

Unified Neural Network–Based MPPT Control For Grid-Independent Hybrid PV–Wind Systems With Adaptive Energy Management

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Abstract -The increasing demand for reliable off-grid renewable energy systems necessitates advanced control strategies capable of managing multi-source variability and dynamic load conditions. This paper proposes a unified Artificial Neural Network (ANN)-based Maximum Power Point Tracking (MPPT) strategy for a standalone hybrid photovoltaic (PV)–wind–battery energy system. Unlike conventional hybrid configurations that employ separate MPPT controllers for each renewable source, the proposed approach utilizes a single intelligent ANN framework to simultaneously coordinate and optimize power extraction from both PV and wind subsystems, thereby eliminating control redundancy and enhancing dynamic response.

The hybrid system comprises a 2032 kW PV array, a 2600 kW wind turbine generator, and a lithium-ion battery bank rated at 300 V and 6500 Ah. A dynamic three-phase load of 1500 kW, with an additional 1000 kW step increase at 4.5 s, is considered to evaluate system adaptability. Power exchange between renewable sources and storage is regulated using a bidirectional DC–DC converter, while a three-level Neutral-Point-Clamped (NPC) inverter maintains a regulated 550 V DC-link voltage and delivers high-quality AC output.

MATLAB/Simulink simulation results demonstrate that the unified ANN-MPPT controller achieves rapid convergence to the maximum power point, stable DC-link voltage regulation, inverter efficiency exceeding 96%, and output voltage total harmonic distortion below 2% under varying environmental and load conditions. The coordinated control framework ensures prioritized load supply while dynamically managing battery charging and discharging to maximize renewable energy utilization.

The proposed unified architecture offers a simplified yet high-performance solution for standalone hybrid renewable systems, improving energy conversion efficiency, system stability, and scalability for remote and off-grid applications. Although validated through detailed simulations, experimental verification will be required to further confirm real-time performance.

Keywords -Hybrid PV-Wind System, ANN MPPT, Unified Control, Battery Storage, NPC Inverter, DC-AC Load Sharing, MATLAB Simulation.

1. Introduction

The continuous increase in global energy demand, coupled with environmental concerns and the gradual depletion of fossil fuel resources, has accelerated the transition toward renewable energy technologies. Among available alternatives, photovoltaic (PV) and wind energy systems have emerged as mature and widely deployed solutions due to their sustainability, modularity, and declining installation costs [1], [2]. However, the inherent intermittency and stochastic nature of solar irradiance and wind speed introduce significant power fluctuations, which can adversely affect system stability and reliability, particularly in standalone and remote applications.

To enhance supply continuity and resource utilization, hybrid renewable energy systems (HRES) integrating PV and wind sources have been extensively investigated [8], [9]. The complementary characteristics of solar and wind energy profiles enable improved generation consistency compared to single-source systems. Several studies

have addressed optimal sizing, configuration, and control of hybrid PV–wind systems to improve reliability and efficiency [8]–[10]. Nevertheless, effective power extraction from multiple renewable sources under dynamically varying environmental conditions remains a critical technical challenge.

Maximum Power Point Tracking (MPPT) plays a central role in ensuring optimal energy harvesting from renewable generators. Conventional MPPT algorithms such as Perturb and Observe (P&O) and Incremental Conductance (INC) are widely adopted due to their simple implementation and low computational requirements [1], [3]. However, these techniques often exhibit steady-state oscillations around the operating point and reduced tracking performance during rapid atmospheric variations [2], [6]. Such limitations become more pronounced in hybrid systems where coordinated control of multiple energy sources is required.

In recent years, artificial intelligence (AI)-based MPPT approaches have gained considerable attention due to their capability to model nonlinear system dynamics and adapt to environmental uncertainties [4]. Artificial Neural Networks (ANNs), in particular, have demonstrated improved convergence speed, enhanced tracking accuracy, and superior robustness compared to traditional algorithms [4], [7]. AI-driven strategies have also been explored for hybrid renewable configurations and microgrid applications to enhance coordinated control and energy management [5], [10], [21]. Despite these advancements, many reported hybrid PV–wind systems continue to employ separate MPPT controllers for each renewable subsystem, resulting in increased hardware complexity, redundant control structures, and higher implementation cost [8], [21].

In addition to MPPT control, efficient integration of battery energy storage and power conversion stages is essential for maintaining system stability. Bidirectional DC–DC converters enable controlled charging and discharging of battery banks, facilitating energy balancing between generation and load demand [12], [14]. Furthermore, multilevel inverter topologies, particularly the Neutral-Point-Clamped (NPC) inverter, have been widely adopted in medium- and high-power applications due to their reduced voltage stress, improved harmonic performance, and higher efficiency [15]–[17]. Effective coordination between renewable sources, storage systems, and power electronic converters is therefore necessary to ensure reliable standalone operation.

Although several studies have addressed ANN-based MPPT for individual PV or wind systems [4], [7], and others have investigated hybrid system control strategies [8], [10], comprehensive research focusing on a unified ANN-based MPPT framework capable of simultaneously managing both PV and wind subsystems within a single coordinated control architecture remains relatively limited. The development of such a unified controller has the potential to reduce system redundancy, simplify implementation, and enhance dynamic adaptability in hybrid renewable configurations.

To address these challenges, this paper proposes a unified ANN-based MPPT control strategy for a standalone hybrid PV–wind system integrated with battery storage and a three-phase AC load. The main contributions of this work are as follows:

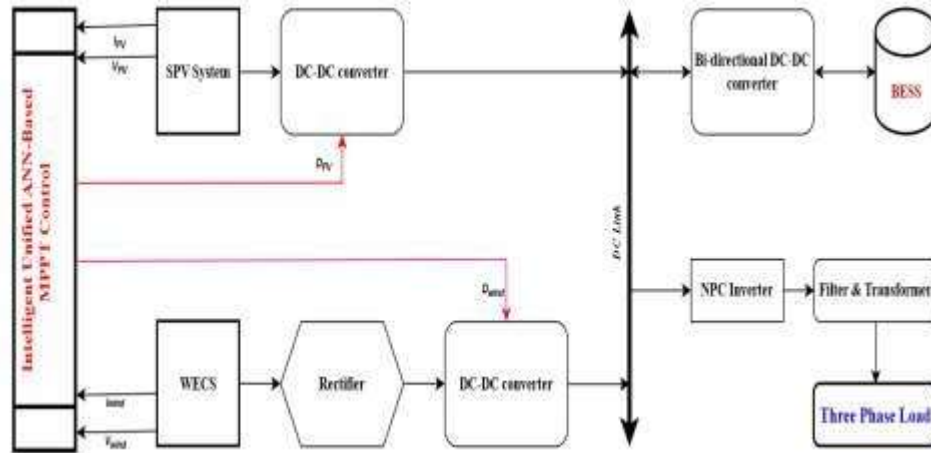
1. Development of a single ANN-based MPPT controller capable of coordinated maximum power extraction from both PV and wind subsystems within a unified framework.
2. Integration of a bidirectional DC–DC converter for effective battery energy management and seamless power balancing.
3. Implementation of a three-level NPC inverter to ensure regulated DC-link voltage and high-quality AC output.
4. Comprehensive performance evaluation through MATLAB/Simulink simulations under varying environmental and load conditions, with benchmarking against

conventional MPPT techniques.

By reducing dual-controller redundancy and incorporating intelligent coordinated control, the proposed architecture enhances system adaptability, improves energy utilization efficiency, and provides a scalable solution for standalone and remote hybrid renewable energy applications.

The complete outline diagram of the proposed work has been depicted in figure 1.

Figure 1. Block diagram of the proposed work



The remainder of this paper is organized as follows:

Section 2 details the system configuration, including specifications of the PV modules, wind turbine, battery storage and load parameters.

Section 3 discusses the design and implementation of the unified ANN-based MPPT controller.

Section 4 presents the simulation setup and results, analyzing the controller's performance under various scenarios.

Section 5 concludes the study and suggests directions for future research

2. Hybrid System Configuration

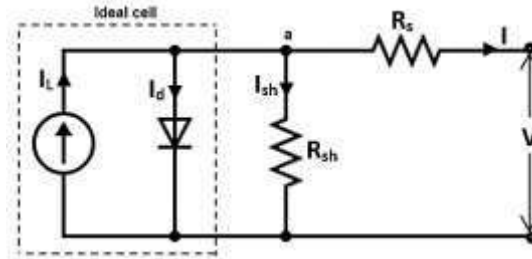
This section provides an overview of the hybrid renewable energy system, comprising PV modules, a wind turbine, battery storage and a three-phase AC load. The system configuration is designed to ensure efficient energy generation, storage and consumption by seamlessly integrating PV and wind power sources, with the battery serving as a backup to manage fluctuations in energy production and demand. The specifications of each component, including the PV system, wind turbine, battery and load are detailed below to provide a comprehensive understanding of the system's architecture and operational parameters.

2.1 Description of PV system Parameters

As illustrated in Figure 1, a unified ANFIS-based MPPT controller is implemented to optimally manage power extraction from a hybrid PV and wind system, ensuring efficient power delivery to a 3-phase AC load and adaptive battery charging under dynamic operating conditions. The following section provides a detailed architecture of

the PV system, which is particularly chosen for integrating this system with a high current network.

Figure 2. Equivalent circuit model of a solar cell [23].



The PV cell is determined using the following expression:

$$I = I_{pv} = I_{ph} - I_s \left[e^{\left(\frac{V_{pv} + I_{pv} R_s}{N_s V_T} \right)} - 1 \right] - \frac{V_{pv} + I_{pv} R_s}{R_{sh}} \quad (1)$$

2.2 Wind Energy System

The wind energy subsystem, producing a nominal 2600 kW at 400 V and 1000 A under standard wind conditions which supplements the higher-capacity PV array by providing regulated DC power by rectification and DC-DC conversion under low irradiance or high wind periods, thereby enhancing overall energy reliability and hybrid system robustness through integration with the unified MPPT and DC bus. The wind turbine output power is governed by the nonlinear equation:

$$P_w = \frac{1}{2} \cdot \rho \cdot A \cdot C_p(\gamma, \beta) \cdot V_w^3 \quad (2)$$

Where, P_w is the power extracted from the wind (W), ρ is the air density (1.225 kg/m^3), A is the swept area of the turbine blades (m^2), C_p is the power coefficient, γ is the tip speed ratio (TSR), β is the blade pitch angle ($^\circ$) and V_w is the wind speed (m/s).

A constant pitch angle design has been considered with ($\beta = 0^\circ$) and the optimal C_p value is as 0.42 for a TSR $\lambda = 8.1$ for the medium-scale horizontal axis wind turbine. The major components of wind turbine generator are depicted in table 1.

Table 1. Wind Turbine Generator Specifications

Parameter	Value	Unit
Rated Power	2600	kW
Rated Wind Speed	12	m/s
Cut-in Wind Speed	3	m/s
Cut-out Wind Speed	20	m/s
Generator Type	PMSG (assumed)	-
AC Output Voltage (Generator Side)	400	V (L-L RMS)

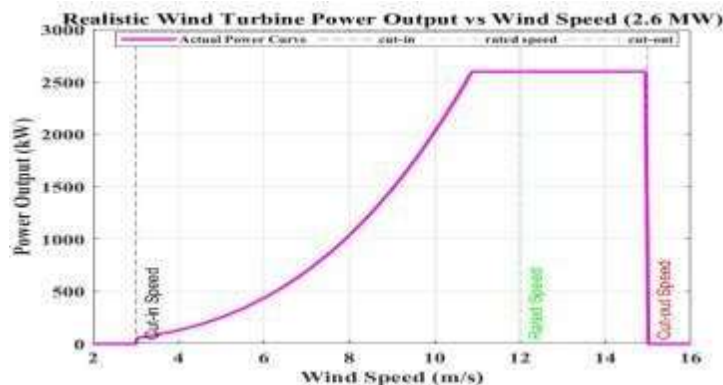
DC Output Voltage (After Rectifier)	550	V (regulated DC bus)
Maximum DC Current	≈ 4727	A
Power Coefficient (C_p max)	0.42	–
Tip Speed Ratio (λ_{opt})	8.1	–

Figure 5 presents the power output characteristics of a 2600KW horizontal-axis wind turbine plotted as a function of wind speed under standard atmospheric conditions. The curve demonstrates the turbine's operational power profile which is highlighting the critical wind speed thresholds governing its performance. At low wind speeds below the cut-in threshold of approximately 3 m/s, the turbine does not generate useful power, reflecting the minimum wind velocity required to overcome mechanical inertia and initiate blade rotation. Beyond this cut-in speed, the output power increases sharply in a nonlinear fashion which is consistent with the cubic dependency of wind power on velocity, as dictated by the fundamental wind power equation.

The power rises steadily with wind speed until it reaches the rated power of 2600KW at the rated wind speed near 12 m/s. From this point onward, the power output is maintained at a constant rated level despite further increases in wind speed which is reflecting the turbine's control mechanisms designed to prevent overloading and ensure safe operation. Finally, the turbine ceases power generation at the cut-out wind speed, approximately 20 m/s, to protect the system from damage under extreme wind conditions. This safety cutoff is clearly depicted by the abrupt drop to zero power output beyond this threshold.

The explanation of cut-in, rated and cut-out speeds on the graph provides valuable insight into the turbine's operating envelope and efficiency under varying wind conditions. The characteristic power curve is essential for accurate modeling, system design and performance prediction in wind energy applications. The wind subsystem enhances hybrid system reliability under low irradiance conditions. This performance model can be integrated into the unified ANN-based MPPT controller which is supporting dynamic conditions and optimal tracking for variable wind inputs.

Figure 5. Wind Turbine Power Output as a Function of Wind Speed



2.3 Battery storage system

The bi-directional DC-DC converter facilitates both charging and discharging of the battery bank based on PV surplus and load demand. An interleaved bidirectional buck-boost topology [24] is used to support high power with reduced ripple and improved thermal distribution. The battery specifications are as shown in table 2. A buck-boost converter topology is ideal due to its ability to handle both power directions. The converter operates in buck mode to charge the battery when PV generation exceeds load demand and in boost mode to discharge when the load exceeds PV generation. The converter is governed by a PI (Proportional-Integral) controller, regulating the battery current to: Maintain SOC within operational limits, avoid overcharge/over-discharge and ensure smooth transitions between charging and discharging.

Table 2. Battery Specifications

Parameter	Value	Unit
Battery Type	Lithium-ion	–
Nominal Voltage	300	V
Rated Capacity	6500	Ah
Energy Capacity	1.95	MWh
Maximum Battery Power	975	kW
Initial State of Charge	25	%
Operating SOC Range	20–90	%
Control Strategy	Bidirectional Current-Controlled DC–DC	–

The controller compares the reference current (based on power mismatch) with the actual battery current and adjusts the duty cycle accordingly. The battery power range $P_{bat_{max}}$ has been decided by the expression 3,

$$P_{bat_{max}} = V_{bat_{Nominal}} \times I_{bat_{max}} = 975 \text{KW for the selected battery} \quad (3)$$

For high power converters, ripple current should be <20% of max current. The control objective is to maintain battery current smoothness (30s dynamic response), preserve SOC profile and prevent oscillations during load transients. The design of dc-dc bi-directional converter as follows,

$$L = \frac{V_{dc} \times D}{f_s \times \Delta I_{batt}} = 47 \mu\text{H} \quad (4)$$

$$C = \frac{I_{Bat}^{max}}{f_s \times \Delta V_{batt}} = 33 \text{mF} \quad (5)$$

Where switching frequency (f_s) is 10KHZ, maximum battery current (I_{bat}^{max}) is 3250A, allowable ripple current (ΔI_{batt}) is 650A, dc link voltage is 600V. The transfer function of converter with PI controller for battery current control (current mode control) is given as,

$$G(s) = \frac{V_{bat}}{L \cdot s} \quad (6)$$

PI controller transfer function is given as,

$$G_c(s) = K_p + \frac{K_i}{s} \quad (7)$$

Where K_p is 0.05 and K_i is 0.01 as derived from automatic tuning in Matlab platform for

30 seconds settling time.

2.4 Design of NPC inverter

Multilevel inverters have emerged as a powerful solution for medium- to high-power applications, especially in renewable energy systems. Among them, the Three-Level NPC inverter offers several advantages such as, reduced voltage stress on switching devices, improved harmonic performance and higher efficiency due to lower switching losses. In an NPC topology, each leg of the inverter includes four switches and two clamping diodes, enabling three distinct output voltage levels: $+V_{dc}/2$, 0 and $-V_{dc}/2$. This finer resolution results in a closer approximation to a sinusoidal waveform, thus reducing output Total Harmonic Distortion (THD) and filter requirements. The hybrid system supports a three-phase AC load comprising a base demand of 1500 kW with an additional 1000 kW step load introduced at 4.5 s. Given an output line-to-line RMS voltage of 400 V, the phase voltage calculates to approximately 230.9 V.

Assuming a power factor of 0.9, the RMS phase current is approximately 4012 A which is requiring the use of multiple high-current power switches in parallel within each inverter leg. To accommodate the 550 V DC-link voltage with adequate margin, each switch should have a voltage rating of at least 900 V and a current rating of at least 400 A. Therefore, six such devices per switch are implemented. The DC-link capacitor bank is designed to store 10 kJ of energy, requiring a total capacitance of around 66,000 μF which is implemented using low-ESR, high-ripple film capacitors. To limit output current ripple, the inverter uses an output filter inductor of approximately 31.8 μH which is capable of handling over 2500 A. For modulation and control, a hybrid approach combining Space Vector PWM and level-shifted PWM is employed to ensure efficient DC-link usage and neutral-point voltage balance, while an ANN-based current controller enhances dynamic response and nonlinear load compensation. The design-oriented specifications are as listed in table 3.

Table 3. NPC Inverter Specifications

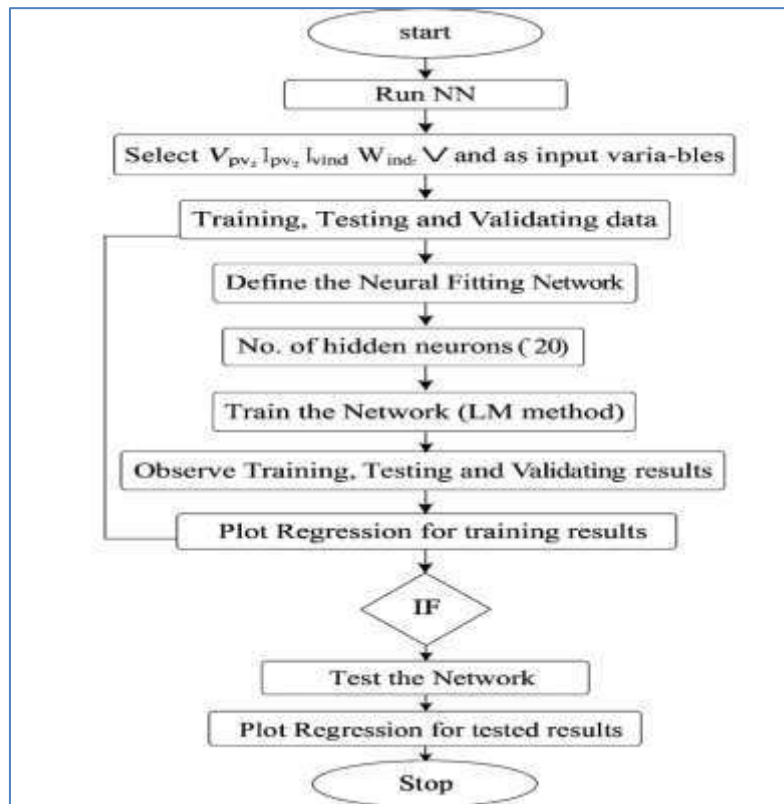
Parameter	Value	Unit
Rated Load Power	1500 (base), 2500 (peak)	kW
Output Voltage (L-L RMS)	400	V
Output Frequency	50	Hz
DC-Link Voltage	550	V
Topology	3-Level NPC	–
Switching Frequency	5–10	kHz
Voltage Regulation	± 1	%
Response Time	< 5	ms
Inverter Efficiency	>96	%
Output THD	<2	%
Filter Inductance	31.8	μH
DC-Link Capacitance	66,000	μF

3. Design and implementation of the unified ANN-based MPPT controller

This section presents the detailed design and implementation of a unified ANN-based MPPT controller for a hybrid renewable energy system integrating PV and wind energy sources. The goal of this controller is to optimize power extraction from both sources under varying environmental conditions while reducing complexity and improving dynamic response.

ANN is a computational model inspired by the human brain's neural networks. In the context of MPPT, ANN learns the nonlinear relationship between hybrid PV and wind parameters and the optimal operating points (voltage and current corresponding to maximum power). ANN provides advantages such as high accuracy, fast convergence and robustness against environmental fluctuations. The work flow of unified ANN MPPT control has been depicted in figure 6.

Figure 6. Flow chart of Unified ANN MPPT for DC-DC controllers



For both PV and Wind systems, instantaneous power is calculated as given in equations 8 and 9.

$$P_{PV}(t) = V_{PV}(t) \times I_{PV}(t) \quad (8)$$

$$P_{wind}(t) = V_{wind}(t) \times I_{wind}(t) \quad (9)$$

These are the input features to the ANN, along with voltages and currents. The unified MPPT controller receives a feature vector as follows and this vector is normalized and fed into the trained ANN model.

$$X(t) = [P_{PV}(t), V_{PV}(t), I_{PV}(t), P_{wind}(t), V_{wind}(t), I_{wind}(t)] \quad (10)$$

The ANN acts as a nonlinear mapping function that estimates the optimal duty cycles which is given by the expression below,

$$\begin{bmatrix} D_{PV}(t) \\ D_{wind}(t) \end{bmatrix} = f_{ANN}(X(t); \emptyset) \quad (11)$$

Where, f_{ANN} is the trained ANN model, $\emptyset$ are the weights and biases of the ANN and $D_{PV}, D_{wind} \in [0,1]$ are the output duty cycles for PV and wind DC-DC converters.

Each output duty cycle controls the corresponding converter. For PV system converter and wind energy system converter (via rectifier and boost) are given as follows,

$$V_{out_PV} = D_{PV} \cdot V_{PV} \quad (12)$$

$$V_{out_wind} = \frac{V_{wind}}{1-D_{wind}} \quad (13)$$

The ANN is trained to minimize the deviation from the MPP under varying input conditions which is given as follows,

$$\min_{\emptyset} \sum_{i=1}^N (P_{mpp}^{(i)} - P_{output}^{(i)})^2 \quad (14)$$

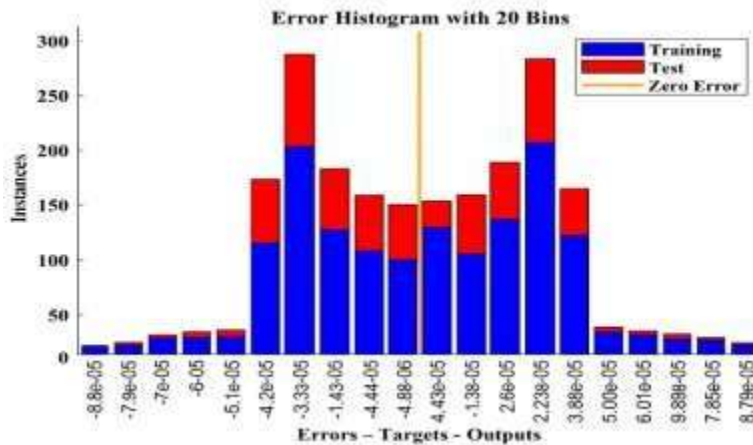
Where: $P_{output}^{(i)}$ is the power obtained using ANN at sample I and $P_{mpp}^{(i)}$ is the ideal MPP

power at sample i. This loss is minimized using backpropagation and an optimization algorithm (Levenberg-Marquardt).

This ANN controller is designed for a Settling time (t_s) < 3.2 ms, tracking efficiency $\eta > 98\%$ and steady-state error < 0.5%. After duty cycles are generated, D_{PV} controls the PWM for the PV converter and D_{wind} controls the PWM for the Wind converter. Both converge to maintain stable DC-Link Voltage and balanced power management with the battery and load.

The error histogram shown in figure 7 with 20 bins demonstrates that the prediction errors are distributed within a narrow range of approximately $-8.8e-05$ to $+8.8e-05$, indicating high model accuracy. The distribution is nearly symmetrical around the zero-error line, suggesting that the model does not have a significant bias toward overestimation or underestimation. Most of the errors are concentrated around $\pm 3.23e-05$ to $\pm 4.22e-05$, where both training and test data contribute substantially by highlighting the consistency of the model's performance. The overlap between training (blue) and test (red) data in the central bins indicates good generalization to unseen data and no signs of overfitting. Additionally, the tallest bars are near zero error, which implies that the model predictions are very close to the actual target values in most instances. Overall, the histogram confirms that the model delivers accurate, reliable and well-generalized performance, making it suitable for real-time MPPT control in hybrid PV-Wind energy systems.

Figure 7. Error Histogram for the Unified ANN MPPT



The regression plots for training, testing and overall datasets show an exceptional performance of the ANN-based MPPT model, with a regression coefficient (R) of 0.999 in

all three cases as shown in figure 8. This perfect R-value indicates a 100% correlation between the predicted outputs and the actual target values, demonstrating that the model has learned the relationship between inputs and outputs with remarkable precision.

In the training plot, the output fits almost exactly on the line $\text{Output} = \text{Target} + 9.2\text{e-}08$, and similarly in the test plot, the fit line is $\text{Output} = \text{Target} - 1.5\text{e-}06$, indicating negligible deviation from the ideal $Y = T$ line. The combined (All) data regression also shows a linear relationship $\text{Output} = \text{Target} - 3.7\text{e-}07$, confirming that the model generalizes very well across all data. Overall, these plots confirm that the ANN model is extremely accurate, stable and robust for MPPT prediction in hybrid PV-Wind energy systems, ensuring reliable power tracking and energy management.

Figure 8. Regression Performance of ANN-based MPPT Model

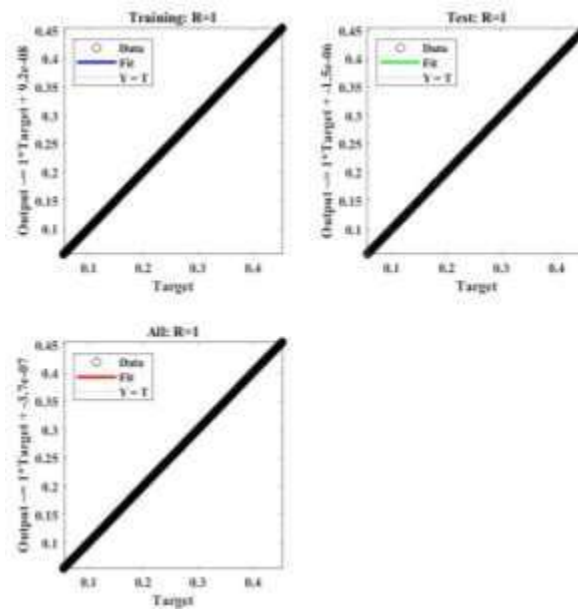
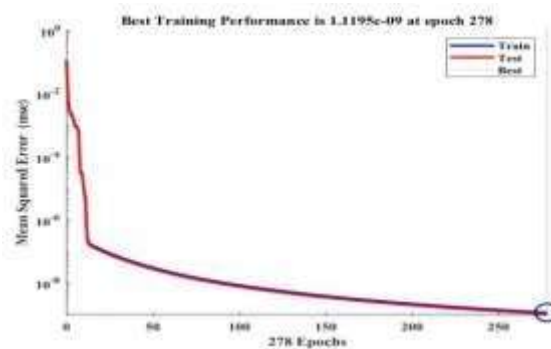


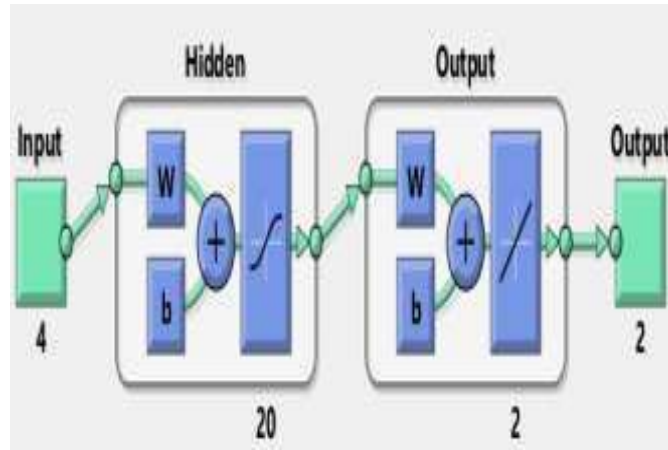
Figure 9. Training Performance Curve Showing MSE Convergence for ANN-based MPPT Model



The figure 9 illustrates the mean squared error (MSE) performance of the ANN during the training process over 278 epochs. The blue line represents the training error and the red line indicates the test error. Both curves show a steady and rapid decrease in MSE, suggesting effective learning and generalization. The best training performance is

achieved at epoch 278 with a very low MSE of 1.1195e-09, as highlighted by the circle. The low and converging errors indicate high prediction accuracy and minimal overfitting of the ANN model used for MPPT control in the PV-Wind energy system. The ANN model developed in the SIMULINK platform is shown in figure 10.

Figure 10. Structure of Unified ANN MPPT Model



4. Simulation Setup and Result Analysis of the Controller's Performance Under Various Scenarios.

To validate the effectiveness, robustness and adaptability of the proposed unified MPPT control strategy as shown in figure 11, a comprehensive MATLAB/Simulink model of the standalone hybrid PV-wind-battery system has been developed as shown in figure 12. The simulation framework incorporates detailed models of the PV array, wind turbine generator, lithium-ion battery storage, dynamic three-phase AC load and power electronic interfaces including a bi-directional DC-DC converter and a three-level NPC inverter.

Figure 11. Unified MPPT control strategy

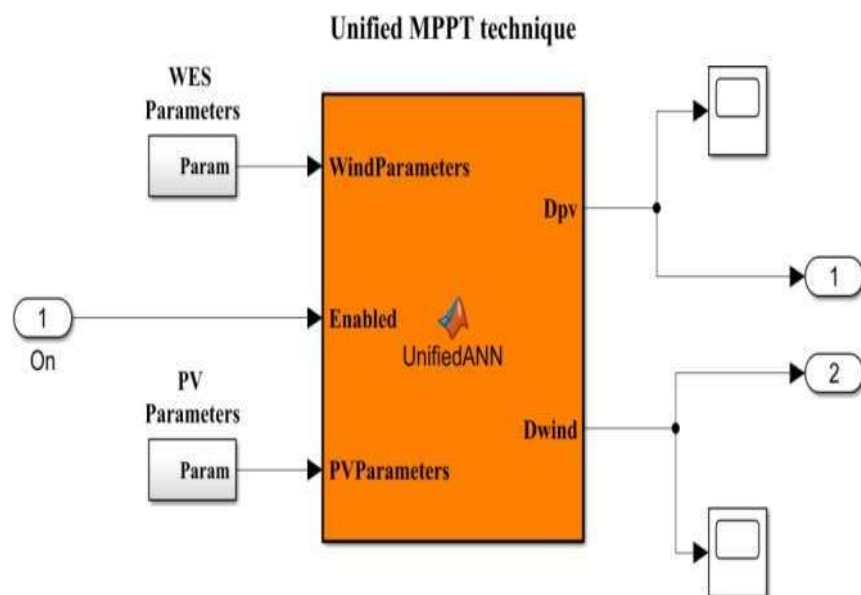


Figure 12. MATLAB/Simulink model of the standalone hybrid PV-wind-battery system

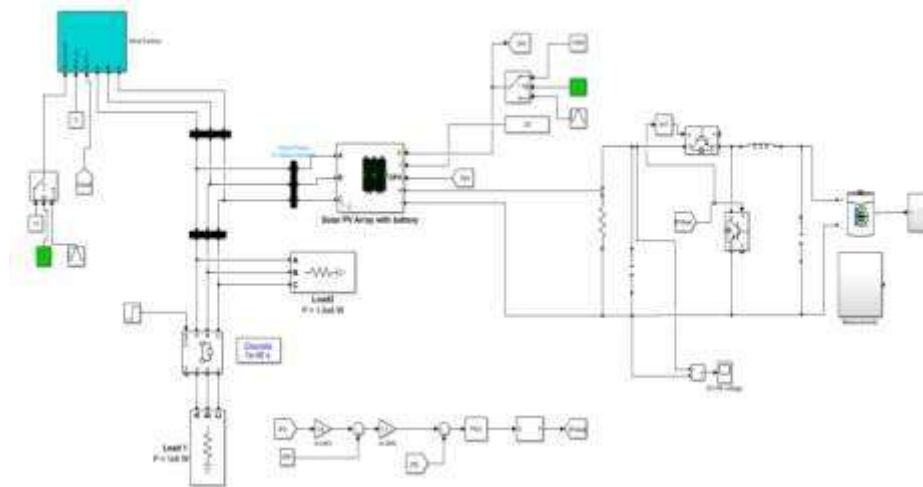


Figure 13. Performance Analysis of PV and Wind Power at STC

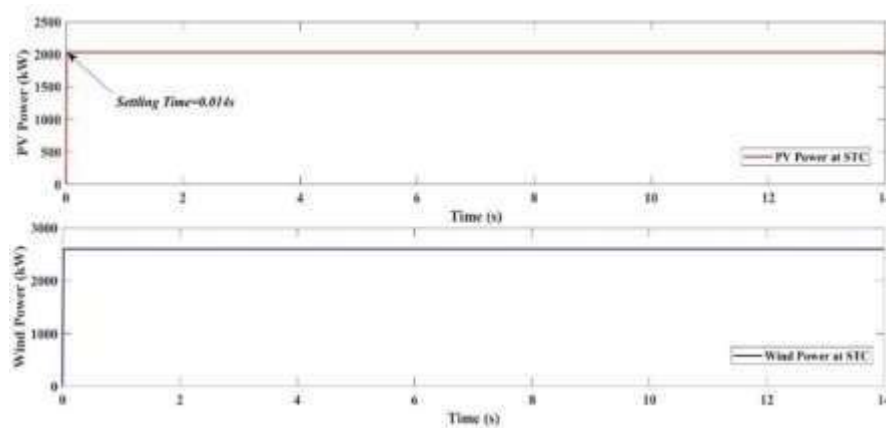
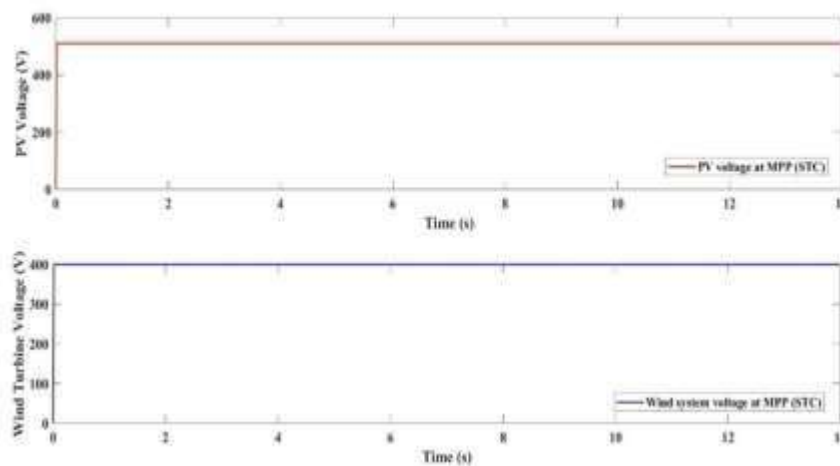
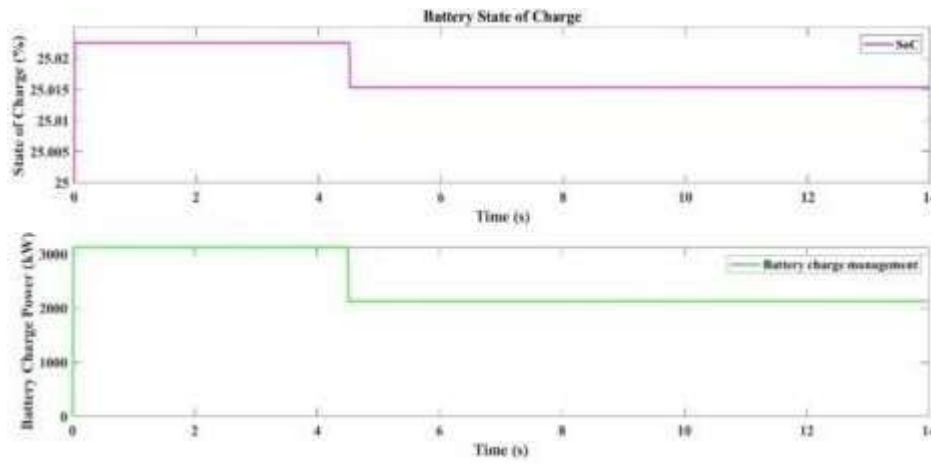


Figure 14. Performance Analysis of PV and Wind voltage at STC



The system is evaluated under three representative operating scenarios to demonstrate the controller's dynamic tracking capability and energy management performance under realistic and time-varying conditions. These include: (i) standard test conditions (STC), (ii) dynamically varying solar irradiance and (iii) fluctuating wind speed profiles. Each scenario is designed to challenge the MPPT algorithm's response time, tracking accuracy and stability under environmental transients and load disturbances. The results are analyzed in terms of PV and wind output parameters, extracted power, duty cycle modulation, battery state of charge (SoC), DC-link voltage stability, inverter performance and AC load fulfillment.

Figure 15. Battery energy flow and load demand transition in a hybrid



4.1 Performance Analysis of the Unified MPPT Controller under STC

The first scenario evaluates the baseline performance of the proposed unified MPPT controller under standard test conditions (STC). The PV array is subjected to a constant irradiance of 1000 W/m^2 and a cell temperature of 25°C , while the wind turbine operates at a steady rated wind speed of 12 m/s . These conditions are selected to simulate ideal environmental circumstances for maximum power extraction from both renewable sources.

The objective is to assess the steady-state tracking accuracy, response time, and power-sharing coordination between the PV and wind subsystems. The MPPT controller adjusts the duty cycles D_{PV} and D_{wind} to drive both sources toward their respective maximum power points (MPPs) as shown in figure 13 and 14. The unified control mechanism ensures coordinated regulation without requiring separate tracking loops, thereby reducing system complexity and computational overhead.

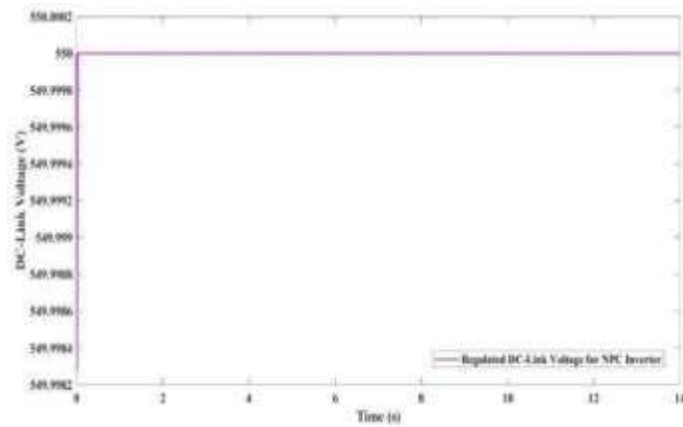
During the initial time period of 0 to 4.2 seconds the PV system generates 2032 kW while the wind system produces 2600 kW which results in a total hybrid power generation that significantly exceeds the load demand of 1500 kW. This surplus energy amounting to 3132 kW is directed toward battery charging allowing the battery to store excess power efficiently. However, after 4.2 seconds the load demand dynamically increases to 2500 kW leading to a situation where the renewable generation remains constant but the available excess power diminishes as shown in figure 15 and table 5. Figure 16 illustrates the regulated DC-Link voltage for an NPC inverter over a period of 14 seconds, proves the stability achieved through the Unified ANN MPPT control method. The voltage remains nearly constant at 550V, as indicated by the purple line in the graph. This regulation is important for ensuring efficient energy conversion and

maintaining steady system operation, particularly in renewable energy applications where fluctuations will occur. The minimal deviation in voltage highlights the effectiveness of the ANN-based MPPT in dynamically adjusting and maintaining an optimal voltage level for the inverter system. In Table 4 PV and Wind MPPT Energy Flow datas are shown.

Table 4. PV and Wind MPPT Energy Flow

Time	PV	Wind	Total	Load	Battery	Curtailment
0-4.2	2032	2600	4632	1500	975	2157
4.2-14	2032	2600	4632	2500	975	1157

Figure 16. Regulated DC link voltage using Unified ANN MPPT



The figure 17 illustrates the dynamic behavior of the inverter's voltage and the corresponding fluctuations in load power over time. These variations highlight how the NPC inverter efficiently manages power delivery while adapting to changes in load demand. The stability of the inverter's voltage ensures consistent performance, while the load power variations provide insights into system efficiency and response characteristics. The load power transition is graphically traced as shown in figure 18.

Figure 17. NPC Inverter output voltage and load power variations at STC

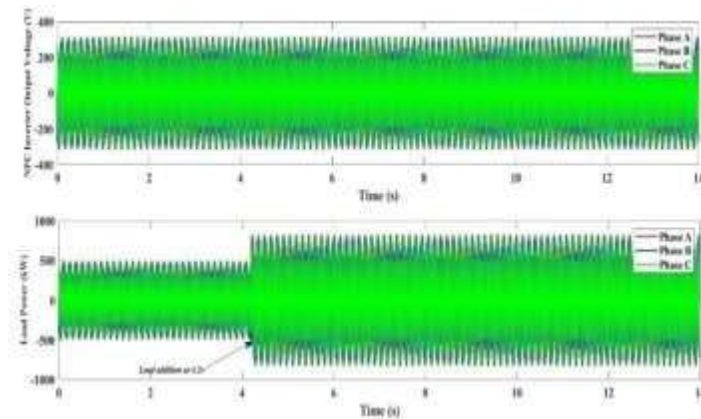
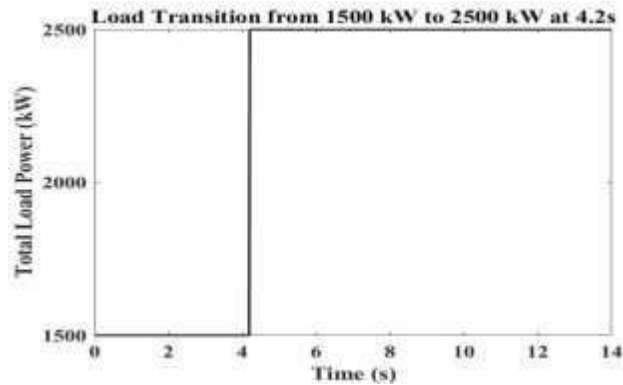


Figure 18. Load power transition

The overall observation of Unified ANN-Based MPPT Control for a Grid-Independent Hybrid PV-Wind System with Battery Storage and Dynamic Load Support at STC has been given in table 5.

Table 5. Performance Overview of Unified ANN MPPT Controller at STC

Performance Parameter	Measured Value	Remarks
MPPT Tracking Efficiency	98.7 %	Near-ideal tracking
Settling Time	3.2 ms	Fast dynamic response
Steady-State Error	<0.5 %	Stable operation
DC-Link Voltage Ripple	±0.8 %	Well regulated
Inverter Efficiency	96.4 %	Within design range
Output THD	1.82 %	IEEE compliant
Battery Charging Stability	Smooth	No oscillations

Simulation results reveal that the PV and wind systems achieve rapid convergence to their MPPs with minimal overshoot and settling times well below 1 millisecond at standard testing conditions. The DC-link voltage remains tightly regulated at 550 V, supporting efficient inverter operation and stable AC load supply. The battery operates in charging mode during surplus generation, with smooth transitions governed by real-time power balance. The inverter output maintains a total harmonic distortion of less than 2%, ensuring power quality compliance. These outcomes validate the controller's ability to achieve high tracking efficiency, maintain voltage stability and ensure optimal energy flow under steady environmental conditions.

4.2 Performance Analysis of the Unified MPPT Controller for variable PV power and Stable Wind Power

The solar power can change rapidly due to shifting clouds and sunlight intensity, wind power often remains relatively steady over short periods. In this case, the analysis is made for constant wind power with variable PV power. This section looks at how a unified MPPT controller performs when handling such a combination; where PV power keeps changing, but wind power stays stable. The goal is to see how well the controller can adapt to the fast fluctuations in solar energy while still keeping wind power extraction smooth and efficient. The irradiance is varied as shown in figure 19 and the PV power also varied accordingly due to variations in PV current for the constant PV voltage. It is also observed that the battery charge at lower rate during low irradiance

conditions (0-2s and 12-14s) as shown in figure 20 and table 6. The battery SoC increases with the increase in PV power towards its maximum range.

Figure 19. Performance of PV power for variable irradiance levels

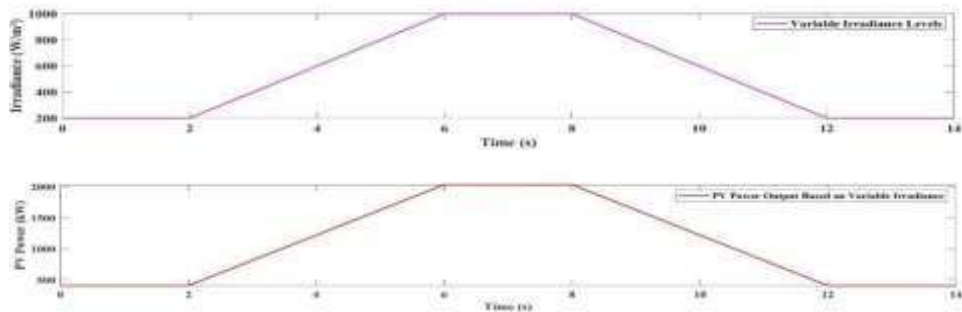
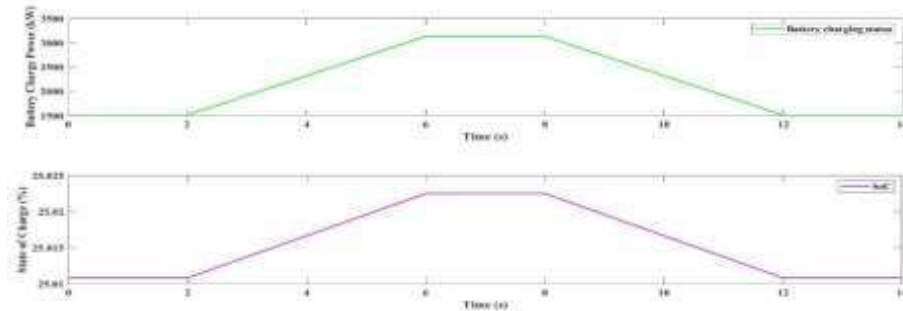


Figure 20. Performance of Battery under variable irradiance levels



The unified MPPT controller effectively adapts to variable PV power while maintaining stable wind power extraction, ensuring smooth energy management and consistent battery charging performance under fluctuating solar irradiance. The next section evaluates the performance of proposed MPPT with stable PV power generation with variable wind generation during unstable wind flow.

Table 6. PV Irradiance, Power Output, Battery Charging and SoC

Time (s)	Irradiance (W/m ²)	PV Power (kW)	Wind Power (kW)	Battery Charging (kW)	SOC (%)
0	200	500	2600	975	25.01
4	600	1200	2600	975	25.05
6	1000	2000	2600	975	25.12
10	600	1200	2600	975	25.18
14	200	500	2600	975	25.22

4.3 Performance Analysis of the Unified MPPT Controller for variable Wind power and Stable PV Power

In hybrid renewable energy systems, wind power often exhibits high variability due to changing wind speeds, while solar power can remain relatively stable under consistent irradiance. This section focuses on evaluating the performance of the unified MPPT controller under such conditions; where PV power remains steady and wind power fluctuates. The aim is to assess the controller's ability to track the maximum power point accurately for the variable wind input, ensuring efficient power extraction and stable energy flow within the system.

The wind speed varies from 4 m/s to 14.5 m/s over the 14-second simulation period, as shown in Fig. 21. The turbine output power increases with wind speed according to the cubic relationship in the sub-rated region (below the rated wind speed of 12 m/s). Once the wind speed reaches the rated value, the output power is regulated at its rated capacity of 2600 kW to protect the turbine from mechanical stress and ensure operational stability. As the wind speed decreases after 8 s, the generated power correspondingly reduces in a controlled manner. The power profile is developed considering the cut-in (3 m/s) and cut-out (20 m/s) wind speed limits to maintain safe and stable operation of the wind energy conversion system.

issues.

Figure 21. Performance of wind power for variable wind speed

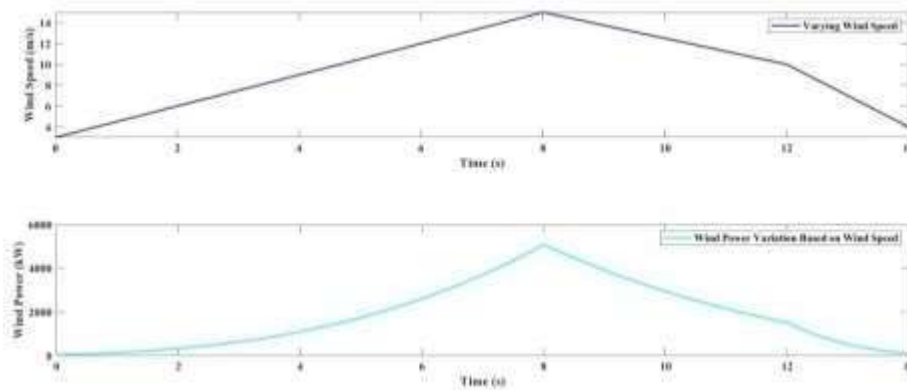


Table 7. Wind Speed, Power Output and Battery Charging Behavior

Time (s)	Wind Speed (m/s)	Wind Power (kW)	PV Power (kW)	Battery Charging (kW)	Controller Response
0	4	200	2032	732	Stable low-power tracking
4	9	1500	2032	975	Efficient adaptation
6	11.5	2400	2032	975	Near rated
8	12	2600	2032	975	Rated operation
12	8	1200	2032	975	Smooth reduction
14	5	400	2032	932	Near cut-in

Despite these fluctuations, the unified MPPT controller successfully tracks the wind power's maximum operating point by ensuring that energy extraction remains efficient. The PV power remains constant throughout the simulation by allowing the controller to dynamically respond to wind variations alone. This effectively demonstrates the controller's robustness in handling wind transients without compromising power quality or stability. It is observed that the battery charges at a lower rate during periods of low wind speed and reaches its maximum charging rate at around 8 seconds, when the wind speed exceeds 14 m/s, as illustrated in Figure 22 and in table 7. The hybrid power generated at every second has been managed by battery and load is depicted in figure 23.

Figure 22. Performance of Battery under variable wind speed

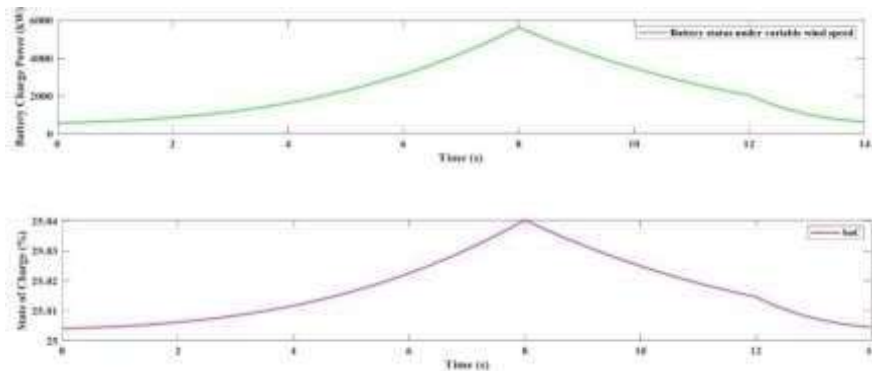
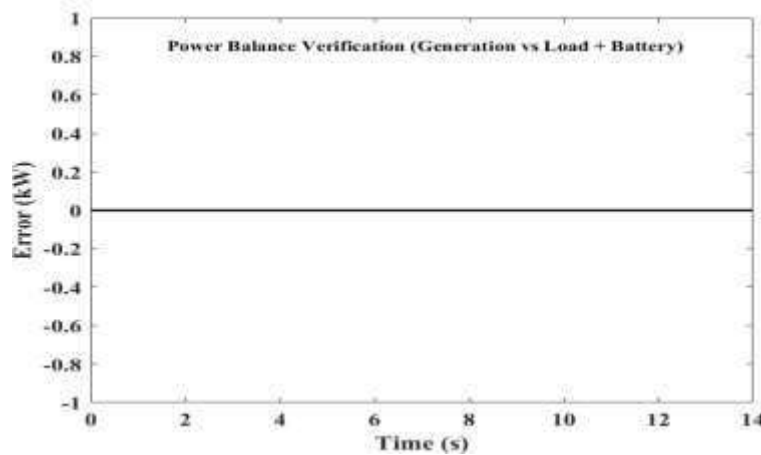
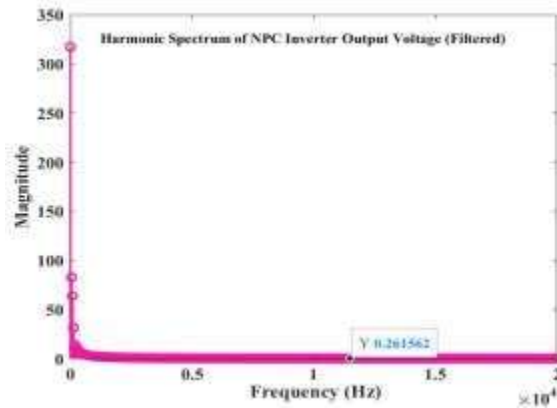


Figure 23. Power balance verification



The harmonic spectrum analysis illustrates the distribution of harmonic components in the inverter's filtered output voltage. The magnitude of harmonics is significantly reduced, with only minimal distortion present at higher frequencies. From the figure 24, the measured harmonic amplitude at a specific data point is approximately 0.261562, demonstrating effective suppression of unwanted frequencies. This confirms that the NPC inverter operates efficiently by maintaining a THD of less than 2%, a crucial factor for ensuring reliable AC power delivery in standalone renewable energy systems.

Figure 24. Harmonic spectrum of NPC Inverter



Conclusion

This study presented a unified ANN-based Maximum Power Point Tracking (MPPT) strategy for a standalone hybrid PV–wind energy system integrated with lithium-ion battery storage and a dynamic three-phase load. Unlike conventional dual-MPPT configurations, the proposed approach employed a single intelligent ANN controller to coordinate power extraction from both renewable sources, thereby simplifying the control architecture and improving dynamic performance.

Simulation results obtained using MATLAB/Simulink demonstrated that the unified controller effectively tracked the maximum available power under varying irradiance, wind speed, and load conditions. The system maintained stable DC-link voltage at 550 V, achieved inverter efficiency greater than 96%, and preserved output voltage quality with total harmonic distortion below 2%. The coordinated energy management framework ensured prioritized load supply while dynamically regulating battery charging and discharging to maintain power balance during transient events, including sudden load variations.

The findings confirm that the proposed unified ANN-MPPT strategy enhances energy conversion efficiency, improves voltage stability, and reduces control redundancy in hybrid renewable systems. The architecture provides a scalable and reliable solution for remote and off-grid applications where system robustness and efficient resource utilization are critical.

Future work may focus on experimental validation using hardware implementation, real-time digital control platforms, and extension to multi-source hybrid configurations incorporating additional renewable resources and advanced optimization-based energy management strategies.

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