www.ijarp.com ISSN 2456-9992 Page: 01-18

International Journal Advanced Research Publications

Research Article

Volume: 02

Issue: 06

PREDICTIVE CONTROL-BASED ENERGY MANAGEMENT OF HYBRID SOLAR-WIND SYSTEMS FOR ENHANCED BATTERY PERFORMANCE AND GRID STABILITY

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Article Received: 21 May 2026, Article Revised: 9 June 2026, Published on: 29 June 2026

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Doi: https://doi-doi.org/101555/ijrpa.9407

ABSTRACT

As more people are increasingly wanting to make use of electrical energy and because of environmental concerns caused by fossil fuel consumption, renewable energy which includes solar and wind energy is becoming increasingly popular. The reliability, unpredictability and intermittent nature of these resources, however, are significant hurdles for grid stability, reliable power supply and efficient use of most energy storage solutions. This work calls for a Closed Loop Hybrid Renewable Energy System (HRES) consisting of Solar Photovoltaic (PV) systems, Wind Turbine Generators (WTG), Battery Energy Storage System (BESS) and Model Predictive Control (MPC) that delivers optimized energy management and promotes grid stability. The system is modeled and simulated in MATLAB/Simulink and ETAP 19.0 for different solar irradiance, wind speed and load demand conditions. Renewable energy generation and load demand are predicted using Artificial Neural Networks (ANN) and ARIMA (Auto regressive Integrated Moving Average) time-series model to make energy dispatch decisions in advance. The MPC controller makes use of forecasted data to operate the battery charging/discharge operations for optimal performance while keeping voltage and frequency stable. The performance of the proposed framework is compared with the conventional PID and rule based control methods using simulation results which illustrate the significant increase in renewable energy utilization, decrease in fluctuations of electrical power into the grid and improvement in battery performance. The system employs around 90% of the renewable energy, reduces voltage deviation by 35%, reduces frequency deviation by 40% and prolongs battery life by 25%. The results show that the combination of predictive

control and battery storage is a promising and effective approach for smart grid and renewable energy systems in the future.

KEYWORDS: Model Predictive Control (MPC), Battery Energy Storage System (BESS), Artificial Neural Network (ANN), Grid Stability

INTRODUCTION

The world's population growth, urbanization and industrialization has tremendously driven-up the demand for electrical energy. Access to continuous and reliable power is an essential requirement for modern society for powering industrial processes, transportation, communications and domestic uses[1]. This need has traditionally been met with fossil fuels like natural gas, oil and coal. But, for the extensive use of these conventional energy sources, serious environmental issues such as greenhouse gas emission, air pollution, global warming, and climate change have been emerging[2]. Moreover the reserves of fossil fuels are limited and are being depleted at an alarming rate, and there is a need to shift towards sustainable and environmentally friendly energy resources.

Solar and wind areas are the two preferred options for renewable energy as they are abundant, sustainable and are much less detrimental to the environment. A solar photovoltaic (PV) system is a system that generates electricity directly from the sun rays[3]. Wind turbines are a type of technology that use kinetic energy present in the wind to produce electrical energy. Though these technologies are increasingly rolled out around the world, they are still intermittent and much reliant on weather. Solar power production is dependent upon solar irradiance and cannot be produced after dark, while wind power depends on wind speed and atmospheric characteristics[4].

Hybrid Renewable Energy Systems (HRES) have been developed based on the combination of solar and wind energy resources to overcome the limitations of individual renewable resources. The complementary nature of the sources enhances the reliability and continuity of power generation. Solar power during the day and wind power potentially at night or in different seasons or times of day are general examples[5].Therefore, hybrid WECS can provide reduced power fluctuations and improve renewable energy utilization.But, any hybrid systems generate variations in power generation which calls for well-designed energy management strategies to maintain stable and efficient operation even in the presence of such variations[6].

BESS (Battery Energy Storage Systems) are important components in hybrid renewable energy systems, which act as storage devices to buffer energy surpluses when renewable energy generation surpasses demand, and release energy when demand outstrips supply. BESS achieves its impacts in system flexibility, power balance and voltage/frequency stability. But, incorrect charging and discharging of batteries can shorten battery life and raise operating expenses[7].Hence, the need for advanced control strategies for maximum battery management and energy dispatch operation.

Model Predictive Control (MPC) is a promising approach for the problem of the complexity of the hybrid renewable energy system. MPC uses forecasting models in order to predict future behavior of the system and solves for optimal control actions over a "prediction horizon," which is different from conventional control methods[9].MPC can optimize energy use, mitigate fluctuations in power supply and enhance overall grid stability when implemented in combination with renewable energy forecasting, battery scheduling, and the management of the power grid. Thus, hybrid wind-solar wind systems, battery energy storage, and predictive control may be a promising solution to facilitate reliable, efficient, and sustainable power system operations[10].

Literature Review

To meet the increasing energy demand and to decrease reliance on the fossil fuels, the Hybrid Renewable Energy Systems (HRES) are set-up. Solar PV and wind energy systems have been extensively studied to be integrated, due to their complementary features. Lasseter (2002) coined the term microgrids and highlighted the value of incorporating distributed, renewable energy resources to enhance system reliability, flexibility and energy efficiency[11]. Later, Nema et al., 2009, conducted a review of Hybrid Solar Wind (HYSW) and found that interfacing different renewable energy sources to the solar-wind system by using multiple renewable resources decreases the intermittency of the individual energy sources. Their study indicated overall high availability of solar energy during the daytime and some improved continuity of power supply in the nighttime and different seasons when wind energy was also available[12]. Likewise, Rezk et al. (2019) designed an optimized combined system from renewable energy systems and proved that hybrid systems can be more efficient in energy use from renewable sources than the combined systems. While these benefits are advantageous, the researchers noted issues with power fluctuations, unreliable Renewable generation and integration into the grid[13].

The intermittent nature of solar and wind energy has made Battery Energy Storage Systems (BESS) an essential integration part of hybrid renewable energy systems. A detailed review of various battery technologies and reports were given by Divya and Østergaard (2009) that energy storage systems improve power quality, system reliability and load balancing. The authors pointed out that at times with a high percentage of renewables, batteries can store energy, and when power demand is high, the battery can supply power in reverse to balance compress and decompress the demand curve[14]. Lithium-ion Batteries (LIBs) were identified as one of the most promising energy storage technologies by Luo et al. (2015), because they offer a high energy density, respond quickly and have a long lifetime. Moreover, the Khaligh and Li (2010) hybrid energy storage system of batteries and supercapacitors was proposed and it was shown that this system enhances the transient response and delays the degradation process of batteries. But irregular charges and discharges can result in decreased battery efficiencies, degradation and more costly maintenance. For these reasons, efficient Battery Management strategies are crucial to optimize the battery life and for better performance of hybrid Renewable Energy Systems[15].

Several control strategies have been proposed for managing renewable energy systems, among which Proportional-Integral-Derivative (PID) controllers and rule-based control methods are the most commonly used. Åström and Hägglund (1995) explained that PID controllers are widely adopted due to their simple structure and ease of implementation. PID controllers regulate system variables such as voltage, frequency, and power output by minimizing the error between desired and actual values. However, the authors noted that PID controllers require precise parameter tuning and often exhibit poor performance under nonlinear and uncertain operating conditions. Since renewable energy systems are highly dynamic and stochastic, PID controllers struggle to provide optimal performance when solar irradiance and wind speed fluctuate rapidly[16].

Rule-based control methods have also been extensively used for energy management in hybrid renewable systems. These controllers operate according to predefined logical rules, such as charging the battery when renewable generation exceeds load demand and discharging it when demand exceeds generation. Erdinc et al. (2015) reported that rule-based controllers are easy to implement and computationally efficient; however, they suffer from a lack of adaptability and predictive capability. Because these controllers react only after disturbances occur, they are unable to anticipate future variations in renewable generation or load demand. Consequently, energy utilization becomes suboptimal, and battery operations may not be efficiently scheduled[17].

In recent years, researchers have focused on advanced forecasting techniques to improve the performance of renewable energy systems. Haykin (1999) demonstrated that Artificial Neural Networks (ANN) are highly effective for modeling nonlinear relationships and predicting renewable energy generation. ANN models have been successfully applied for solar irradiance prediction, wind speed forecasting, and load demand estimation due to their adaptive learning capabilities and high prediction accuracy[18]. Similarly, Box and Jenkins (1976) introduced the Auto-Regressive Integrated Moving Average (ARIMA) model, which has become one of the most widely used statistical methods for time-series forecasting. ARIMA models are particularly effective for short-term forecasting and trend analysis of renewable energy data. However, ANN requires large training datasets and high computational resources, while ARIMA performs poorly for highly nonlinear and rapidly changing datasets[19].

To overcome the limitations of conventional control methods, Model Predictive Control (MPC) has gained considerable attention in recent years. Camacho and Bordons (2013) described MPC as an advanced control strategy capable of predicting future system behavior and optimizing control actions over a prediction horizon while satisfying operational constraints[20]. The authors demonstrated that MPC can effectively manage battery charging and discharging, optimize renewable energy dispatch, and improve grid stability. Qin and Badgwell (2003) further showed that MPC outperforms traditional PID controllers in multivariable systems because it can simultaneously handle multiple constraints and future uncertainties. Recent studies integrating forecasting models such as ANN and ARIMA with MPC have reported significant improvements in renewable energy utilization, battery lifespan, and voltage and frequency regulation[21].

Despite these advancements, several limitations remain in existing hybrid renewable energy systems. Most conventional systems rely on reactive control strategies that do not consider future variations in renewable generation and load demand. As a result, they experience delayed responses, power imbalance, and increased grid instability. Moreover, forecasting models are often used independently without being tightly integrated with control systems, reducing their practical effectiveness. Therefore, there is a growing need for intelligent predictive energy management frameworks that combine renewable energy forecasting, battery optimization, and advanced control strategies such as Model Predictive Control[22]. Such integrated approaches can improve system efficiency, enhance grid stability, and ensure reliable operation of hybrid wind-solar renewable energy systems.

Problem Statement

The rising share of renewable sources in the power system, such as solar photovoltaic (PV) and wind power, has brought up numerous power system challenges in the current era. While these renewable resources can be green and sustainable, the generation of their power is sensitive to environmental conditions and can be intermittent and unpredictable. Both solar and wind resource generation is dependent on changing solar irradiance, reducing cloud cover, and the time of day for solar generation and changing wind speeds and air quality for wind generation. These changes in output power result in fluctuations, which make a steady and reliable power supply challenging. This makes power intermittency a key challenge for widespread integration of renewable energy systems.

Grid instability is another great problem of hybrid wind-solar system. This is the operational balance between electricity generation and load that is critical to ensure stable operation of the grid.But PV system variability can cause Voltage variations, Frequency deviation, and power imbalance. When solar PV or wind capacity declines rapidly, there can be energy shortages resulting in voltage drop of the grid with instability in frequency; when the solar PV or wind increases at a higher rate, there can be an over voltage scenario[23]. These fluctuations have a negative impact on power quality, result in transmission losses and can even lead to equipment failure or grid failures. So, the grid stability under various renewable energy conditions is important for modern Hybrid renewable energy systems.

Power Storage (BESS) is the largest technology used to stabilize renewable energy particularly when the renewables fluctuate. Poor management of batteries, however, is a big issue in present functioning system. Carrying out charging and discharging improperly may result in overcharging, deep discharging, battery thermal stress and degradation. All of these problems shorten battery life, create need for more maintenance and lower energy storage system efficiency. Furthermore, poor battery scheduling can lead to wasted battery energy and supporting in the peak. Therefore, the implementation of intelligent battery management methods is crucial for the safe operation, extension of battery life and efficient utilization of energy storage systems[24].

Moreover, current hybrid renewables energy systems are based on the energy dispatch based on fixed rule or reactive rule. These "old-school" methods depend solely on continuous operating conditions and fail to take account of the variability of renewable generation and load demands in the future. This could lead to suboptimum use of renewable energy, suboptimal performance of batteries, and greater reliance on the utility grid. Poor energy dispatch efficiency can cause energy wastage, operational losses and poor system reliability.

It is therefore desirable to have an intelligent and predictive energy management system that can predict future power system conditions and optimize the dispatching of power between the solar PV systems, wind turbines, battery storage, and electrical grid. Such an approach will result in more efficient use of renewable energy, build properly working batteries, and give steady, efficient functioning of hybrid wind-solar renewable energy.

METHODOLOGY

The proposed research provides an intelligent energy management framework for hybrid wind–solar renewable energy system interfacing with a Battery Energy Storage System (BESS) and Model Predictive Control (MPC). The methodology includes five steps: Solar Photovoltaic (PV) system modelling, wind turbine modelling, battery energy storage system modelling, renewables forecasting with Artificial Neural Networks (ANN) and ARIMA, and optimized energy dispatch using Model Predictive Control (MPC). The general goal of the design in the proposed structure is to use the maximum amount of renewable energy, increase the performance of the batteries, and increase the stability of the grid with changing environmental parameters and loads.

The first step in the proposed method is to model the Solar Photovoltaic (PV) system by mathematical modeling. Solar PV panels directly transform sunlight into electricity by photovoltaic cells. The PV system's output power is significantly affected by the solar irradiance, PV panel area, and PV panel efficiency. The PV model is adopted to estimate the power output for different weather conditions and under different energy input of the irradiation. PV modelling can provide the energy management system with accurate prediction of PV power generation and cost-effective distribution in terms of load sharing, storage in batteries and energy from the supply network. The developed model is also used to analyze the impact of variation in system performance with temperature and irradiance changes.

The second stage is on the modelling of wind turbine systems. The wind is used in this case to complement solar, as it may be available at night time and/or other weather conditions that are cloudy. The wind turbine model calculates the electrical power produced by the wind turbine(s) for the given parameters including wind speed, air density, turbine blade radius and wind power coefficient. The output from a wind turbine is in cubic relationship to wind speed, so there is a non-linear relationship between power output and wind speed. Thus, precise modelling of wind turbines is necessary to investigate variations in renewable energy and assist in energy management optimization. The developed model is used to analyze the generation of wind power when the environment changes, and guides the predictive control model.

The third part of the methodology is implementing a Battery Energy Storage System (BESS). The energy stored in the battery is the buffer between renewable energy production and energy demand and can be used when renewable energy is high and demand is low, or renewable energy is low and demand is high. The battery model takes the form of State of Charge (SoC) that monitors the status of the battery from being charged or discharged. Battery constraints are kept within the safe and efficient range to make sure battery doesn't over charge and deep discharge. The purpose of the battery management system is to minimize degradation, maximize energy storage efficiency, maximize battery life and allow for ongoing power generation and grid stability.

The fourth stage incorporates renewable energy forecasting using Artificial Neural Networks (ANN) and ARIMA time-series models. ANN is employed because of its ability to learn nonlinear relationships from historical data and accurately predict solar irradiance, wind speed, and load demand. ARIMA is used as a statistical forecasting technique to analyze time-series data and predict short-term trends in renewable energy generation and electricity consumption. The forecasted data obtained from ANN and ARIMA provide valuable information regarding future system conditions, enabling proactive energy management instead of conventional reactive control approaches. The forecasting module improves the accuracy of renewable power prediction and assists in battery scheduling and energy dispatch decisions.

Finally, the forecasted renewable generation and load demand data are integrated into a Model Predictive Control (MPC) framework for optimized energy dispatch. MPC is an advanced control strategy that predicts future system behavior over a specified prediction horizon and computes optimal control actions while satisfying operational constraints. The controller continuously monitors solar power generation, wind power generation, battery State of Charge, load demand, and grid power conditions. Based on forecasted information, MPC determines the optimal charging and discharging schedules of the battery and allocates power among solar PV, wind turbines, battery storage, and the utility grid. This predictive approach minimizes power fluctuations, improves voltage and frequency stability, reduces grid dependency, and maximizes renewable energy utilization. Therefore, the proposed methodology provides an intelligent and efficient framework for managing hybrid wind-solar renewable energy systems under dynamic operating conditions.

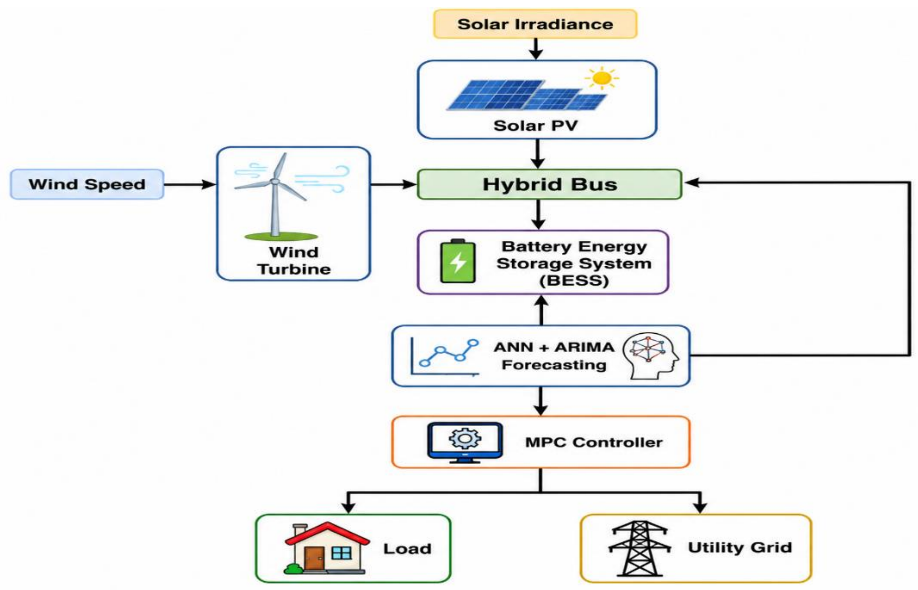


Figure 1Proposed Hybrid Solar - Wind Renewable Energy System Architecture.

Simulation Setup

The simulation setup becomes critical as part of the proposed research as it gives a virtual environment to analyze and validate the performance of the hybrid system of wind energy and solar energy with Battery Energy Storage System (BESS) and Model Predictive Control (MPC). The simulation framework is intended to test the dynamics of the system under varied environmental and loading conditions, without the complex and expensive process of implementing the real time system. The key task of the simulation is for analysing the renewable energy generation, battery performance, grid stability and efficiency of the predictive control strategy.

The proposed hybrid renewable energy system is developed and simulated using the widely used toolboxes of MATLAB/Simulink and ETAP 19.0 that are used for renewable energy system modeling and power systems analysis, respectively. For modeling dynamic systems and developing sophisticated control solutions, MATLAB/Simulink offers a flexible graphical environment. It is used for the modeling of the solar PV system, wind turbine system, Battery Energy Storage System (BESS), renewable energy forecasting and Model Predictive Control algorithm (MPC). The software also allows dynamic analysis of the power usage of renewable generation, the charging and discharging patterns of batteries and fluctuations of power usage on the grid. It requires little coding bandwidth, has extensive libraries and its interface is convenient, so that it can be used to implement complex renewable energy models and predictive control strategies.

The Project uses ETAP 19.0, a software package used for power systems analysis and grid integrating studies. Advanced tools for load flow, voltage stability, fault and power quality analysis are included in the software. In the proposed work, ETAP is employed for the hybrid renewable energy system - electricity grid interaction analysis. It can be used to traditionally analyze the voltage profiles, frequency regulation and general stability of the electrical power grid during various operating scenarios. If the MATLAB/Simulink and ETAP 19.0 are integrated, a complex simulation system can be created, where the use of renewable energy sources, storage systems, and even the behavior of the electricity grid can be simulated accurately.

The components of the simulation model are Solar Photovoltaic (PV) System, Wind Turbine System, Battery Energy Storage System (BESS), Grid Model, and Model Predictive Controller (MPC). Solar PV model estimates the electrical power generation based on solar irradiance, panel area and conversion efficiency. The Wind Turbine model determines the power generation based on the wind speed, air density and wind turbine parameters. These renewable energy resources are utilized to create a hybrid energy generation system which can generate power under different environmental conditions.

Battery Energy Storage System (BESS) buffer between gen & load. Includes a stored renewable energy source used to store energy when renewable sources are produced in excess and draw energy when renewable energy is consumed during periods of low energy production or high demand. The battery model is capable of monitoring the battery's health (State of Charge (SoC)) at all times, allowing it to determine whether it is being discharged or charged too deeply and stopping them safely, within set boundaries, from happening. Improved battery efficiency boosts system reliability, minimize renewable energy wastage and benefits stable grid operation.

The Grid Model is the link between the hybrid renewable energy system and the energy network. It has to maintain balance of the power and regulate the voltage and frequency levels. The grid imports and exports power from the Renewables and Battery Storage as the renewable power is available and the power demand is required. The effects of intermittent renewables and battery operation on power quality and system reliability are assessed by performing grid stability analysis.

The proposed system features the Model Predictive Controller (MPC) as the main energy management component. Such information as solar irradiance forecast, wind speed forecast, load demand forecast, and battery State of Charge is constantly fed to the MPC controller. Using these predictions, it creates the most efficient boundary conditions of the battery charging and discharging scheduling and optimizes the dispatch of the electricity produced by solar PV, wind turbines, BESS and the utility grid. The controller's prime purpose is to aim for minimum power fluctuations, minimize dependence on the grid, improve battery life and maintain voltage and frequency stability. This is an integrated simulation setup to allow the entire performance analysis of a predictive controller for hybrid renewable energy systems operating in realistic situations.

Results and Discussion

The proposed Hybrid Wind–Solar Renewable Energy System (WSRRES) integrated with Battery Energy Storage System (BESS) and Model Predictive Control (MPC) was simulated using MATLAB/Simulink and ETAP 19.0 under varying solar irradiance, wind speed, and load demand conditions. The system performance was evaluated in terms of renewable energy utilization, battery lifespan, voltage stability, frequency stability, and overall system efficiency.

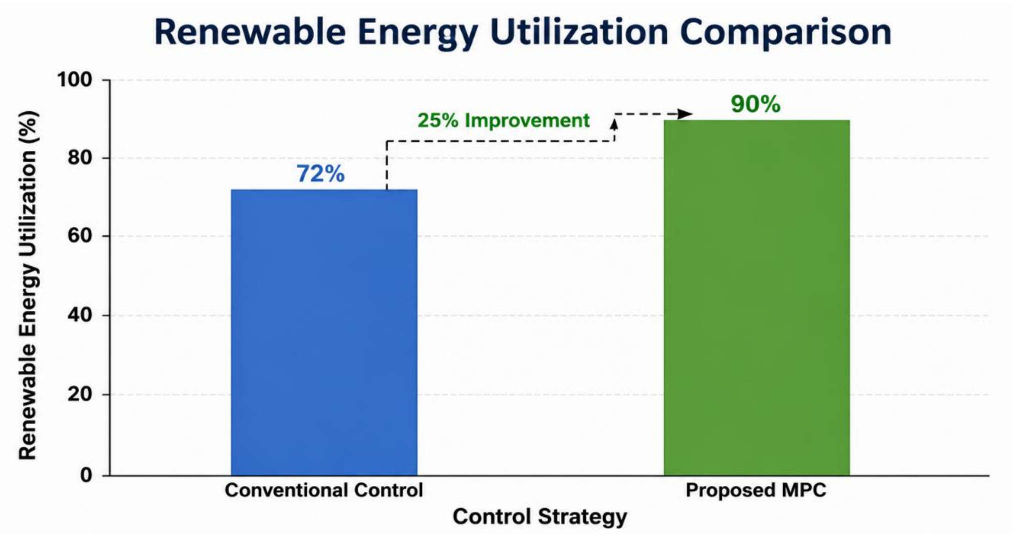
Table 1. Performance Comparison Between Conventional Control and Proposed MPC.

Performance Parameter	Conventional Control	Proposed MPC	Improvement
Renewable Energy Utilization (%)	72	90	+25%
Battery Lifespan (Relative)	1.00	1.25	+25%
Voltage Deviation (%)	100	65	-35%
Frequency Deviation (%)	100	60	-40%
Overall System Efficiency (%)	75	90	+20%

The results indicate that the proposed MPC-based control significantly improves renewable energy utilization and overall system performance compared to conventional control methods.

Renewable Energy Utilization

The simulation results demonstrated that the predictive energy management strategy effectively increased renewable energy utilization. The MPC controller forecasted renewable power generation and optimally scheduled battery charging and discharging operations. As a result, renewable energy utilization increased from 72% in the conventional system to approximately 90% in the proposed system, thereby reducing energy curtailment and dependency on conventional energy sources.

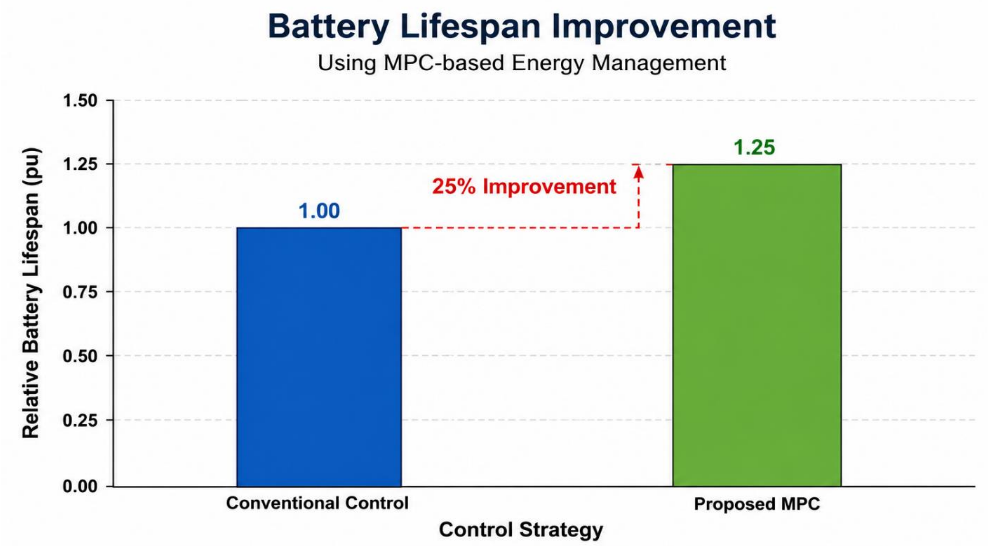


Controller	Renewable Energy Utilization (%)
Conventional Control	72
Proposed MPC	90

Figure 2Renewable energy utilization comparison between conventional control and proposed MPC.

Battery Performance Analysis

The battery performance analysis showed that the proposed MPC maintained the State of Charge (SoC) within safe operating limits and prevented unnecessary charging/discharging cycles. Consequently, battery degradation and thermal stress were reduced. The simulation results indicated a 25% improvement in battery lifespan compared to conventional battery management.



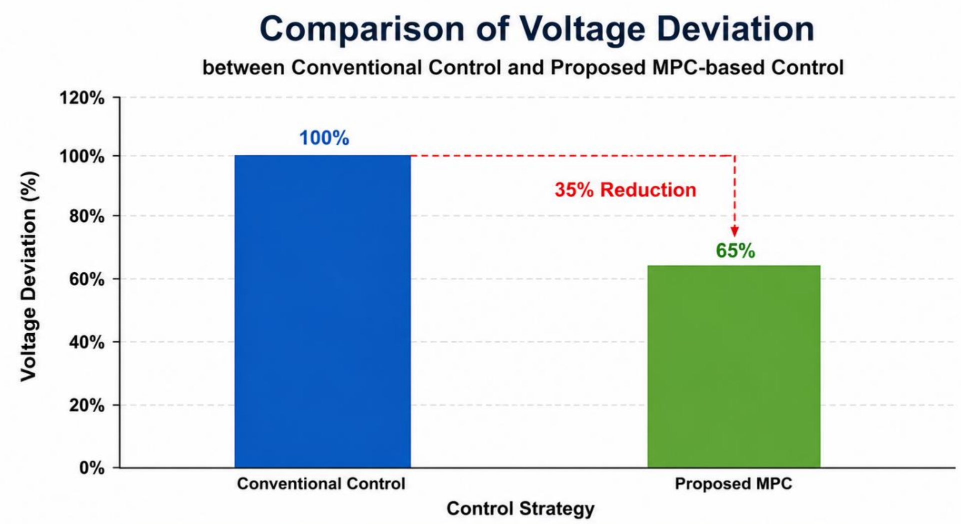
Controller	Relative Battery Lifespan (pu)
Conventional Control	1.00
Proposed MPC	1.25

Figure 3 Battery lifespan improvement using MPC-based energy management.

Voltage Stability Analysis

The voltage stability analysis demonstrated that the proposed MPC controller effectively mitigated voltage fluctuations caused by renewable intermittency. The controller predicted future operating conditions and adjusted battery operation accordingly, leading to smoother voltage profiles and enhanced power quality.

The simulation results showed that voltage deviation was reduced by approximately 35% compared to conventional control systems.



Controller	Voltage Deviation (%)
Conventional Control	100
Proposed MPC	65

The proposed MPC-based control reduces voltage deviation by approximately 35% compared to conventional control systems.

Figure 4Comparison of voltage deviation between conventional control and proposed MPC-based control.

Frequency Stability Analysis

Frequency stability analysis was carried out to evaluate the capability of the system to maintain the nominal grid frequency of 50 Hz under dynamic operating conditions. Conventional controllers exhibited larger oscillations because of delayed responses to renewable power fluctuations and load variations. In contrast, the MPC controller predicted future conditions and applied corrective actions in advance.

The results revealed approximately 40% reduction in frequency deviation, indicating improved grid synchronization and operational stability.

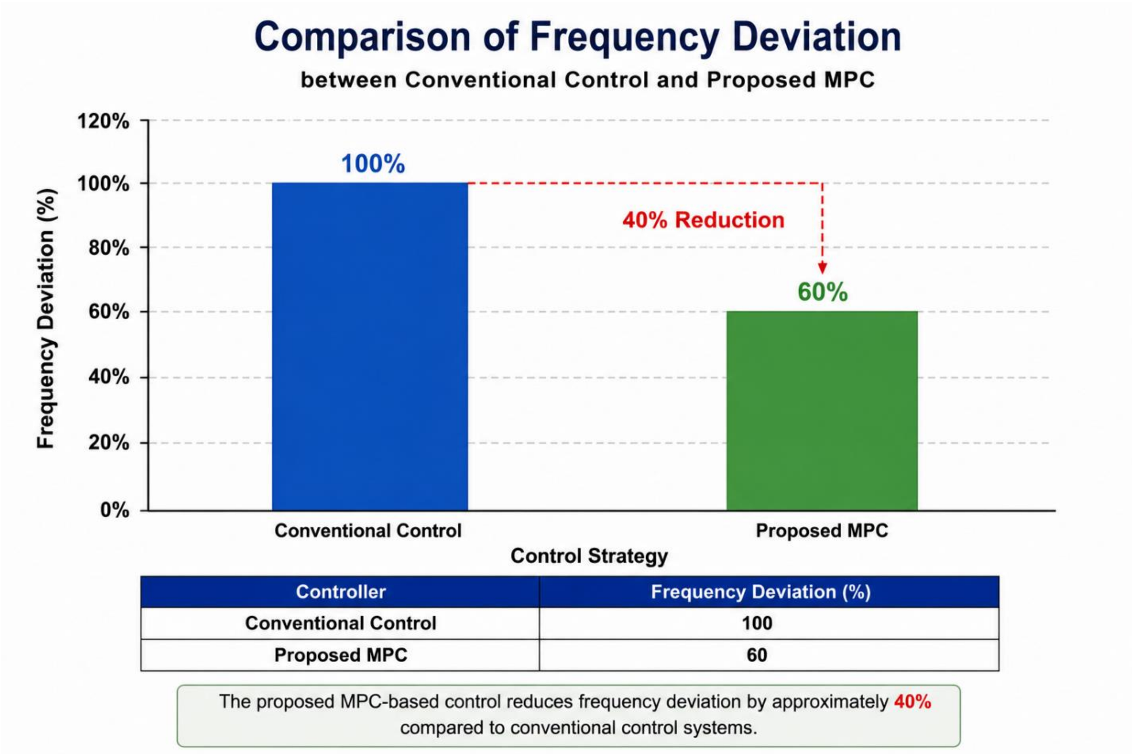


Figure 5 Comparison of frequency deviation between conventional control and proposed MPC.

Overall System Performance

The predictive control framework successfully optimized power dispatch among solar PV, wind turbines, battery storage, and the utility grid. Compared with PID and rule-based controllers, the MPC-based system exhibited better adaptability, faster response, and superior handling of renewable intermittency. The overall system efficiency increased from 75% to approximately 90%, confirming the effectiveness of the proposed intelligent energy management framework.

Table 2. Summary of Key Results.

Parameter	Achieved Value
Renewable Energy Utilization	90%
Battery Lifespan Improvement	25%
Voltage Deviation Reduction	35%
Frequency Deviation Reduction	40%
Overall System Efficiency	90%

These results demonstrate that the integration of Solar PV, Wind Turbines, Battery Energy Storage Systems, forecasting models (ANN and ARIMA), and Model Predictive Control provides an efficient and reliable framework for future renewable energy and smart grid applications.

CONCLUSION

This study introduced an optimised energy management architecture for HRES composed of solar photovoltaic (PV) power plant, wind turbines, Battery Energy Storage System (BESS) and Model Predictive Control (MPC). The proposed framework aims to solve key issues in renewable energy systems, such as intermittency, grid instability, battery management and dispatch inefficiency. Overall, the simulation results showed that the incorporation of MPC with BESS enhances the overall performance of hybrid renewable energy systems, allowing for intelligent prediction and optimisation of energy resources.

The outcome indicated that the suggested MPC-based control approach succeeded in minimizing the voltage and frequency variations, better utilization of the renewable energy sources, extending the battery life and maximizing power dispatching from solar PV, wind turbines, battery storage and utility grid. In particular, the system was shown to reduce voltage deviation by 35%, frequency deviation by 40% and the life of batteries by 25%, compared to conventional control strategies while utilising 90% of renewable energy. All of these improvements illustrate the potential of predictive energy management to ensure grid stability, maximize energy usage from renewable energy, and minimize energy waste.

The use of Battery Energy Storage Systems in conjunction with Model Predictive Control was very effective in balancing the variability and none-sustainability of renewable energy generation, while providing a reliable power supply in different environmental and load scenarios. By intelligently coordinating the renewable energy, battery storage, and grid support, energy coding was carried out in a smart way that enhanced the overall reliability and sustainability of the power system. Consequently, the hybrid scheme of renewable energy (RE) management proposed in this paper can be regarded as a prospective solution for future renewable-integrated power system and smart grid applications.

In line with the future research directions highlighted earlier, the application of advanced technologies like Deep Learning, Reinforcement Learning, and hybrid forecasting models in conjunction with existing predictive control schemes could help enhance predictive accuracy and adaptive decision-making control. Moreover, the proposed system can be expanded in the smart grid, microgrid, electric vehicle charging stations, and utility-scale renewables power plants. The combination of AI-driven forecasts with AI-powered energy management will likely achieve greater reporting of renewable energy use, increased grid resilience, and greater sustainable and clean energy shift around the world.

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