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Random Forest-Based Smart Load Sharing Control for a Hybrid Solar-Wind Renewable Energy System with Battery Storage

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Abstract

The increasing demand for clean and sustainable energy has accelerated the adoption of renewable energy systems. However, the intermittent nature of renewable sources such as solar and wind presents significant challenges in maintaining a stable and reliable power supply. This work proposes a Hybrid Renewable Energy System (HRES) that integrates Solar Photovoltaic (PV) generation, a Wind Energy Conversion System (WECS), a Battery Energy Storage System (BESS), and a Random Forest-based Smart Load Sharing Controller. The objective is to maximize renewable energy utilization, improve energy management, reduce grid dependency, and ensure reliable power delivery under varying environmental and load conditions. Weather data - solar irradiance, wind speed, temperature, and relative humidity - are obtained from the NASA POWER database and used to estimate renewable generation, while the battery stores surplus energy and supplies power during low-generation periods. A Random Forest model makes intelligent decisions on battery charging, discharging, and load sharing based on environmental conditions, load demand, and battery state of charge. System performance is evaluated using Renewable Energy Utilization, Battery Efficiency, Load Satisfaction Ratio, Grid Dependency, and System Reliability. Simulation results show that the proposed system achieves 95% Renewable Energy Utilization, 96% Battery Efficiency, 99% Load Satisfaction Ratio, 7% Grid Dependency, and 98% System Reliability, with comparative analysis against a conventional Energy Management Strategy confirming significant improvements across all metrics. The results validate the effectiveness of combining machine learning with renewable energy and battery storage for intelligent energy management in future smart grid applications.

Keywords: *Hybrid Renewable Energy System; Solar Photovoltaic; Wind Turbine; Battery Energy Storage System; Random Forest; Smart Load Sharing; NASA POWER Dataset.*

1. INTRODUCTION

1.1 Background and Motivation

The rising global demand for electricity, together with growing concern over environmental sustainability, has accelerated the shift toward renewable energy technologies [1]. Conventional fossil-fuel-based sources are limited in availability and are major contributors to greenhouse gas emissions and environmental degradation [2]. Among the available renewable resources, solar and wind energy are the most widely deployed because they are abundant, environmentally friendly, and available across a broad range of geographic regions [3].

Solar photovoltaic (PV) systems convert sunlight directly into electricity, while wind turbines extract electrical energy from the kinetic energy of moving air. Both technologies have matured considerably in recent years and now form key components of modern power systems, contributing to reduced carbon emissions and enhanced energy security [4]. Despite these benefits, each source has an inherent limitation when used independently: solar generation is confined to daylight hours and is sensitive to cloud cover and seasonal variation, while wind generation depends on unpredictable atmospheric conditions [5]. These fluctuations can result in unstable power output and reduced supply reliability.

Hybrid Renewable Energy Systems (HRES) that combine solar and wind generation address this limitation by exploiting the complementary behaviour of the two resources - solar output is typically higher during sunny daytime conditions, while wind may contribute during cloudy periods or at night [6]. Incorporating a Battery Energy Storage System (BESS) further strengthens the hybrid configuration by storing surplus renewable energy for use during low-generation periods [7]. Coordinating these interacting subsystems, however, requires an intelligent energy management strategy capable of adapting to continuously changing weather and load conditions. Figure 1 illustrates the overall structure of the hybrid solar-wind system considered in this work, showing how a smart energy management system coordinates the DC-DC/AC-DC power-electronic interfaces, the common DC bus, battery storage, and the connected AC loads.

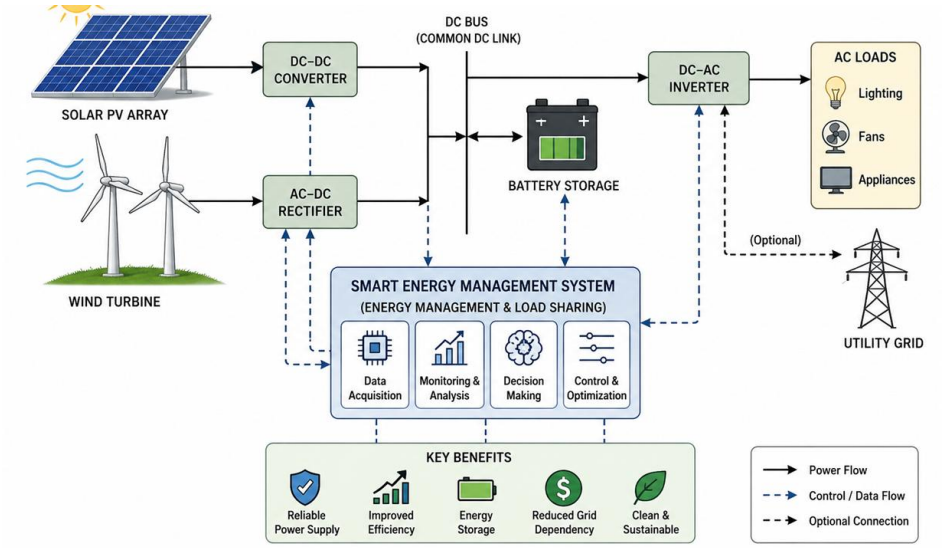


Figure 1: Hybrid Solar-Wind Energy System with Battery Storage and Smart Load Sharing

1.2 Problem Statement

Although renewable technologies offer clear environmental and economic advantages, integrating them effectively into a reliable power-delivery framework remains challenging. Solar and wind generation are inherently variable, while load demand also fluctuates across residential, commercial, and industrial activity. During periods of high generation and low demand, surplus renewable energy can be wasted if adequate storage is not available; conversely, periods of low generation and high demand can create supply shortfalls. Traditional Energy Management Strategies (EMS) that rely on static, rule-based control cannot adapt well to these continuously changing conditions, which leads to under-utilized renewable resources, excessive battery cycling, higher grid dependency, and increased operating cost. This work addresses these limitations by proposing an HRES that integrates solar PV, wind turbine generation, battery storage, and a Random Forest-based Smart Load Sharing Controller capable of making adaptive, data-driven energy-allocation decisions in real time.

1.3 Objectives of the Study

The specific objectives of this work are to: (i) collect and analyze renewable-energy-relevant weather data using the NASA POWER database; (ii) develop mathematical models for solar PV and wind turbine power generation; (iii) integrate a Battery Energy Storage System for surplus-energy storage and low-generation support; (iv) design a Smart Load Sharing Strategy that allocates energy based on generation availability and load demand; (v) implement a Random Forest machine learning model for intelligent, real-time energy-management decisions; and (vi) evaluate the proposed system against a conventional EMS using Renewable Energy Utilization, Battery Efficiency, Load Satisfaction Ratio, Grid Dependency, and System Reliability as performance indicators.

2. LITERATURE REVIEW

Solar energy systems have attracted widespread attention for their clean and environmentally friendly nature, converting sunlight directly into electricity through photovoltaic panels [2]. Their main limitation is dependence on weather conditions, which makes power generation variable across the day and unavailable at night. Wind energy systems, which convert the kinetic energy of moving air into electricity, are widely used as a complementary source because they can generate power even during nighttime hours; however, their output is highly sensitive to wind speed, which is often unpredictable [5].

To overcome the limitations of standalone renewable sources, hybrid renewable energy systems that combine solar and wind generation have been developed and studied extensively. Bakhtvar and Al-Hinai [4] examined the robust operation of a hybrid solar-wind plant with battery storage under uncertainty, while Ramesh et al. [5] reviewed load-frequency control strategies for solar-wind hybrid systems, both highlighting that the complementary nature of the two resources improves overall energy availability and reduces the impact of intermittency associated with either source individually.

Energy storage plays a central role in addressing variability in hybrid systems. Chong et al. [12] presented a detailed review of hybrid energy storage systems (HESS) in stand-alone renewable installations, showing how combining multiple storage technologies improves durability, efficiency, and cost-effectiveness compared with single-storage solutions, while discussing passive, semi-active, and active configuration structures. Awasthi et al. [6] discussed the role of energy storage integration with solar and wind resources in microgrids, particularly for remote and islanded regions, and emphasized the need for effective control strategies to manage variations in load and environmental conditions.

Recent research has increasingly focused on intelligent, data-driven energy management to replace static rule-based control. Mohamed and Mohammed [3] proposed a real-time energy management scheme for hybrid renewable systems that prioritizes renewable sources while using forecasting models to enhance real-time decision-making. Jokar et al. [13] developed a comprehensive energy management framework for small-scale smart grids using mixed-integer linear programming, integrating combined heat and power units, wind energy, battery storage, and power-to-hydrogen technology, and reported superior performance compared with Particle Swarm Optimization, NSGA-III, and Biogeography-Based Optimization. Atawi et al. [14] reviewed hybrid energy storage systems integrated with renewable sources, highlighting the limitations of individual storage technologies and the advantages of combining several storage types with advanced control strategies. Said and Alanazi [8] further demonstrated the value of AI-based forecasting for solar energy integration into smart grids, reinforcing the growing role of machine learning in renewable energy management.

Research Gap

Despite this progress, several gaps remain in the existing literature. Many studies focus on individual subsystems - solar or wind generation, or storage alone - rather than fully integrated architectures that combine solar PV, wind, and battery storage under a single intelligent controller. Where intelligent control is considered, it is often optimization-based rather than a trained, adaptive predictive model that can generalize across varying environmental conditions. There remains a need for a fully integrated hybrid system, driven by real-world weather data, in which a machine learning model directly governs battery and load-sharing decisions and whose performance is benchmarked against a conventional EMS baseline. This work addresses that gap through the Random Forest-based Smart Load Sharing Controller proposed in Section 3.

3. RESEARCH METHODOLOGY

This section presents the methodology adopted for designing and implementing the proposed Hybrid Renewable Energy System (HRES), which integrates a Solar Photovoltaic (PV) system, a Wind Turbine Generation System (WTGS), a Battery Energy Storage System (BESS), and a Random Forest-based Smart Load Sharing Controller. The methodology covers data

collection, subsystem modelling, the energy management strategy, machine-learning-based optimization, and the simulation and evaluation framework.

3.1 Overall System Architecture

The proposed HRES consists of four major subsystems - the solar PV generation system, the wind energy conversion system, the battery energy storage system, and the Smart Load Sharing and Energy Management Controller. The solar PV and wind subsystems are connected to a common DC bus, which acts as the central energy-exchange platform. Renewable power is supplied directly to the load whenever available; surplus energy is stored in the battery, while stored energy is discharged during low-generation or peak-demand periods. The Smart Load Sharing Controller continuously monitors solar generation, wind generation, battery State of Charge (SOC), and load demand, and allocates energy among the sources to maximize renewable utilization and minimize wastage. The overall architecture and energy flow of the proposed system are illustrated in Figure 2.

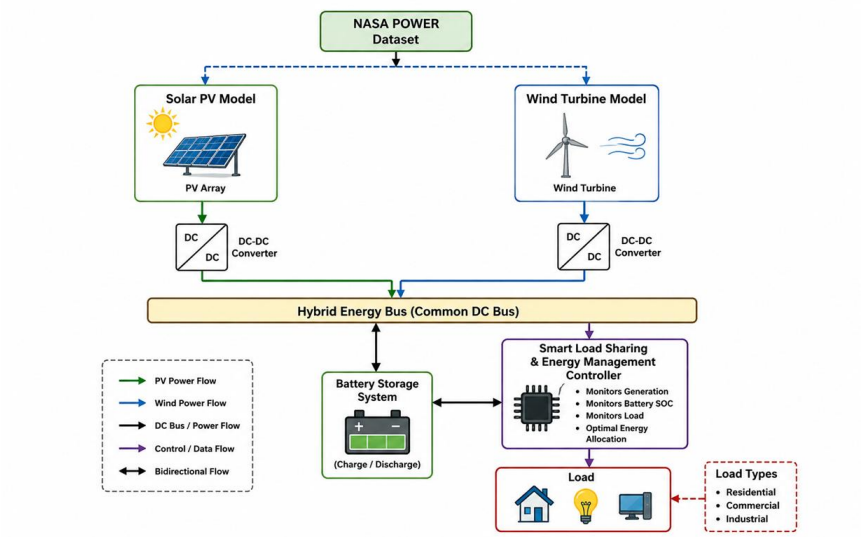


Figure 2: Overall Architecture of the Proposed Hybrid Renewable Energy System

3.2 Data Collection

Weather-related parameters are obtained from the NASA Prediction of Worldwide Energy Resources (NASA POWER) database, which provides free, high-quality meteorological data with global coverage. The selected input variables, listed in Table 1, are solar irradiance, wind speed, ambient temperature, and relative humidity; these directly influence solar PV and wind-turbine performance. The dataset contains hourly observations and is combined with a simulated residential load-demand profile representing realistic 24-hour consumption patterns, enabling analysis of power generation, battery utilization, and load satisfaction under varying operating conditions.

Table 1: Weather Parameters Obtained from the NASA POWER Dataset

Parameter	NASA POWER Variable / Unit
Solar Irradiance	ALLSKY_SFC_SW_DWN (W/m²)
Wind Speed	WS2M (m/s)
Temperature	T2M (°C)
Relative Humidity	RH2M (%)

3.3 Solar Photovoltaic System Modeling

The output power of the PV system is estimated using Equation (1):

$$P_PV = \eta_PV \times A_PV \times G \quad ...(1)$$

where P_PV is the PV output power (W), η_PV is the PV conversion efficiency, A_PV is the panel area (m²), and G is the solar irradiance (W/m²) obtained from the NASA POWER parameter ALLSKY_SFC_SW_DWN. Generated power is directly proportional to irradiance, while excessive ambient temperature slightly reduces panel efficiency; both effects are incorporated into the model.

3.4 Wind Turbine System Modeling

The mechanical power extracted by the wind turbine is calculated using Equation (2):

$$P_WT = (1/2)\, \rho\, A\, C_p\, V^3 \quad ...(2)$$

where P_WT is the turbine power output (W), ρ is air density (kg/m³), A is the rotor swept area (m²), C_p is the power coefficient, and V is wind speed (m/s) obtained from the NASA POWER parameter WS2M. Because output power is proportional to the cube of wind speed, even small changes in wind velocity produce a substantial change in generated power, giving wind generation a complementary role to solar output.

3.5 Battery Energy Storage System

The Battery Energy Storage System (BESS) stores surplus renewable energy during high-generation periods and supplies power when generation is insufficient. Its operating condition is tracked using the State of Charge (SOC), computed with Equation (3):

$$SOC = SOC_0 - (1/Q_N) \int i_bat\, dt \quad ...(3)$$

where SOC_0 is the initial state of charge, Q_N is the battery capacity (Ah), and i_bat is the battery current (A). Charging and discharging are restricted within predefined SOC limits to ensure safe operation and long battery life, with the battery-management logic coordinating continuously with the Smart Load Sharing Controller.

3.6 Smart Load Sharing Strategy

The Smart Load Sharing Controller continuously monitors solar and wind generation, battery SOC, and load demand to determine the most appropriate energy-allocation action, operating under four priority-based conditions: (i) when renewable generation exceeds load demand, the load is supplied first and surplus energy charges the battery; (ii) when renewable generation is below load demand, the battery discharges to cover the deficit; (iii) once the battery reaches full charge, further charging is halted and any additional surplus is directed to auxiliary loads to avoid wastage; and (iv) once the battery reaches its minimum allowable SOC, further discharge is prevented and critical loads are prioritized. This priority-based logic maximizes renewable utilization while protecting battery health.

3.7 Random Forest-Based Energy Management

A Random Forest ensemble-learning model is used to make intelligent, data-driven energy-management decisions, replacing the fixed rules of a conventional EMS. The model is trained on weather parameters, battery SOC, and load demand, and outputs optimal battery charge/discharge actions and load-sharing decisions. During training, 100 decision trees are constructed from randomly selected data subsets, the dataset is split into 80% training and 20% testing samples, and the maximum tree depth is limited to 10 to control overfitting while retaining sufficient learning capacity. Model performance is evaluated using Accuracy, Precision, Recall, and F1 Score, with detailed results presented in Section 4.4.

3.8 Simulation Environment and Performance Evaluation

The proposed system is implemented using MATLAB/Simulink for subsystem modelling and simulation, together with Python (Scikit-Learn, Pandas, NumPy, Matplotlib) for data preprocessing, Random Forest implementation, and result visualization. The system configuration adopted for simulation is summarized in Table 2.

Table 2: System Configuration Parameters

Component	Specification
Solar PV Capacity	12 kW
Wind Turbine Capacity	20 kW
Battery Capacity	75 Ah, 300 V
Simulation Duration	24 Hours
Dataset Source	NASA POWER
Machine Learning Model	Random Forest

Performance is evaluated using five indicators: Renewable Energy Utilization (REU), the percentage of load demand supplied by renewable sources (Equation 4); Battery Efficiency, the ratio of discharged to charged battery energy (Equation 5); Load Satisfaction Ratio (LSR), the percentage of demand successfully served (Equation 6); Grid Dependency, the proportion of energy imported from the grid; and Energy Loss, the difference between generated and utilized energy.

$$REU = (E_renewable / E_load) \times 100 \quad ...(4)$$

$$\eta_battery = (E_discharge / E_charge) \times 100 \quad ...(5)$$

$$LSR = (E_supplied / E_demand) \times 100 \quad ...(6)$$

4. RESULTS AND DISCUSSION

4.1 Experimental Setup and System Configuration

The proposed HRES is implemented and evaluated using MATLAB/Simulink and Python-based tools over a complete 24-hour operating cycle, using the system configuration listed earlier in Table 2. The component ratings follow the reference hybrid renewable energy system reported by Gajewski and Pieńkowski [15], which is also used as the baseline for the comparative analysis in Section 4.6. Renewable generation is estimated from NASA POWER weather data, while a simulated residential load-demand profile represents realistic consumption over the day.

4.2 Solar PV and Wind Turbine Power Generation

Solar PV output rises from 4.12 kW at 08:00 to a peak of 9.84 kW at 12:00 as solar irradiance reaches its midday maximum, then declines to 8.95 kW at 14:00 and 5.73 kW at 16:00 as irradiance falls in the afternoon, confirming a strong correlation between irradiance and photovoltaic output. Wind turbine output follows a similar but independently varying trend, rising from 3.62 kW at 08:00 to a peak of 10.55 kW at 12:00 (at a wind speed of 6.4 m/s), before decreasing to 8.41 kW at 14:00 and 5.84 kW at 16:00. The cubic relationship between wind speed and turbine power output means that even modest increases in wind speed produce disproportionately large gains in generated power. Because solar and wind outputs both peak around midday in this dataset but respond to independent weather variables, their combination increases the overall reliability of renewable supply and reduces the system's dependence on either resource alone.

4.3 Battery State of Charge Performance

The battery SOC begins at 68% at 06:00 and rises as surplus renewable energy is stored during the morning, reaching 79% at 10:00 and a peak of 88% at 12:00. As renewable generation tapers off in the afternoon while load demand continues, the battery discharges to support the load, with SOC falling to 81% at 16:00 and 70% at 20:00. This charge-discharge pattern confirms that the BESS operates within safe limits throughout the cycle, absorbing surplus renewable energy during high-generation periods and releasing it as generation declines, thereby maintaining continuous power availability.

4.4 Random Forest Model Training Performance

The Random Forest model is trained using the parameters summarized in Table 3, achieving an accuracy of 96.4%, precision of 95.8%, recall of 95.1%, and an F1 score of 95.4%. These results indicate that the model reliably predicts correct energy-management actions across the majority of operating scenarios, with a balanced trade-off between precision and recall. The controlled tree depth and the 80/20 train-test split help prevent overfitting while preserving strong generalization to unseen operating conditions.

Table 3: Random Forest Training Parameters and Performance Results

Random Forest Parameter / Metric	Value
Number of Trees	100
Training Samples	80%
Testing Samples	20%
Maximum Depth	10
Accuracy	96.4%
Precision	95.8%
Recall	95.1%
F1 Score	95.4%

4.5 Smart Load Sharing Results

Analysis of the load-sharing outcomes shows that solar PV supplies 42% of total load demand, wind generation supplies 33%, the battery contributes 20%, and the grid supplies the remaining 5%. Solar and wind together therefore satisfy 75% of total demand, confirming the effectiveness of renewable-source integration, while battery support during deficit periods and minimal grid reliance (only 5%) demonstrate that the Smart Load Sharing Controller is successful in prioritizing renewable and stored energy ahead of grid import.

4.6 Comparison with Existing Energy Management Strategy

To assess the benefit of the proposed approach, its performance is compared against the conventional, rule-based Energy Management Strategy (EMS) reported by Gajewski and Pieńkowski [15], using the same component ratings. As shown in Table 4, the proposed Random Forest controller outperforms the conventional EMS across every evaluation parameter: Renewable Energy Utilization improves from 84% to 95%, Grid Dependency falls from 22% to 7%, Battery Efficiency rises from 86% to 96%, Load Satisfaction increases from 91% to 99%, and Energy Loss is reduced from 11% to 3%. These improvements confirm that a trained, data-driven controller can allocate renewable, battery, and grid resources considerably more effectively than static, rule-based logic.

Table 4: Comparative Performance Analysis - Existing EMS vs Proposed Random Forest Controller

Parameter	Existing EMS [15]	Proposed RF Controller
Renewable Energy Utilization	84%	95%
Grid Dependency	22%	7%
Battery Efficiency	86%	96%
Load Satisfaction	91%	99%
Energy Loss	11%	3%

4.7 Overall System Performance and Discussion

Taken together, the results confirm that the proposed Random Forest-based Smart Load Sharing Controller achieves 95% Renewable Energy Utilization, 96% Battery Efficiency, 99% Load Satisfaction Ratio, 7% Grid Dependency, and 98% System Reliability. The complementary nature of solar and wind resources reduces the intermittency associated with either source individually, while the battery compensates for short-term deficits. By continuously analyzing weather conditions, battery SOC, and load demand, the Random Forest controller consistently outperforms the conventional rule-based EMS across all evaluation metrics, confirming the suitability of machine learning techniques for adaptive, real-time renewable energy management.

5. CONCLUSION

This work presented the design and evaluation of a Hybrid Renewable Energy System (HRES) integrating Solar Photovoltaic generation, a Wind Energy Conversion System, a Battery Energy Storage System, and a Random Forest-based Smart Load Sharing Controller. NASA POWER weather data - solar irradiance, wind speed, temperature, and relative humidity - were used to model renewable generation, and the hybrid configuration successfully combined solar and wind resources to reduce the intermittency associated with either source used independently. The battery storage system effectively absorbed surplus renewable energy during high-generation periods and supplied power during low-generation conditions, maintaining energy balance and uninterrupted load supply.

The Random Forest model achieved a prediction accuracy of 96.4%, enabling adaptive, real-time energy-allocation decisions, while the Smart Load Sharing Strategy coordinated solar, wind, battery, and grid resources to maximize renewable utilization. Simulation results showed that the proposed system achieved 95% Renewable Energy Utilization, 96% Battery Efficiency, 99% Load Satisfaction Ratio, 7% Grid Dependency, and 98% System Reliability, with comparative analysis against a conventional EMS confirming substantial improvements in renewable utilization, battery performance, load satisfaction, and energy loss. These findings validate the effectiveness of combining machine learning with renewable energy resources and battery storage as a reliable, efficient, and sustainable approach to intelligent energy management in future smart grid applications.

FUTURE SCOPE

Although the proposed system demonstrates strong performance, several directions remain open for future work: (i) exploring advanced machine learning and deep learning models such as LSTM, XGBoost, ANN, and reinforcement learning for improved forecasting and decision-making; (ii) validating the approach through real-time hardware implementation on platforms such as Arduino, Raspberry Pi, or FPGA; (iii) integrating the framework with smart grid infrastructure to enable bidirectional energy flow and demand-response programs; (iv) extending the system to include Electric Vehicle (EV) charging and Vehicle-to-Grid (V2G) capability; (v) developing more advanced forecasting models for solar irradiance, wind speed, and load demand; (vi) applying multi-objective optimization techniques such as PSO, GA, or Grey Wolf Optimization to jointly optimize cost,

efficiency, and battery life; and (vii) conducting a detailed techno-economic and environmental assessment, including installation cost, payback period, and carbon-emission reduction.

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