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Intelligent MPPT Control for PV-Wind in Hybrid Microgrid System Using ANN Optimized Hippopotamus Algorithm

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Abstract: ***The increasing demand for renewable energy integration in hybrid microgrids necessitates intelligent control strategies to optimize power generation. Accurately tracking the Maximum Power Point (MPP) under fluctuating environmental conditions remains a significant challenge in hybrid photovoltaic (PV)–wind energy systems. To address this, the paper introduces an innovative MPPT method that employs an Artificial Neural Network (ANN) optimized using the Hippopotamus Algorithm (HA). This approach is specifically designed to enhance power extraction efficiency within a hybrid PV-wind configuration integrated into a microgrid environment. The proposed HA-ANN MPPT technique exhibits superior tracking efficiency, reduced steady-state oscillations, and faster convergence compared to conventional methods. Simulation results demonstrate that the HA-ANN MPPT improves power extraction efficiency under dynamic weather conditions while minimizing energy losses. Furthermore, the hybrid microgrid's overall performance, stability, and reliability are significantly enhanced. This research highlights the effectiveness of bio-inspired optimization algorithms in renewable energy applications and their potential to revolutionize MPPT strategies in hybrid microgrids. The proposed HA-ANN MPPT offers a promising solution for maximizing power utilization, ensuring sustainable energy management, and supporting the global transition toward renewable energy-based smart grids.***

Keywords: Hippopotamus Algorithm, Artificial Neural Network, Hybrid Microgrid, PV-Wind System, Renewable Energy Optimization

1. Introduction

In recent years, the shift toward renewable energy has accelerated considerably, fueled by the global demand for clean, sustainable, and environmentally friendly power solutions [1]. Hybrid microgrids that combine photovoltaic (PV) and wind energy technologies are gaining widespread recognition as efficient and reliable alternative systems for meeting energy needs while lowering reliance on conventional fossil fuels [2]. Due to the variable and nonlinear nature of these renewable sources, advanced control strategies are essential to maximize energy harvesting and ensure efficient operation [3]. MPPT is a crucial strategy for ensuring maximum energy harvesting from renewable sources, enhancing the efficiency and reliability of hybrid microgrids [4].

Traditional MPPT techniques, often encounter challenges such as delayed convergence, oscillations at steady state, and decreased accuracy when environmental conditions change rapidly [5][6]. To address these issues, researchers have investigated artificial intelligence (AI)-driven solutions, especially Artificial Neural Networks (ANNs) for MPPT, given their capacity to learn and adapt to the complex, nonlinear relationship between power and voltage [7]. However, the performance of ANN-based MPPT is highly dependent on its training process, which requires efficient optimization techniques to achieve accurate and fast convergence [8].

This research introduces a novel MPPT approach utilizing an ANN optimized by the Hippopotamus Algorithm (HA) for hybrid PV-wind microgrids. HA is a recently developed bio-inspired optimization technique that mimics the cooperative and adaptive behaviors of hippopotamuses in their natural habitat [9]. By leveraging HA's exploration and exploitation capabilities, ANN training is significantly enhanced, leading to improved MPPT performance. The proposed HA-ANN MPPT is evaluated through simulations and compared with conventional methods to validate its superiority in terms of tracking speed, accuracy, and stability [10].

2. System Description

The designed hybrid microgrid combines solar photovoltaic (PV) modules, a wind turbine generator (WTG), and a battery energy storage system (BESS), and AC loads, all interconnected to a main grid. The PV system utilizes an MPPT-controlled inverter to optimize solar energy conversion, while the wind turbine operates with a variable-speed generator and a power converter to maintain stable AC output. The BESS, managed by a bidirectional converter, balances power fluctuations by storing excess energy and supplying power during deficits. The AC load profile comprises residential, commercial, and industrial users, supported by a load management system that maintains consistent voltage and frequency levels. Grid integration is achieved through a grid-connected inverter coupled with a phase-locked loop (PLL), allowing two-way power flow to improve system reliability and stability. This setup maximizes the use of renewable energy sources while providing a dependable and uninterrupted power supply.

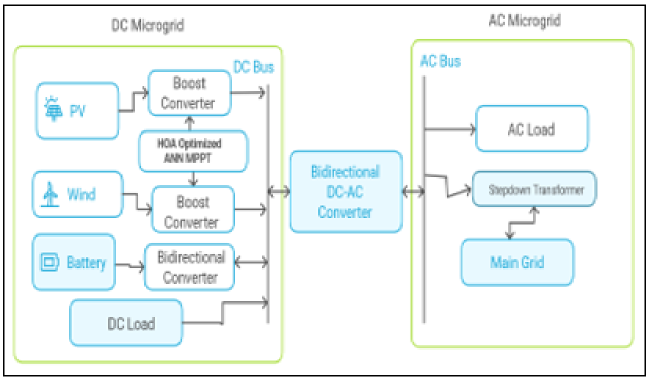

Figure 1: Proposed Hybrid Microgrid scheme

a) PV Modeling

The photovoltaic (PV) system in the hybrid microgrid converts solar energy into electrical power through an array of solar panels. The performance of a PV system depends on solar irradiance, temperature, and panel characteristics. A widely used approach to model PV behavior is the single-diode equivalent circuit, It includes, a series resistance (R_s), a current source, a diode, and a shunt resistance (R_p) [11]. The output current (I_{pv}) from the PV module can be expressed as:

$$I_{pv} = I_{ph} - I_d - I_p \tag{1}$$

Here, I_{ph} represents the photocurrent, *Id* denotes the current flowing through the diode, and I_p refers to the leakage current across the shunt resistance (R_p). The diode current is expressed as:

$$I_d = I_s \left[exp\left(\frac{q(V+IRs)}{nkT}\right) - 1\right] \tag{2}$$

In this equation, I_s denotes the reverse saturation current, q is the elementary charge (1.602×10^{-19} C), V represents the output voltage of the PV module.

The output power of a photovoltaic (PV) module exhibits a highly nonlinear behavior and is significantly influenced by environmental factors, making the use of a MPPT algorithm essential for effective energy harvesting [12]. MPPT algorithms continuously regulate the operating voltage and current to maximize power transfer via a DC-DC converter. Due to the fluctuating availability of solar energy, implementing real-time MPPT control is vital for enhancing both the performance and reliability of hybrid microgrid systems [13].

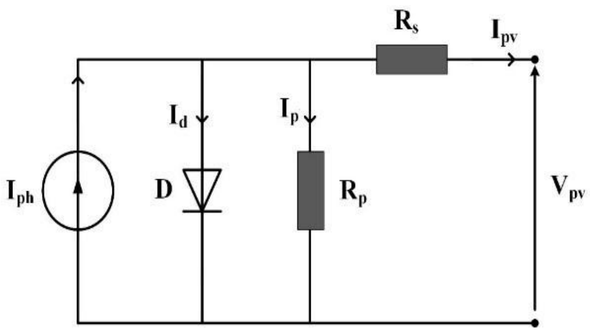

Figure 2: PV Equivalent Circuit

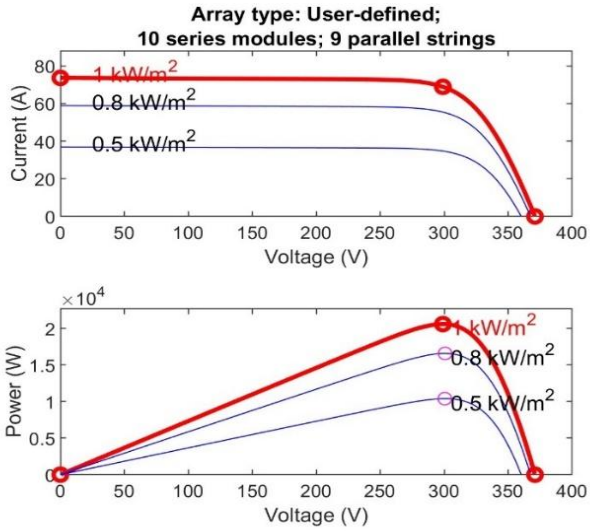

Figure 3: IV & PV Characteristics of PV

b) Wind Turbine Modeling

Wind turbines channel the kinetic energy from the wind and transform it into mechanical energy, which is again converted into electrical power through a generator. The amount of power generated is influenced by factors such as wind velocity, air density, the swept area of the rotor, and the turbine's power coefficient (*Cp*). The aerodynamic power captured from the wind can be calculated using the following expression [14]:

$$P_w = \frac{1}{2}\rho A C_p V_w^3 \tag{3}$$

In this formula, *Pw* represents the wind power captured, ρ is the air density measured (kg/m³), A is the rotor's swept area (m²), V_w denotes the wind speed (m/s), and *Cp* is the power coefficient, which varies based on the tip-speed ratio (λ) and the blade pitch angle (β). The TSR (λ) can be expressed as follows [15]:

$$\lambda = \frac{R\Omega}{V_w} \tag{4}$$

The *Cp* indicates how efficiently a wind turbine converts the kinetic energy of the wind into mechanical energy. As stated by Betz's Law, the theoretical maximum efficiency for energy extraction from wind is limited to 59.3% [16]. However, real-world turbines typically operate at lower efficiencies due to losses caused by mechanical and aerodynamic factors. Mechanical energy produced by the turbine is converted into electrical energy using various types of generators, such as DFIG, PMSG, and SCIG. The selection of the generator plays a crucial role in determining the system's efficiency and the applied control strategy [17]. To maintain reliable grid connection, power electronic converters are employed to regulate both voltage and frequency. Since wind energy is inherently variable, implementing a MPPT strategy is essential to maximize energy capture by continuously adjusting parameters like rotor speed and blade pitch angle. To improve tracking accuracy under dynamic wind conditions, advanced MPPT techniques utilizing Artificial Neural Networks (ANNs) and bio-inspired optimization algorithms have been investigated [18].

c) Battery Controller

Figure 4 illustrates the battery control system equipped with a bidirectional regulator. In a hybrid microgrid, the Battery Energy Storage System (BESS) plays a vital role in mitigating power fluctuations, maintaining voltage stability, and improving overall system reliability. The battery controller oversees both charging and discharging operations via a bidirectional DC-DC converter, which manages power exchange between the battery and the DC bus. This control system comprises a PI controller, a PWM unit, and a switching pulse circuit responsible for operating the converter.

The control strategy is based on maintaining the DC bus voltage (V_{dcBus}) at the reference voltage (V_{ref}) by adjusting the duty cycle of the bidirectional converter. The PI controller processes the error signal between V_{ref} and V_{dcBus}, ensuring minimal steady-state error and fast dynamic response. The output of the PI controller determines the duty cycle (D) of the PWM signal, which is fed to the switching pulse generator. The generated PWM signals control the semiconductor switches of the bidirectional converter, facilitating smooth power exchange between the battery and the DC bus.

During surplus power conditions (high renewable generation), the converter operates in buck mode, charging the battery by stepping down the DC bus voltage. Conversely, during power deficits (low renewable generation), it switches to boost mode, discharging the battery to maintain V_{dcBus} stability. The bidirectional power flow ensures continuous operation of AC loads and seamless integration with the main grid. The optimized tuning of the PI controller improves transient response, reduces voltage ripples, and enhances overall system efficiency. Advanced optimization techniques, such as Artificial Neural Networks (ANN) and metaheuristic algorithms, can further improve PI controller performance for dynamic load variations.

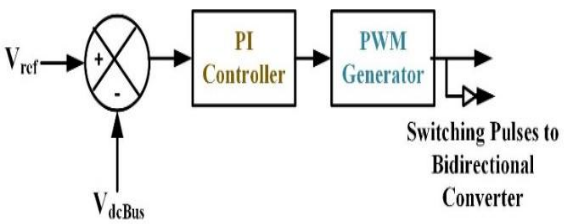

Figure 4: Battery Control

d) Interlinking Converter Control logic

The converters current control method in the d-q reference frame is depicted in Fig.4. The interlinking converter enables bidirectional power flow between the AC and DC subsystems of a hybrid microgrid, ensuring voltage and frequency stability. The control logic is based on the d-q reference frame transformation, which converts three-phase voltages and currents (V_a,V_b,V_c and I_a,I_b,I_c) into d-q components using Park's transformation. This simplifies power regulation, where the d-axis controls active power and the q-axis manages reactive power. A PLL synchronizes the reference frame to the grid frequency.

The controller continuously monitors the SOC of the BESS to determine power exchange. When SOC is high, power is exported to the grid, and when low, the system prioritizes charging. A PI controller processes the error between reference (Vref) and measured DC bus voltage (V_{dcBus}), generating control signals for voltage regulation. The computed d-q control signals are then transformed back into abc components using the inverse Park transformation and fed into the PWM generator. The switching pulses produced by PWM generator drive the Voltage Source Converter (VSC), ensuring seamless power exchange while maintaining microgrid stability. Optimized tuning methods, such as Artificial Neural Networks (ANNs) and metaheuristic algorithms, enhance PI controller performance, improving dynamic response and reducing voltage deviations

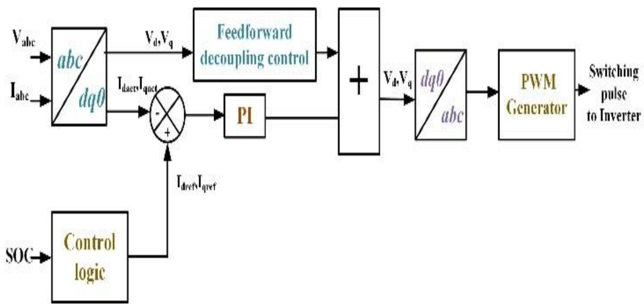

Figure 5: Control of Interlinking Converter

3. HOA-ANN MPPT

a) Procedure of HOA

The MPPT technique based on an Artificial Neural Network (ANN) optimized using the Hippopotamus Algorithm (HA) significantly improves the performance of hybrid photovoltaic (PV)–wind energy systems. It does so by continuously adapting the operating point in response to variations in environmental conditions. The step-by-step process is outlined as follows:

1) Data Acquisition: Real-time measurement of solar irradiance, temperature, wind speed, voltage, and current from PV and wind energy sources is conducted. The acquired data is normalized and fed into the ANN-based MPPT controller for real-time prediction of the optimal duty cycle.
2) Artificial Neural Network (ANN) Training: The ANN is trained using historical PV and wind power datasets, where inputs include solar irradiance, temperature, wind speed, and voltage, and the output is the optimal duty cycle of the DC-DC converter. A supervised learning

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approach, such as Levenberg-Marquardt backpropagation, minimizes tracking error and improves adaptability.

3) Hippopotamus Algorithm (HA) Optimization: HA, a metaheuristic optimization algorithm inspired by hippopotamus social behavior, fine-tunes the ANN's weight and bias parameters. Candidate ANN configurations are evaluated iteratively, with the best model selected based on Mean Squared Error (MSE) and convergence speed.
4) Real-Time MPPT Execution: The optimized ANN continuously predicts the Maximum Power Point (MPP) using real-time input variables. The DC-DC converter duty cycle is adjusted accordingly, ensuring optimal power extraction.
5) Performance Validation: The MPPT system is monitored, and efficiency is evaluated under dynamic environmental conditions. The HA-ANN MPPT demonstrates faster convergence and higher tracking accuracy compared to conventional methods.

This hybrid approach significantly improves tracking speed, efficiency, and adaptability, making it well-suited for hybrid renewable energy microgrids.

4. Results & Discussions

The proposed scheme is simulated using MATLAB, where the HOA-optimized ANN-based MPPT is applied to both the PV and wind subsystems. The convergence behavior of the Hippopotamus Optimization Algorithm (HOA) for the PV and wind systems is illustrated in Figures 6 and 7, respectively. The optimization process achieved a best score of 0.0064 for the PV system and 0.9801 for the wind system, indicating effective convergence and optimal performance in both cases.

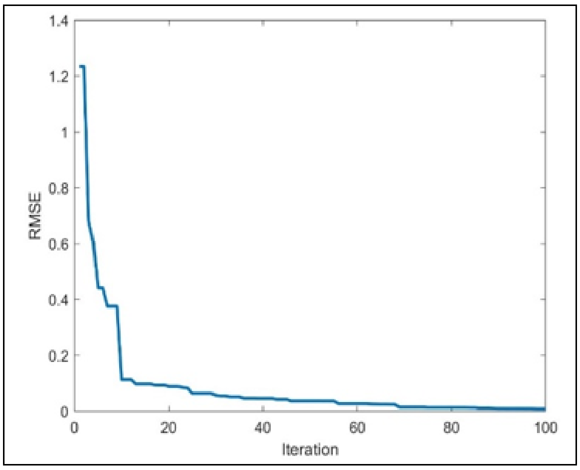

Figure 6: Convergence plot For PV MPPT using HOA

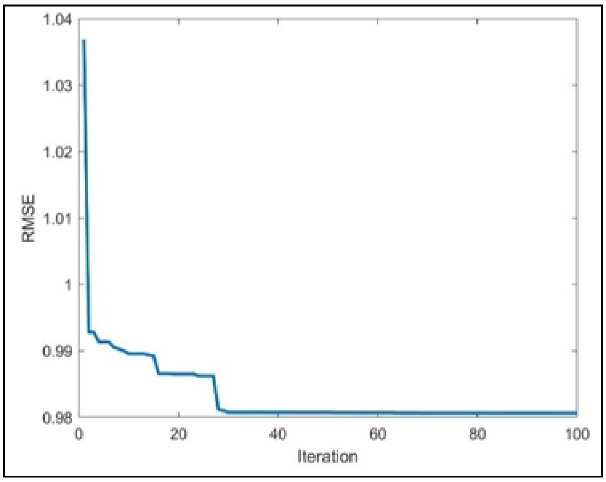

Figure 7: Convergence plot For Wind MPPT using HOA

The PV system is tested under varying irradiance conditions: 1000 W/m² from 0 to 1 second, 800 W/m² during 1–2 seconds and again from 3–4 seconds, and 500 W/m² between 2–3 seconds. Figure 8 illustrates the power contribution within the DC microgrid, which includes the PV, wind, battery, and DC load components. The wind subsystem operates at a wind speed of 12 m/s for the duration of 0–2 seconds, followed by a reduced speed of 10 m/s from 2–4 seconds.

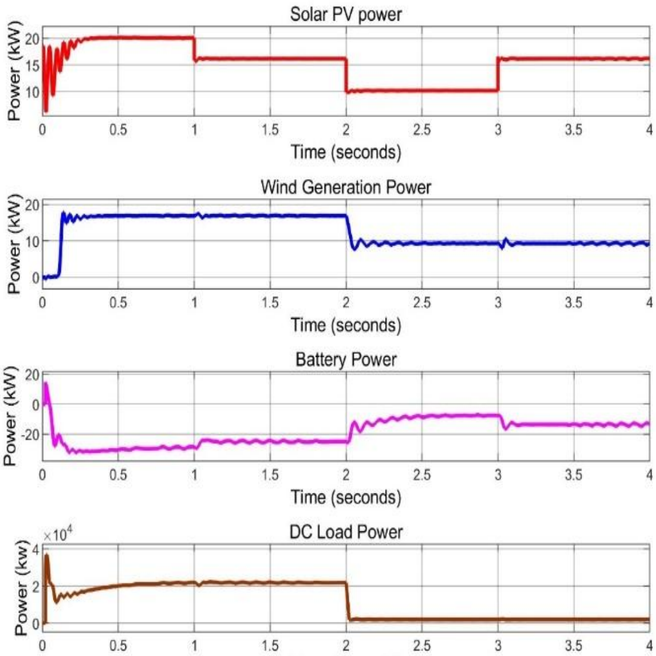

Figure 8: Powers of DC Microgrid

Table 1 presents the PV power output recorded at different time intervals under varying irradiance conditions.

Table 1: Efficiency Analysis of the HOA-Driven ANN MPPT

Irradiance (W/m^2)	Theoretical Power (kW)	Measured Power (kW)	Efficiency (%)
1000	20.58	20.12	97.76
800	16.57	16.18	97.65
500	10.38	10.06	96.92

Table 1 summarizes the efficiency of the proposed HOA-ANN MPPT algorithm under different irradiance levels. When operating at 1000 W/m², the system achieves a measured output of 20.12 kW compared to a theoretical maximum of 20.58 kW, corresponding to an efficiency of 97.76%. At an irradiance of 800 W/m², the output reaches 16.18 kW against a theoretical value of 16.57 kW, resulting in 97.65% efficiency. Under lower irradiance conditions of 500 W/m², the system produces 10.06 kW, while the expected power is 10.38 kW, leading to an efficiency of 96.92%.

5. Conclusion

This research presents the Hippopotamus Algorithm (HA) optimized Artificial Neural Network (ANN) MPPT for efficient power extraction in a hybrid PV-Wind microgrid. The proposed method enhances the tracking accuracy, convergence speed, and adaptability under varying environmental conditions compared to conventional MPPT techniques. The performance evaluation under different irradiance levels demonstrates the effectiveness of the HOA-ANN MPPT in maintaining high efficiency. At a solar irradiance of 1000 W/m², the system achieves a measured power output of 20.12 kW, closely matching the theoretical value of 20.58 kW and resulting in an efficiency of 97.76%. When the irradiance level drops to 800 W/m², the output power is recorded at 16.18 kW compared to the expected 16.57 kW, maintaining a high efficiency of 97.65%. Under lower irradiance conditions of 500 W/m², the system produces 10.06 kW against a theoretical maximum of 10.38 kW, corresponding to an efficiency of 96.92%. These results indicate that the HOA-ANN MPPT significantly enhances power tracking performance, reducing losses and improving system reliability. Furthermore, the metaheuristic optimization of ANN parameters ensures faster convergence and robustness against sudden irradiance and wind speed fluctuations. The findings confirm that the proposed MPPT technique outperforms conventional methods making it a promising solution for hybrid renewable energy microgrids.

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