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An Integrated Hybrid Power Supply For Distributed Generation Applications Fed by Non Conventional Energy Sources

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Abstract: This study introduces an innovative energy management strategy for hybrid power systems. The proposed system is designed to efficiently regulate power distribution among various energy sources—such as photovoltaic (PV) panels, wind turbines, and fuel cells—to meet load demands. It utilizes a combination of artificial neural networks (ANN) and fuzzy logic controllers (FLC) to control power flow. Specifically, the ANN is employed to perform maximum power point tracking (MPPT) for the different renewable sources connected at the DC link. Both the ANN-based and FLC-based MPPT techniques were evaluated in a hybrid setup incorporating PV modules, a wind turbine, and a fuel cell, each connected through DC–DC converters. The model's performance was tested under various operating conditions to analyze its dynamic behavior. Results indicate that the hybrid configuration delivers higher power output compared to using individual sources alone. The system is suitable for both standalone and grid-connected applications. Simulation results, conducted using MATLAB/Simulink, reveal that the ANN-based MPPT method outperforms the FLC approach in optimizing power extraction from the PV, wind, and fuel cell systems under DC load conditions.

Keywords: Hybrid Power Supply, ANN, ML, Python, Non-Conventional Energy Sources.

1. Introduction

On January 30, 2020, the World Health Organization (WHO), through its International Health Regulations Emergency Committee, declared the outbreak of the novel coronavirus (COVID-19) a "public health emergency of international concern. In the pursuit of a sustainable and environmentally responsible energy future, renewable energy sources have emerged as key contributors. Among these, solar and wind energy stand out as highly promising technologies for clean power generation. Their global adoption has grown more rapidly than many experts initially projected. However, the variable nature of these renewable resources introduces challenges related to stability and power quality, which are less prevalent in traditional power systems. This dynamic interaction between fluctuating energy input and demand necessitates effective energy flow management to ensure system reliability [1], extend the life of system components (such as fuel cell membranes), and maintain uninterrupted power delivery.

To address these challenges, the development and research into alternative energy systems have been significantly motivated. Over the last decade, technologies like solar photovoltaic (PV) panels and wind turbines (WT) have gained prominence due to their abundance, environmental benefits, maturity, and cost-effectiveness. Additionally, fuel cells (FC) have been integrated into hybrid systems to meet increasing energy demands efficiently [2].

While several studies have explored energy management strategies for hybrid systems, many relied on conventional control techniques. For example, Wang and Nehrir proposed strategies for managing energy in DC-linked wind/PV/FC systems, while Ahmed and colleagues addressed power fluctuation issues using ultra-capacitor-supported hybrid systems. Onar et al. also contributed similar strategies. However, many of these methods employed linear proportional-integral (PI) controllers, which have shown limitations in adapting to rapid environmental changes [3]. Hybrid renewable energy systems (HRES) present an excellent opportunity for distributed power generation. Notably, wind energy systems are experiencing the fastest growth in installed capacity among all renewable technologies. These systems are particularly attractive due to their technological maturity and cost efficiency. Likewise, PV systems offer high flexibility in scale and are easily integrated with DC–DC converters for effective energy conversion [4].

The method proposed in this study introduces a real-time energy management strategy governed by a hierarchical control framework. This system integrates four energy sources—PV panels, wind turbines, and fuel cells—at a common DC-link. The block diagram of this hybrid power setup is shown in Figure 1. PV and wind systems are emphasized due to their sustainability and cost-free resource inputs. Using DC–DC converters, these systems achieve stable output through the Maximum Power Point Tracking (MPPT) technique [5].

Several MPPT algorithms exist to optimize power extraction, with the Perturb and Observe (P\&O) method being commonly employed for its simplicity. Alternative MPPT strategies have also been developed specifically for fuel cell systems [6]. Recent studies indicate that incorporating artificial intelligence (AI), such as fuzzy logic and neural networks, enables precise control of fuel cells, maintaining them within high-efficiency operating zones.

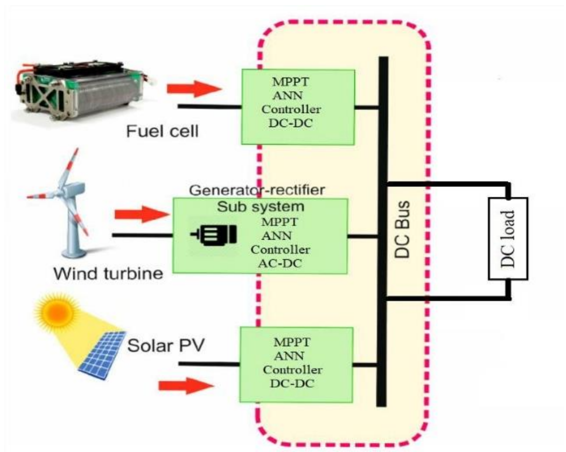

Figure.1: Energy Conversation Module

This paper presents an adaptive energy management system that uses fuzzy logic and artificial neural networks to control power distribution in a stand-alone hybrid power system. The MPPT approach is applied to maximize the output from each energy source—PV, WT, and FC—combined at a shared DC-link, resulting in a unified and efficient hybrid energy supply [7].

Various techniques have been developed to accurately estimate the optimal capacity of energy systems, among which the Perturb and Observe (P&O) method is widely used for Maximum Power Point Tracking (MPPT) due to its simplicity and ease of implementation. Additionally, several alternative MPPT strategies have been specifically tailored for fuel cell (FC) systems. Prior research has also demonstrated that artificial intelligence approaches can effectively manage fuel cell operation in hybrid vehicles, maintaining performance within high-efficiency zones [8]. In light of this, the present study proposes an adaptive power management approach for stand-alone hybrid energy systems, utilizing fuzzy logic and artificial neural networks. The MPPT technique is implemented to extract maximum power from photovoltaic (PV) panels, wind turbines (WT), and fuel cells. All these energy sources are integrated at a common DC-link, enabling the system to deliver a stable and combined power output—effectively forming a robust hybrid power system [9].

2. Related Work

Mathematical Analysis Of Photo-Voltaic Pv , Wind Turbine And Fuel Cell Systems.

Figure 2 illustrates the equivalent circuit model of a photovoltaic (PV) cell. In real-world applications, individual PV cells are assembled into larger units known as PV modules. These modules can be interconnected in series or parallel configurations to form PV arrays, which are commonly used in solar power generation systems. In the circuit, the current source IphI_{ph}Iph symbolizes the photocurrent generated by the cell. The parameters RshR_{sh}Rsh and RsR_{s}Rs represent the cell's inherent shunt and series resistances, respectively. The equivalent model of a complete PV array is depicted in Figure 2.

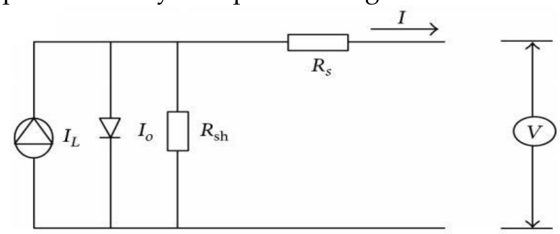

Figure2. PV cell equivalent circuit

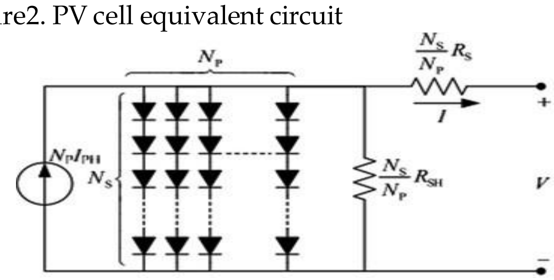

Figure 3. Equivalent circuit of solar array.

Wind Turbine Modelling

A Wind Turbine Induction Generator (WTIG) system involves two main energy conversion stages. Initially, the kinetic energy from the wind is transformed into mechanical energy, which is subsequently converted into electrical energy. The internal structure of the wind turbine system is illustrated in Figure 3. Wind strikes the rotor blades, causing them to rotate and transfer energy to the rotor shaft. To achieve the desired high rotational speed required by the generator, a gearbox is employed between the rotor shaft and the generator. The mechanical power transmitted. through the shaft is then converted into electrical power by the connected induction generator.

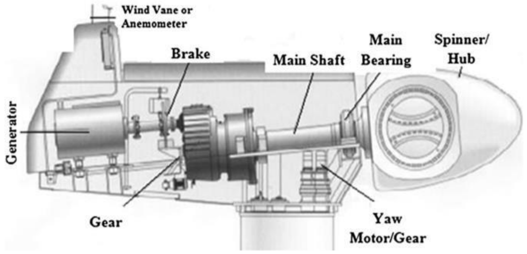

Figure. 3 Cross section showing the arrangement of internal parts of a wind turbine

When wind conditions fluctuate, the resulting power output under varying conditions is organized in matrix form for analysis[11]. Ultimately, the electrical energy generated from the wind turbine system can be mathematically represented using a cubic equation, as shown in Equation (4).

In this equation:

- PmP_m represents the mechanical power (W),
- CpC_p is the power coefficient,
- ϱ\rho is the air density (kg/m³),
- AA is the swept area of the rotor blades (m²),
- λ\lambda denotes the tip-speed ratio,
- VV is the wind speed (m/s), and
- β\beta is the pitch angle (rad).

This relationship is derived based on aerodynamic principles, allowing the transfer of power characteristics from one turbine design to another.

The power available in the wind can be expressed as:

Pw=12ϱAV3P_w = \frac{1}{2} \rho A V^3

The aerodynamic efficiency of a wind turbine is characterized by the power coefficient Cp(β,λ)C_p(\beta, \lambda), which reflects the effectiveness of converting wind energy into mechanical energy. Here, β\beta refers to the blade pitch angle, the degree to which the blade is twisted along its length, while λ\lambda is the tip-speed ratio—defined as the ratio of the rotor's tangential speed to the incoming wind speed.

The power captured by the turbine rotor can be calculated using:

Pwt=12ϱACpV3P_{wt} = \frac{1}{2} \rho A C_p V^3

Alternatively, it can also be expressed in terms of rotor shaft speed (ωs\omega_s) and rotor radius (RR):

Pwt=T·ωsP_{wt} = T \cdot \omega_s

In an idealized scenario with no energy losses and an infinite number of rotor blades, the theoretical maximum value for the power coefficient—known as the Betz limit—is Cpmax=0.593C_{p_{max}} = 0.593.

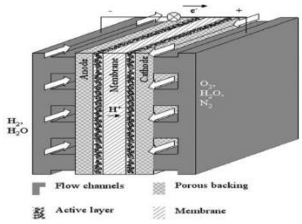

Fig. 4 Model representation of a proton exchange membrane fuel cell.

Fuel Cell Model Equations

A fundamental fuel cell model incorporates the governing principles of mass conservation, thermal energy, momentum, species transport, and electric charge balance. These five core equations collectively describe the physical and chemical behavior within the cell. The model integrates these equations through source terms that account for electrochemical reactions and electro-osmotic drag occurring in the polymer electrolyte membrane[12]. These interconnected processes are represented in vector form to capture the complex interactions and dynamics within the fuel cell system.

Maximum Power Point Tracking (MPPT) Techniques

The efficiency of renewable energy sources such as wind turbines (WT), photovoltaic (PV) systems, and fuel cells (FC) can be significantly enhanced through Maximum Power Point Tracking (MPPT) techniques. These methods ensure that each energy source operates at its optimum power point under varying environmental conditions. Several MPPT strategies are widely adopted, including P&O, INC, FLC, and NN methods. When the initial voltage of the PV array or the rotor speed of the wind turbine deviates from the optimal values, adjustments are required to bring each system back to its maximum power operating point.

In this study, MPPT is employed to extract the maximum possible power from a hybrid energy system composed of PV, WT, and FC components. This harvested power is then transferred efficiently to the load using a DC/DC converter. The converter serves as a power interface between the source and the load, adjusting the duty cycle to change the apparent load impedance.

By matching this impedance to the source at its peak power point, the maximum amount of power can be delivered. Thus, implementing MPPT techniques is essential for ensuring that each module operates at its peak efficiency [13].

Fuel Cell Mathematical Modeling

The mathematical modeling of a basic fuel cell system involves five key physical domains: mass transport, momentum, species concentration, thermal energy, and electric charge. These equations are interlinked through source terms that represent electrochemical reactions and electro-osmotic drag within the polymer electrolyte membrane (PEM). This coupled system is typically expressed in vector form using a set of differential equations.

The continuity equation describes mass conservation within porous electrodes made of carbon fiber or cloth. Reactant gases are distributed across the catalyst layer, and the porosity of the electrode medium is incorporated into the continuity equation, given by:

∂(ερ)∂t+∇·(ερU)=0\frac{\partial (\varepsilon \rho)}{\partial t} + \nabla \cdot (\varepsilon \rho \mathbf{U}) = 0

Where:

- ∇\nabla is the vector differential operator,
- ρ\rho is the fluid density,
- ε\varepsilon is the porosity of the material,
- U\mathbf{U} is the flow velocity vector,
- tt is time.

This forms one of the foundational equations for modeling PEMFC performance, alongside others governing momentum and species transport.

Artificial Neural Networks: Levenberg-Marquardt Algorithm

The Levenberg-Marquardt (LM) algorithm is a powerful optimization method frequently used to train artificial neural networks, especially in regression tasks involving squared error loss functions. It offers a compromise between the speed of Newton's method and the stability of gradient descent.

The loss function typically used is:

E=∑i=1mei2E = \sum_{i=1}^{m} e_i^2

Where eie_i is the error for the ithi^{th} training example, and mm is the total number of samples. To optimize this, the algorithm computes:

- The Jacobian matrix (J): contains partial derivatives of the errors with respect to each parameter.
- The gradient vector (g): obtained as g=JTeg = J^T e, where ee is the vector of errors.
- The Hessian approximation (H): estimated as H=JTJ+λIH = J^T J + \lambda I, where λ\lambda is a damping parameter and II is the identity matrix.

The parameter update rule is defined as:

θnew=θ−(JTJ+λI)−1JTe\theta_{new} = \theta - (J^T J + \lambda I)^{-1} J^T e

When λ\lambda is large, the algorithm behaves like gradient descent, making small updates. As the error decreases and convergence improves, λ\lambda is reduced, transitioning the method toward Newton's algorithm for faster convergence. If an iteration fails to reduce the error, λ\lambda is increased to restore stability.

This adaptive behavior allows the Levenberg-Marquardt algorithm to achieve rapid and robust convergence, making it well-suited for training neural

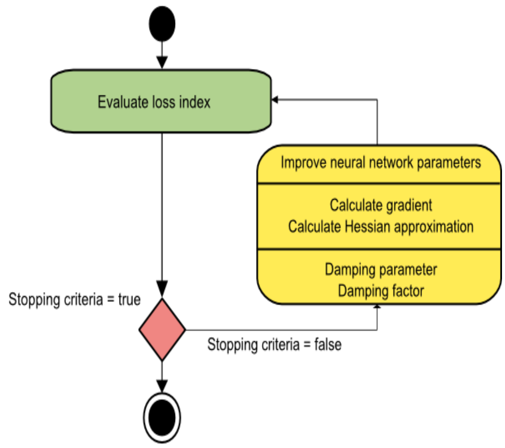

Figure.1 . Workflow Mechanism

3. Results

Simulation Analysis Using MATLAB/Simulink

A simulation study has been conducted using MATLAB/Simulink to evaluate the performance of a hybrid renewable energy system in delivering maximum power to a resistive load. The system was modeled and analyzed under various conditions to assess its effectiveness. The simulation results compare the input power and voltage before the boost converter—without employing a fuzzy logic controller-based MPPT—with the output after the boost converter, where MPPT is implemented using both Fuzzy Logic Controller (FLC) and Artificial Neural Network (ANN) techniques[14].

This analysis highlights the improvements in power extraction and voltage regulation achieved through intelligent MPPT control strategies.

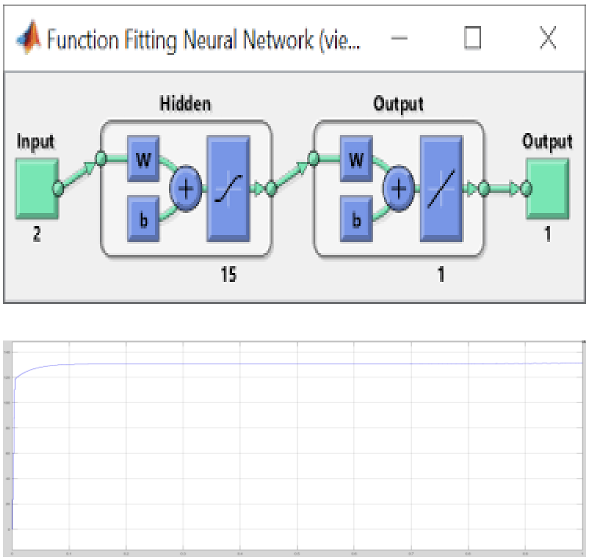

Figure.2 . Internal Working functional Mechanism

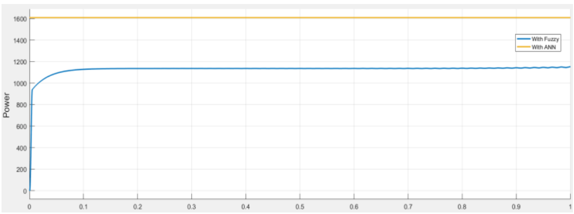

Figure 3. Simulated FLC and MPPT

1. Conclusion and Future Scope

This study introduces an advanced MPPT approach applied to solar PV, wind turbine (WT), and fuel cell (FC) systems within a hybrid energy configuration. The proposed method enables precise and rapid tracking of the maximum power point across varying operating conditions. To assess the effectiveness of different ANN architectures, several performance metrics were defined and evaluated through a series of case studies involving randomly generated scenarios. The findings demonstrate the method's strong robustness against variations in PV system parameters. Simulation results confirm that the MPPT technique significantly enhances the overall efficiency of the hybrid energy system.

The hybrid setup consistently delivers greater power output than individual PV, WT, or FC systems across a range of load conditions. The proposed solution is applicable to both standalone and grid-connected systems. Future work may focus on experimental validation to identify the most cost-effective hardware implementations. Additionally, exploring the balance between investment costs and energy efficiency losses could provide valuable insights for practical deployment.

References

[1]. Esram T, Chapman PL. Comparison of photovoltaic array maximum power point tracking techniques. IEEE Trans Energy Convers 2007;22(2):439–49.

[2]. De Brito MAG, Galotto L, Sampaio LP, de Azevedo e Melo G, Canesin CA. Evaluation of the main MPPT techniques for photovoltaic applications. IEEE Trans Indus Electr 2013;60(3):1156– 67.

[3]. Ishaquea K, Salamb Z. A review of maximum power point tracking techniques of PV system for uniform insolation and partial shading condition. Renew Sustain Energy Rev 2013;19(March):475–88.

[4]. Jain S, Agarwal V. Comparison of the performance of maximum power point tracking schemes applied to single-stage grid-connected photovoltaic systems. IET Electr Power Appl 2007;1(5):753–62.

[5]. Femia N, Granozio D, Petrone S, Spagnuolo G, Vittelli M. Predictive & adaptive MPPT perturb and observe method. IEEE Trans Aerosp Electron Syst 2007;43(3):934–50.

[6]. Casadei D, Grandi G, Rossi C. Single-phase single-stage photovoltaic generation system based on a ripple correlation control maximum power point tracking. IEEE Trans Energy Convers 2006;21(2):562–8.

[7]. Abdelsalam AK, Massoud AM, Ahmed S, Enjeti P. High-performance adaptive perturb and observe MPPT technique for photovoltaic-based microgrids. IEEE Trans Power Electron 2011;26(4):1010–21.

[8]. Qiang M, Mingwei S, Liying L, Guerrero JM. A novel improved variable step-size incremental-resistance MPPT method for PV systems. IEEE Trans Industr Electron 2011;58(6):2427–34.

[9]. Fangrui L, Shanxu D, Fei L, Bangyin L, Yong K. A variable step size INC MPPT method for PV systems. IEEE Trans Industr Electron 2008;55(7):2622–8.

[10]. Sera D, Teodorescu R, Hantschel J, Knoll M. Optimized maximum power point tracker for fast-changing environmental conditions. IEEE Trans Industr Electron 2008;55(7):2629–37.

[11]. Weidong X, Ozog N, Dunford WG. Topology study of photovoltaic interface for maximum power point tracking. IEEE Trans Industr Electron 2007;54(3):1696–704.

[12]. Karlisa AD, Kottasb TL, Boutalisb YS. A novel maximum power point tracking method for PV systems using fuzzy cognitive networks (FCN). Electric Power Syst Res 2007;77(3–4):315–27.

[13]. Kulaksız AA, Akkaya R. A genetic algorithm optimized ANN-based MPPT algorithm for a stand-alone PV system with induction motor drive. Sol Energy 2012;86(9):2366–75.

[14]. Bahgata ABG, Helwab NH, Ahmadb GE, El Shenawyb ET. Maximum power point traking controller for PV systems using neural networks. Renew Energy 2005;30(8):1257–68.