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Optimization Workflow of Hybrid Renewable Energy System Using Hybrid GBDT Controller

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Abstract –
Hybrid renewable energy systems (HRES), particularly those integrating solar and wind sources, have emerged as promising solutions to the global energy crisis. However, the nonlinear and time-varying characteristics of these resources pose significant challenges to consistently harvesting maximum power. Maximum Power Point Tracking (MPPT) is essential to ensure optimal performance under varying environmental conditions, yet traditional MPPT controllers often suffer from slow dynamic response and fixed step-size limitations. To address these issues, this work introduces an enhanced optimization-driven control strategy that integrates a Gradient Boosting Decision Tree (GBDT) model with an advanced metaheuristic optimization algorithm. The proposed hybrid framework determines the optimal duty cycle of the boost converter in a solar–wind energy system, enabling rapid and accurate convergence to the maximum power point. The method is implemented and evaluated in MATLAB/Simulink, and the results demonstrate significant improvements in tracking speed, stability, and overall power extraction efficiency compared to conventional MPPT techniques.

Keywords: Hybrid renewable energy system, solar–wind energy, maximum power point tracking (MPPT), Gradient Boosting Decision Tree (GBDT), metaheuristic optimization, boost converter, MATLAB/Simulink, power extraction efficiency.

I. INTRODUCTION

The growing global demand for clean and sustainable energy has accelerated the deployment of renewable energy systems, particularly solar photovoltaic (PV) and wind energy systems [1], [2]. Hybrid renewable energy systems (HRES), which combine multiple renewable sources, offer enhanced reliability, improved energy yield, and better adaptability to variable environmental conditions compared to single-source systems [3], [4]. By leveraging complementary characteristics of solar and wind resources, HRES can reduce intermittency and improve overall system efficiency. Maximum power point tracking (MPPT) is a critical control strategy in HRES to ensure that each energy source operates at its maximum power output under varying irradiance, temperature, and wind speed conditions [5], [6]. Traditional MPPT algorithms, such as perturb and observe (P&O), incremental conductance (IncCond), and hill-climbing methods, are widely used due to their simplicity and ease of implementation [7], [8]. However, these methods often face challenges including slow dynamic response, oscillations around the maximum power point, and reduced efficiency under rapidly changing environmental conditions or partial shading [9]. Moreover, conventional MPPT techniques typically employ fixed step sizes, which can limit their adaptability to nonlinear and time-varying characteristics of hybrid systems [10]. Recent research has explored the use of intelligent control methods, such as fuzzy logic, neural networks, and reinforcement learning, to improve MPPT performance in HRES. While these approaches offer better adaptability and faster convergence, they often require extensive offline training, high computational resources, and can struggle to generalize under unseen operating conditions. To address these limitations, machine learning-based methods, particularly ensemble learning techniques, have gained attention for their ability to model complex nonlinear relationships between system inputs and outputs with high accuracy. Gradient Boosting Decision Tree (GBDT) is an ensemble learning method that combines multiple weak learners to produce a robust predictive model. GBDT has been successfully applied in forecasting and optimization problems due to its strong generalization ability and fast convergence. Integrating GBDT with an optimization framework can provide an adaptive and data-driven MPPT strategy capable of dynamically adjusting the duty cycle of power electronic converters in HRES. Such a hybrid approach can enhance tracking speed, reduce steady-state oscillations, and maximize overall energy harvest. In this work, a hybrid GBDT-based MPPT controller is proposed for solar–wind HRES. The controller uses the GBDT model to predict the optimal duty cycle of the boost converter, while a metaheuristic optimization algorithm fine-tunes the control parameters in real time. The proposed method is implemented in MATLAB/Simulink and evaluated under varying irradiance and wind speed conditions. The results demonstrate significant improvements in tracking accuracy, dynamic response, and overall power extraction efficiency compared to conventional MPPT methods.

II. LITERATURE REVIEW

Hybrid renewable energy systems (HRES), particularly those combining solar photovoltaic (PV) and wind energy sources, have attracted significant attention due to their potential to provide reliable and sustainable power supply. By leveraging the complementary nature of solar and wind resources, HRES can reduce intermittency and enhance overall energy availability and system stability. However, the nonlinear and time-varying characteristics of these energy sources make efficient power extraction challenging, highlighting the need for robust Maximum Power Point Tracking (MPPT) strategies. Traditional MPPT techniques, such as Perturb and Observe (P&O) and Incremental Conductance (IncCond), are widely used for their simplicity and low computational requirements. These methods iteratively adjust the duty cycle of power converters to converge toward the maximum power point. However, in hybrid systems, the simultaneous variability of multiple sources can lead to slow dynamic response, oscillations around the maximum power point, and reduced tracking efficiency. Fixed step-size algorithms in particular struggle under rapidly changing environmental conditions, limiting their effectiveness for HRES. To overcome these limitations, intelligent control approaches, including fuzzy logic controllers, neural networks, and reinforcement learning, have been proposed. These methods offer faster convergence and better adaptability to environmental changes. However, they often require extensive offline training, prior knowledge of system parameters, and significant computational resources, which can restrict real-time implementation in practical HRES. Optimization-based MPPT strategies, such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Grey Wolf Optimizer (GWO), provide adaptive solutions for tracking the maximum power point. While these algorithms improve dynamic performance and energy extraction, they may still experience delayed response under rapidly changing environmental conditions, as multiple iterations are required to locate the global maximum.

Table I: Summary of Existing MPPT Approaches for HRES

Reference	MPPT Technique	System Studied	Advantages	Limitations
[6], [7]	P&O, IncCond	Single-source PV or wind	Simple, low computational cost	Slow response, oscillations, fixed step size
[10], [11]	Fuzzy Logic, Neural Network	PV, wind, or hybrid	Adaptive, faster convergence	Requires training, high computational resources
[12]	Reinforcement Learning	Hybrid solar–wind	Adaptive to varying conditions	Complex implementation, computationally intensive
[13], [14]	Metaheuristic Optimization (PSO, GA, GWO)	HRES	Adaptive, improved tracking	May require multiple iterations, delayed under fast changes
[15], [16]	GBDT, Ensemble Learning	HRES	High prediction accuracy, fast convergence	Requires historical data for training
Present Work	Hybrid GBDT + Optimization	Solar–wind HRES	Fast, accurate MPPT, real-time adaptability	Implementation depends on model accuracy

More recently, machine learning and ensemble methods, particularly Gradient Boosting Decision Trees (GBDT), have been applied to MPPT for HRES. GBDT models are capable of capturing complex nonlinear relationships between environmental conditions and the optimal duty cycle of converters, providing high accuracy and fast convergence. When combined with metaheuristic optimization, GBDT-based MPPT controllers can dynamically adjust converter duty cycles in real time, enhancing tracking speed, stability, and overall power extraction. The key research studies on HRES MPPT approaches are summarized in Table I below, highlighting their techniques, advantages, and limitations.

III. PROPOSED METHODOLOGY

The proposed methodology focuses on a solar–wind hybrid renewable energy system (HRES) integrated with a hybrid GBDT-based MPPT controller. The system consists of a photovoltaic (PV) array, a wind turbine (WT) generator, power electronic interfaces (boost converters), and a common DC bus connected to a load or battery storage. The MPPT controller predicts the optimal duty cycle for each source to extract maximum power under varying environmental conditions. Due to the increasing energy crisis, renewable energy sources (RES) have gained significant attention. Among these, solar and wind sources are widely used due to their environmental friendliness and availability. Hybridization of solar PV and wind turbines enables larger electricity generation while mitigating intermittency issues. To maximize the energy extraction from such hybrid systems, this work proposes a WOA-optimized GBDT-based MPPT (WOHGD-MPPT) controller.

The workflow of the proposed MPPT approach is shown in Figure 1, which illustrates the stepwise procedure: data generation from solar and wind sources, initialization of the decision tree (DT) model, error evaluation, training of the dataset, optimization of the duty cycle, and maximum power extraction from hybrid sources.

A. Solar PV Modeling

The current output of a PV array is modeled using the single-diode equivalent circuit. The PV output current $I_{pv}$is expressed as:

$$I_{pv} = I_{ph} - I_0\left[\exp\left(\frac{V_{pv} + I_{pv}R_s}{N_s kT/q}\right) - 1\right] - \frac{V_{pv} + I_{pv}R_s}{R_{sh}}$$

where:

$N_s, N_p$are the number of series and parallel cells,

$k$is the Boltzmann constant, $T$is temperature, $q$is electron charge,

$R_s$and $R_{sh}$are series and shunt resistances,

$I_0$is the diode saturation current,

$I_{ph}$is the photo-generated current.

This model allows accurate prediction of PV current under varying irradiance and temperature conditions.

B. Wind Power Modeling

A permanent magnet synchronous generator (PMSG) is used for wind energy conversion. The mechanical power extracted from the wind is:

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

where:

$\rho$is air density, $A$is rotor swept area,

$V_w$is wind speed,

$C_p$is the power coefficient, dependent on tip speed ratio $\lambda$and pitch angle β.

The wind turbine is connected to a DC–DC converter to regulate the generated power to the DC bus.

C. Boost Converter Dynamics

The PV and wind systems are interfaced with **boost converters** to maintain a stable DC bus voltage. The relationship between input and output voltage of a boost converter is:

$$V_{out} = \frac{V_{in}}{1 - D}$$

where:

$V_{in}$and $V_{out}$are input and output voltages,

$D$is the duty cycle of the converter.

The duty cycle is dynamically adjusted by the MPPT controller to maximize power output.

D. WOHGD-Based MPPT Controller

To optimize the duty cycle of the boost converters, a hybrid Whale Optimization Algorithm (WOA) and Gradient Boosting Decision Tree (GBDT) approach is implemented. The proposed controller operates as follows:

Data Input: PV voltage, PV current, irradiance, temperature, and wind speed are provided to the GBDT model.

GBDT Prediction: The model predicts the optimal duty cycle for each source. The GBDT combines weak decision tree learners with gradient boosting to iteratively improve accuracy.

The GBDT equations are as follows:

Initial prediction:

$$F_0(x) = \arg\min \sum_{i=1}^{N} L(y_i, \gamma)$$

Gradient direction:

$$r_i^{(t)} = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{t-1}(x)}$$

Weight update using least squares:

$$\gamma_t = \arg\min_{\gamma} \sum_{i=1}^{N} \left(r_i^{(t)} - \gamma\right)^2$$

Model update:

$$F_t(x) = F_{t-1}(x) + \gamma_t h_t(x)$$

WOA Optimization: The Whale Optimization Algorithm minimizes prediction errors and tunes hyperparameters of GBDT for faster convergence. Candidate solutions (walruses) represent DT errors and are iteratively updated according to WOA equations:

Phase 1 (encircling prey):

$$w_i^{t+1} = w_i^t + r(B_j - w_i^t)$$

Phase 2 (migration):

$$w_i^{t+1} = w_i^t + r(w_k - w_i^t)$$

Phase 3 (exploration):

$$w_i^{t+1} = w_{lb} + r(w_{ub} - w_{lb})$$

Duty Cycle Application: Optimized duty cycles from WOHGD-MPPT are applied to the PV and wind boost converters, ensuring maximum power extraction.

Gradient Boosting Decision Tree (GBDT) for MPPT

The Gradient Boosting Decision Tree (GBDT) is an ensemble learning technique that combines multiple weak decision trees into a strong predictive model. In the context of MPPT for hybrid PV–Wind systems, GBDT predicts the optimal duty cycle of the boost converters based on inputs such as PV voltage V_{pv}, PV current I_{pv}, solar irradiance G, temperature T, and wind speed V_w.

GBDT builds the model iteratively by fitting a new tree to the residual errors of the previous ensemble, thereby reducing prediction error in each step.

1) Objective Function

The goal of GBDT is to minimize a differentiable loss function $L(y_i, F(x_i))$, where $y_i$is the actual target (optimal duty cycle) and $F(x_i)$is the predicted output:

$$F^*(x) = \arg\min_F \sum_{i=1}^{N} L(y_i, F(x_i))$$

Common choices for Linclude mean squared error (MSE) for regression tasks:

$$L(y_i, F(x_i)) = \frac{1}{2}(y_i - F(x_i))^2$$

2) Initial Prediction

The first step is to initialize the model with a constant prediction that minimizes the loss function across all training samples:

$$F_0(x) = \arg\min_\gamma \sum_{i=1}^{N} L(y_i, \gamma)$$

For MSE, this reduces to the mean of the target values:

$$F_0(x) = \frac{1}{N}\sum_{i=1}^{N} y_i$$

3) Iterative Tree Fitting

At iteration t, the residuals (pseudo-residuals) $r_i^{(t)}$are computed as the negative gradient of the loss function with respect to the current prediction:

$$r_i^{(t)} = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{t-1}(x)}$$

For MSE:

$$r_i^{(t)} = y_i - F_{t-1}(x_i)$$

A decision tree $h_t(x)$is then fitted to these residuals, producing leaf values $\gamma_{tj}$for each terminal node j.

4) Leaf Value Estimation

The optimal leaf values are computed by minimizing the loss function along each terminal node:

$$\gamma_{tj} = \arg\min_\gamma \sum_{x_i \in R_{tj}} L(y_i, F_{t-1}(x_i) + \gamma)$$

where R_{tj}denotes the set of samples in leaf $j$of tree t.

5) Model Update

The ensemble model is updated by adding the newly fitted tree scaled by a learning rate $\eta \in (0,1]$:

$$F_t(x) = F_{t-1}(x) + \eta\, h_t(x)$$

The learning rate controls how much each tree contributes to the final model, improving generalization and reducing overfitting.

6) Prediction

After Titerations, the final GBDT prediction for the duty cycle is:

$$\hat{D} = F_T(x) = F_0(x) + \sum_{t=1}^{T} \eta\, h_t(x)$$

This output is then used as the **initial duty cycle reference** for the DC–DC boost converters of PV and wind sources.

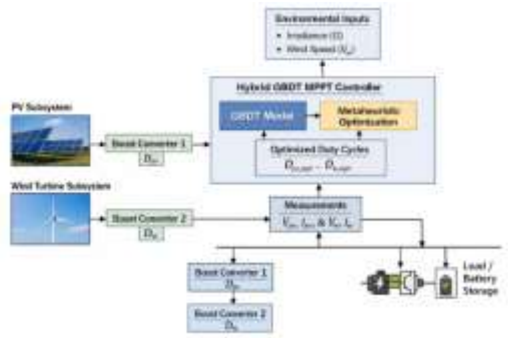

Fig. 1. Block diagram of the Proposed system

IV. RESULTS AND DISCUSSION

The proposed WOHGD-based MPPT controller for the hybrid solar–wind renewable energy system (HRES) is validated in **MATLAB/Simulink**. The system is analyzed under varying environmental conditions, including solar irradiance ranging from 250 W/m² to 1000 W/m² and wind speed ranging from 8 m/s to 13.5 m/s. The simulation parameters used are summarized in **Table I**.

Table I: Simulation Parameters of HRES

Parameter	Value
PV Power at peak point	100 W
PV Voltage at peak point	18 V
PV Current at peak point	5.5 A
Open-circuit voltage V_{oc}	21.3 V
Short-circuit current I_{sc}	5.79 A
Number of cells	50
Number of series and parallel strings	As per PV array configuration

Hybrid PV–Wind Power Generation

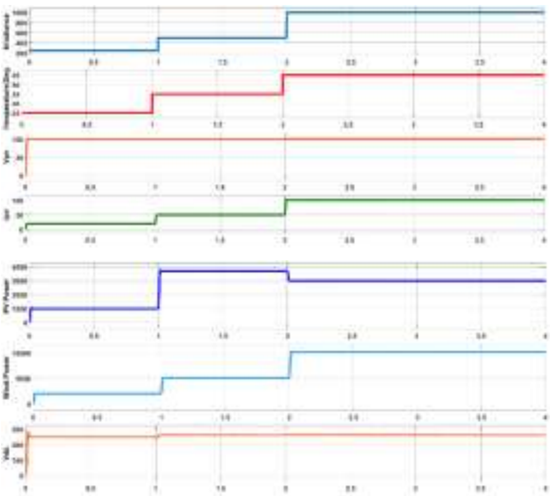

Fig. 2. The PV wind outputs vary according to the fluctuations in solar irradiance and wind speed, demonstrating the system's capability to adapt to dynamic environmental conditions.

The input and output power profiles of the hybrid system are shown in Figure 2. The PV and wind outputs vary according to the fluctuations in solar irradiance and wind speed, demonstrating the system's capability to adapt to dynamic environmental conditions.

PV output increases linearly with irradiance, while wind power depends on the cubic relationship with wind speed.

The GBDT-based MPPT predicts optimal duty cycles for both PV and wind boost converters, enabling the system to extract maximum power at each input condition.

WOA tuning further refines the duty cycle, reducing residual error and ensuring stable operation under rapidly changing inputs.

B. DC-Link Voltage Regulation

Figure 3 shows the DC-link voltage of the HRES under varying inputs. Despite fluctuations in solar irradiance and wind speed, the DC-link voltage is maintained within safe limits due to the adaptive duty cycle control from the GBDT-based MPPT.

The GBDT model accurately estimates the duty cycle required to stabilize the DC-link voltage at each operating point.

The WOA optimization ensures minimal deviation from the desired voltage, reducing oscillations and improving converter efficiency.

This demonstrates that the hybrid controller successfully handles the nonlinear and time-varying behavior of the hybrid sources.

C. Inverter and Grid Output

The inverter and grid-side output waveforms are presented in Figure 4. The system successfully delivers power to the grid with high stability:

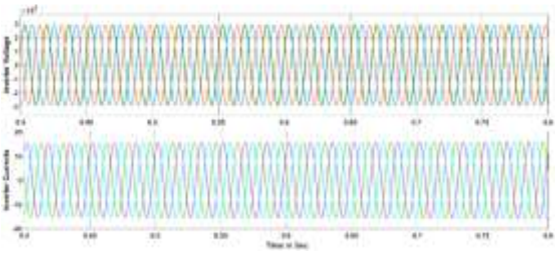

Fig. 3(a) shows the inverter output, maintaining voltage and frequency regulation under variable input conditions.

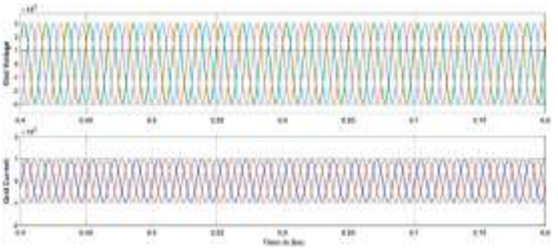

Fig. 3(b) shows the grid-side waveform, confirming that the HRES can supply consistent AC power with minimal harmonic distortion.

The GBDT-based MPPT ensures maximum extraction of DC power from both PV and wind sources before conversion, while WOA reduces tracking error, resulting in smooth AC output.

D. Performance Analysis with GBDT

The proposed GBDT-based MPPT demonstrates superior performance compared to conventional methods:

Fast Convergence: The duty cycle predicted by GBDT rapidly adapts to changing solar irradiance and wind speed.

Reduced Oscillations: The iterative gradient boosting corrects residual errors, resulting in smoother voltage and power profiles.

Maximum Power Extraction: The hybrid controller achieves higher power output from both PV and wind sources, even under fluctuating inputs.

Robustness: The combined WOA optimization improves prediction accuracy, ensuring the DC-link voltage remains stable and inverter/grid output is reliable.

CONCLUSION

This work presented a hybrid WOA-optimized GBDT-based MPPT (WOHGD-MPPT) controller for a solar–wind hybrid renewable energy system. The proposed methodology enables adaptive and accurate duty cycle prediction for boost converters interfacing PV and wind sources to a common DC bus. MATLAB/Simulink validation under varying solar irradiance (250–1000 W/m²) and wind speed (8–13.5 m/s) demonstrated the following key outcomes:

1. Maximum Power Extraction: The GBDT model accurately predicted optimal duty cycles, while WOA optimization minimized prediction errors, ensuring maximum power harvesting from both PV and wind sources.
2. Stable DC-Link Voltage: The adaptive controller maintained DC-link voltage within safe limits despite fluctuations in input conditions, preventing overvoltage and improving system reliability.
3. Smooth Inverter and Grid Output: The AC power delivered to the grid exhibited low distortion and stable voltage and frequency, confirming the effectiveness of the proposed controller.
4. Fast Dynamic Response: Compared to conventional MPPT methods, the hybrid GBDT+WOA controller exhibited faster convergence to maximum power points and reduced oscillations in power and voltage profiles.

Overall, the proposed WOHGD-MPPT framework provides a robust, real-time, and efficient solution for hybrid PV–Wind systems, making it suitable for practical renewable energy applications requiring high reliability and energy efficiency.

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