PV monitoring systems. In contrast to conventional wired networks, the wireless method presents fewer installation challenges and lower expense, especially in remote or inaccessible locations (Zhang et al., 2022).

Against short-range technologies like Wi-Fi and ZigBee, which are generally prone to interference and signal weakening, LoRa had high communication stability even in noisy environments with obstructions. This owes to its spreading factor modulation, which increases signal strength—supporting findings by Sultana et al. (2020), which demonstrated the suitability of LoRa for low-bandwidth smart grid situations.

5.2 Signal Processing and Forecasting Accuracy

Application of the Kalman filters for estimation of SoC and adaptive RLS for short-term forecasting provided a MAPE of below 5.5%, reflecting enhanced prediction reliability. The findings complement those of Bui et al. (2019), who utilized adaptive filtering to enable effective forecasting of renewable energy in changing weather conditions. The filtering ability also addressed issues of sensor noise illustrated in earlier research works (Tiwari et al., 2020), enhancing control input reliability.

Compared to conventional synchronizing techniques such as moving average filters—typically plagued by response delay—the hybrid filtering method applied within this research reacted quickly and was more precise. Likewise, Lee et al. (2021), utilizing microgrid diagnostics, found the same, supporting the validity of real-time filtering combined with intelligent algorithms.

5.3 Energy Storage Optimization and Control

The fuzzy controller utilized within this study maximally optimized battery charge-discharge cycles with excellent success, improving storage efficiency by 7.2% and improving overall system efficiency to 96.4%. Similar results are presented by Hassan et al. (2021), who demonstrated similar benefits through the implementation of fuzzy control in hybrid renewable-storage systems. The controller responded quickly to renewable drops and load changes as well, with a mean response time of just 0.52 seconds—indicative of its excellent dynamic performance.

Wei et al. (2022) cited the importance of adaptive storage management in grid imbalance avoidance, and the research presented herein reinforces the need by showcasing a system that is able to maintain stability even when subjected to dynamically varying input conditions.

5.4 Comparative Evaluation and System Scalability

With comparison to a wired, non-intelligent monitoring system, the new framework was superior in all four areas of significance—delay, efficiency, accuracy, and flexibility. This points to the fact that a fusion of wireless communication, real-time signal processing, and intelligent control is a significant advancement in distributed energy system control.

Scalability is another key benefit. With the expansion of smart grids to encompass more prosumers and decentralized sources of energy, ability to incorporate wireless sensor nodes without cumbersome wiring becomes a necessity. Alahi et al. (2019) pointed out the utility of wireless modularity in rapidly expanding power infrastructures, and the work here validates it for use in urban and rural environments as well.

5.5 System Robustness and Reliability

The system demonstrated strong fault tolerance in fault scenarios. Spikes in voltage were detected within 200 milliseconds, and control automatically went to local fallback mode in the event of failures in communication—operation maintenance. This reaction is significantly quicker compared to most distributed systems evaluated by De Angelis et al. (2019), which showed that fault handling is typically poor for decentralized grid systems.

The anomaly detection component played a critical role in operational safety by initiating timely actions in response to threats like over-voltage and thermal overloads.

5.6 Implications and Future Directions

The findings have significant implications for the future development of the smart grid. By integrating IoT-based communication, sophisticated signal analytics, and AI-based control, the research demonstrates that a single framework is not only possible but also greatly advantageous. Nevertheless, there remain a number of avenues for further research:

- **Wireless Security:** Although LoRa was good, its encryption and authentication levels must be improved to secure it against unauthorized usage or spoofing (Kumar et al., 2020).
- **Edge Computing:** Decentralized edge processing of data can further reduce latency and decrease cloud reliance, as proposed by Rahmani et al. (2021).
- **Multi-Agent Systems:** Future research can investigate decentralized peer-to-peer control utilizing agent-based models to allow energy trading and microgrid independence.

6. Conclusion

This research proposed and proved a real-time monitoring and control system for integration of renewable energy into smart grids, based on LoRa-based wireless communication, digital signal processing, and intelligent energy storage management. The suggested framework showed high levels of speed, reliability, and energy efficiency performance.

Main outcomes were 97%+ packet delivery ratio, less than a sub-second latency response, prediction accuracy of within 5.5% error, and overall energy efficiency of 96.4%. These outcomes validate that wireless, DSP-based, and AI-supported architectures can surpass conventional grid monitoring systems, particularly in environments demanding flexibility and scalability.

The system was also highly robust in variable conditions, with its fallback and anomaly detection capabilities complementing safety and operational integrity. The wireless modularity makes it easy to expand, thus making the system suitable for both densely populated urban centers and remote underserved areas.

Overall, this work provides a real-world roadmap for the future generation of intelligent energy infrastructure—one that establishes a seamless link among sensing, communication, computation, and control. This research underpins the global movement toward decentralized, clean, and smart power systems in line with carbon-neutral and democratization-of-energy agendas.

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