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Analysis of Artificial Intelligence Based MPPT in PV Grid Connected System

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Abstract: - The There has been a rise in the demand for electrical power during the past 10 years. Installing a new power generator (PG) is a costly and time-consuming procedure. For this reason, solar power plants are considered a viable alternative for meeting the current energy demand. But crucial maintenance and output power balance are the key issues facing solar power facilities. In order to reduce output power balance and maintenance problems in solar plants, an appropriate approach is required. This study offers a novel method for tracking the maximum power for hybrid photovoltaic (PV) and wind energy systems (WES): single maximum power point tracking, or MPPT. In the proposed MPPT technique, a radial basis function network (RBFN) control mechanism is based on an artificial neural network (ANN).

Keywords: Economic load PV system, WECS, MPPT, ANN.

I. INTRODUCTION

Energy is essential for the world to maintain all other essential components of civilization and to raise living standards. Issues facing traditional energy sources include rising fossil fuel costs, environmental concerns, and their impact on human health. Researchers are optimistic that they will be able to provide pollution-free power by utilizing renewable energy sources. Examples of clean and infinite sustainable energy sources are the sun, wind, biomass, fuel cells, and water. Among the various renewable energy sources, solar energy is widely utilized to produce electricity because of its easy maintenance and low cost of operation.

Recently, there has been a lot of interest in solar energy harvesting, which is mostly utilized for standalone and grid-connected devices [1]. Most current solar power generation uses solar farms or flat solar panel configurations. The flat solar PV-based energy harvesting devices use a large amount of functional space. In contrast, the solar PV tree-based energy harvesting system only needs a percentage of that land area in order to generate the same quantity of electricity. More efficient than flat panels, the solar PV tree is a tree-shaped configuration of solar panels. One method used in the urban area to produce electrical energy is solar photovoltaic tree-based energy generating, which helps to conserve land and satisfy people's energy needs.

The most feasible method for meeting electricity demand on its own during a power outage is the solar PV tree concept. In addition, it may sell any extra energy it produces to the grid. It is influenced by several elements, including temperature, weather, and the materials of the modules. This article looks at using an artificial neural network (ANN) to boost MPPT efficiency and increase a solar power system's smoothness.

Essential characteristics of the deep learning-based ANN mechanism enable it to optimize the input data and produce the intended outputs. In addition, the ANN approach is currently widely used to forecast expected outcomes and optimize structure complexity in a range of fields. For instance, the ANN methodology is used in [8,] to predict droughts; [9], to investigate how to accurately detect wind speed and predict its consequences; [10], to discuss the particular topic for the city of Ankara using ANN; and [11], to forecast solar system generation using ANN. Therefore, in order to optimize the MPPT output, the ANN mechanism is approximated in this proposed study.

II. DESIGN OF PROPOSED SYSTEM

Wind energy harvesting unit is a mechanical system on the other hand a Solar energy harvesting unit is a electron flow system. At the resultant end the power is obtained. To help in integrating a boost converter is selected with special hybrid calibration. This is the proposed mechanism carrying the DC-DC converter along side the current flow. A structural representation of the links are displayed in the figure 2 of this text for better understanding.

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III. PV System Design

Solar cells make up a single solar panel unit. Herein lies the crux of energy extraction: as electrons traverse the external circuit towards the freewheeling diode, they encounter resistance from the parallel resistor. This resistance prompts the electrons to relinquish their surplus energy, which is dissipated as heat. Meanwhile, the freewheeling diode permits the flow of electrons in a single direction, ensuring that the harvested energy is directed towards productive ends. A solar panel is constructed after all of the solar cells are linked. Solar cells in solar panels are connected in both series and parallel configurations. solar cell is connected to a freewheeling diode and a parallel resistor, a sophisticated dance of electron dynamics unfolds. The freewheeling diode acts as a gatekeeper, ensuring the unidirectional flow of current, preventing undesirable feedback loops that could impede the efficiency of energy extraction. Parallel to this, the resistor serves as a balance, dissipating excess energy and maintaining the stability of the systemWe take into consideration the equivalent circuit diagram of a solar cell, which consists of two resistances, a current source, and a diode, for modeling purposes. Another name for this kind is the single diode solar cell model. One resistance in the pair is linked in series with the current source, while the other is linked in parallel.

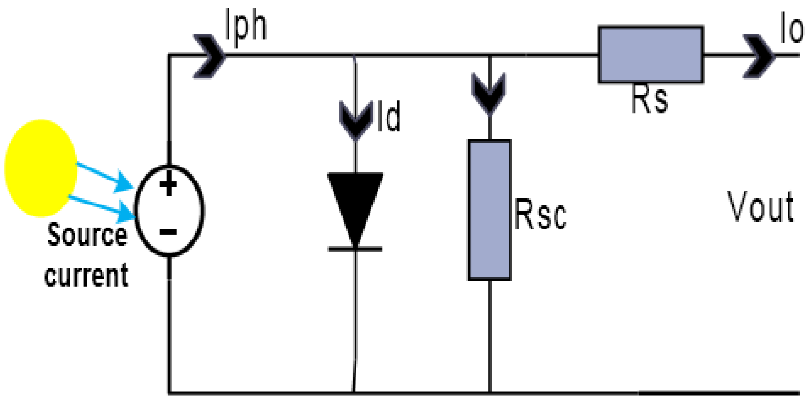

Figure 1. Photovoltaic cell Equivalent circuit

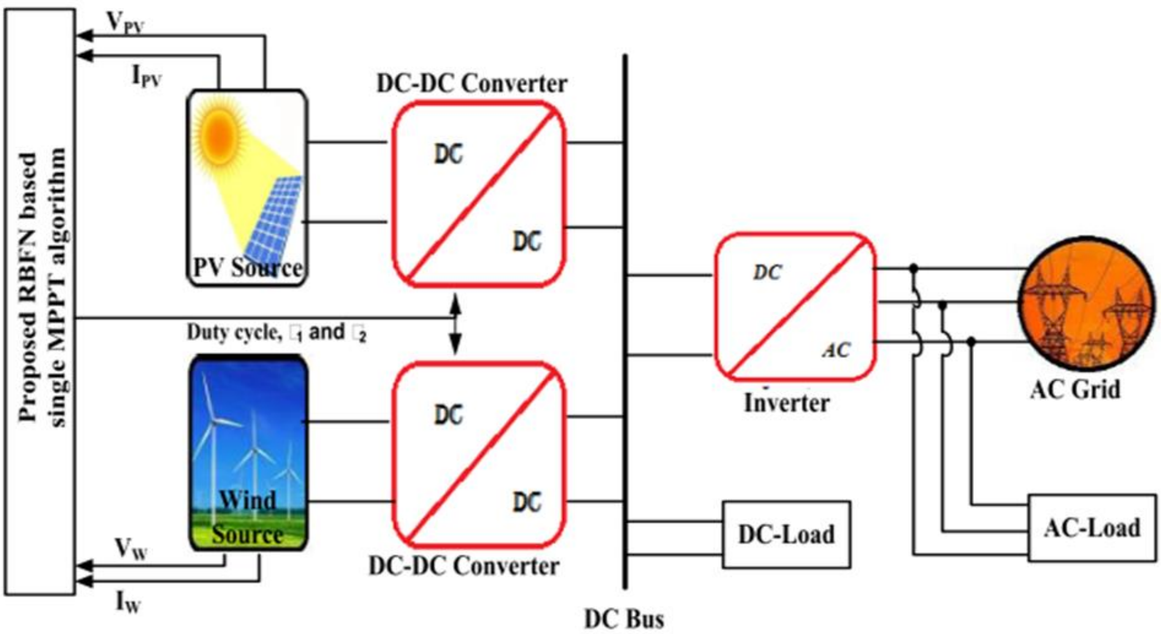

Figure 2. Block Diagram of proposed system

The single diode solar cell model's circuit schematic was displayed in figure 1. Solar cell output voltage is represented by V, while solar cell output current is represented by I.

$$I = I_{ph} - I_0\left[\exp^{\frac{ev_d}{KFT_C}} - 1\right] - \frac{V_d}{R_{sh}}$$

$$I_{ph} = \left[\mu_{sc}(T_c - T_r) + I_{SC}\right] + G$$

$$I_0 = I_{0\alpha}\left(\frac{T_C}{T_r}\right)^3 \exp\left[\frac{eV_g}{KF}\left(\frac{1}{T_r} - \frac{1}{T_C}\right)\right]$$

There is no load transfer when the inductor is in the charging mode; the source voltage only charges it to the necessary level. The switch is open and the diode is forward biased in the second mode [11].Since the charged inductor begins to discharge in this state, it is known as the discharging mode. In this boost converter operating mode.

IV. Wind Energy Conversion System

This embodies a sophisticated assemblage of mechanical and electrical components designed to harness the kinetic energy inherent in wind and convert it into usable electrical power. This intricate system comprises several key elements, each meticulously engineered to optimize energy extraction efficiency and operational reliability.

At its core, a WECS typically incorporates a wind turbine, an aerodynamic apparatus outfitted with multiple blades engineered to capture wind energy. These blades, often constructed from advanced composite materials, are strategically positioned atop tall towers to capitalize on high-altitude wind currents characterized by greater kinetic energy densities. The rotation of the turbine blades in response to prevailing wind velocities initiates the kinetic-to-mechanical energy conversion process, thereby driving an internal rotor assembly connected to a power generator.

WECS necessitates ancillary infrastructure to facilitate energy transmission and grid interconnection, including transformers, switchgear, and transmission lines. These components serve to modulate voltage levels, mitigate power losses, and facilitate bidirectional power flow between the WECS and the grid, thereby enabling seamless energy exchange and optimal utilization of renewable energy resources.

Since it transforms kinetic plays a vital role in the conversion system. The wind turbine and electricity generator are connected by a gear train.

The following formula is used to calculate the mechanical power.

Pm = 0.5ρACp(λ,β)νwind

The variables A, wind, and Cp(λ,β) represent the area swept away by turbine blades (m2), wind, and the power coefficient [14–17], which depends on β (blade pitch angle and tip speed ratio) and λ (air density), which usually takes a value in the range of 1.22–1.3 kg/m3.

ANN-MPPT for wind energy conversion represents a groundbreaking approach to optimizing the performance of wind turbines by leveraging the power of advanced machine learning algorithms. At its essence, this innovative methodology harnesses the computational prowess of artificial neural networks to accurately predict and track the maximum power point (MPP) of wind energy conversion systems, thereby enhancing energy extraction efficiency and operational stability.

Through a process known as training, wherein the neural network learns from historical data, ANN MPPT algorithms acquire the capability to discern intricate patterns and relationships inherent in wind turbine operating conditions, thereby facilitating accurate MPP estimation in real-time.

The iterative nature of ANN MPPT enables continuous adaptation and refinement of predictive models in response to evolving environmental conditions and system dynamics. Through a process of feedback and adjustment, the neural network iteratively refines its predictions, thereby enhancing accuracy and reliability over time. This adaptive capability ensures robust performance across a diverse spectrum of operating scenarios, ranging from benign wind conditions to turbulent gusts or transient load variations.

ANN MPPT for wind energy conversion epitomizes a symbiotic fusion of cutting-edge machine learning techniques and renewable energy technologies, poised to revolutionize the landscape of wind power generation. By harnessing the predictive prowess of artificial neural networks, this transformative approach holds the promise of unlocking unprecedented levels of efficiency, resilience, and sustainability in wind turbine operations, thereby accelerating the global transition towards a greener and more sustainable energy

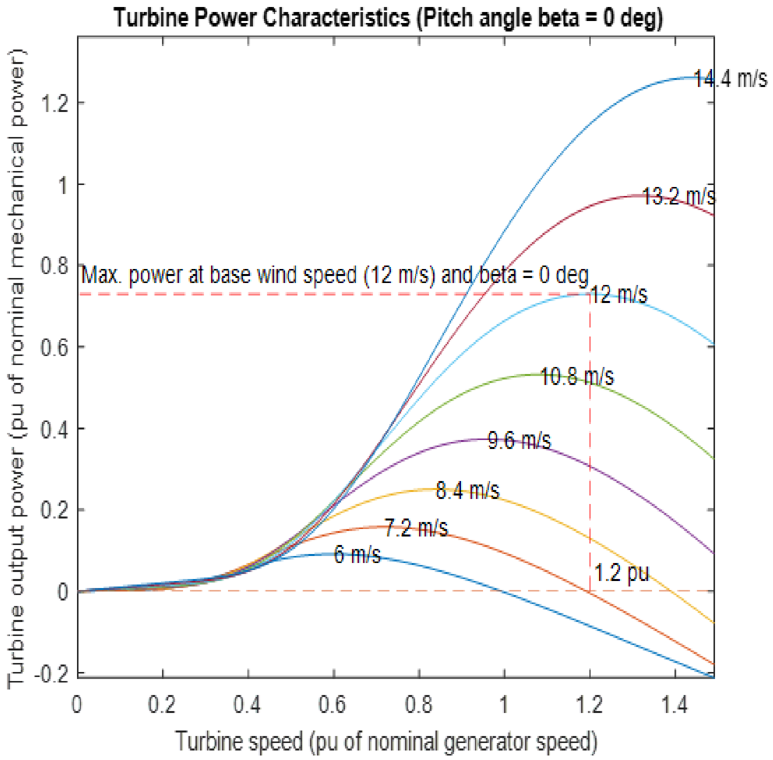

Figure 3

V. ANN MPPT

An RBFN-based network's basic design is shown in Figure 7. The activation function, weights, and connectivity architecture of the system all affect how well the RBFN network performs. The installation of the system becomes more difficult and large-scale since each renewable energy source has its own MPPT controller.

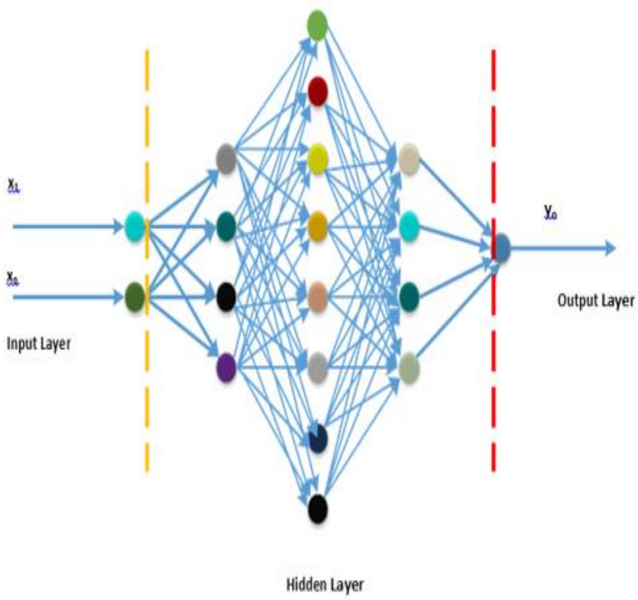

Figure 4

After receiving inputs from every node in the input layer, each neuron in this layer computes the weighted sum of those inputs. Non-linearity is then introduced by applying an activation function. Every neuron's output serves as every other neuron's input in the following layer. The neurons in the second layer process inputs from the neurons in the layer above, compute, and send the outcomes to the layer above. The goal of having more hidden layers is to improve representation and generalization by allowing the network to learn progressively abstract characteristics from the data. This layer is the last one to be concealed before the output layer.

VI. RESULTS AND DISCUSSION

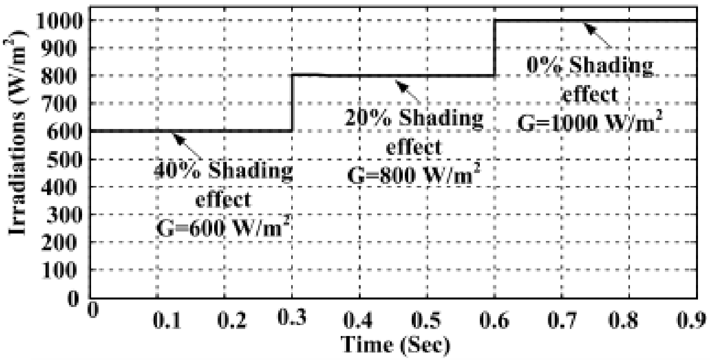

Figure 5. Input Irradiance

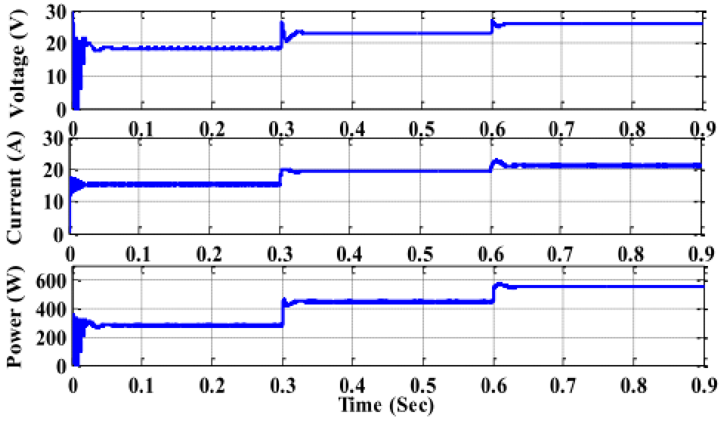

Figure 6. PV output

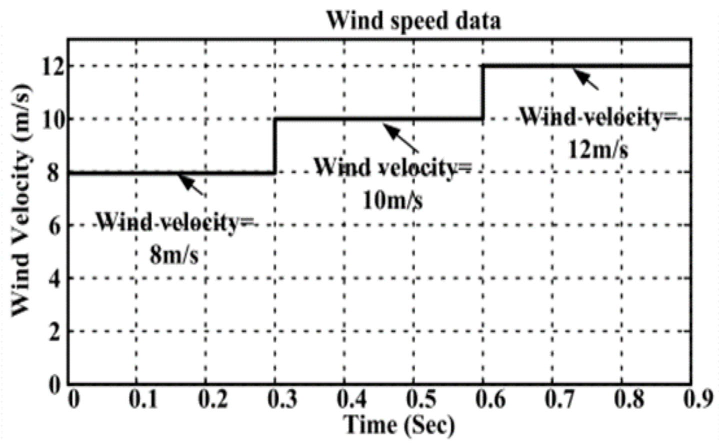

Figure 7. Wind speed input

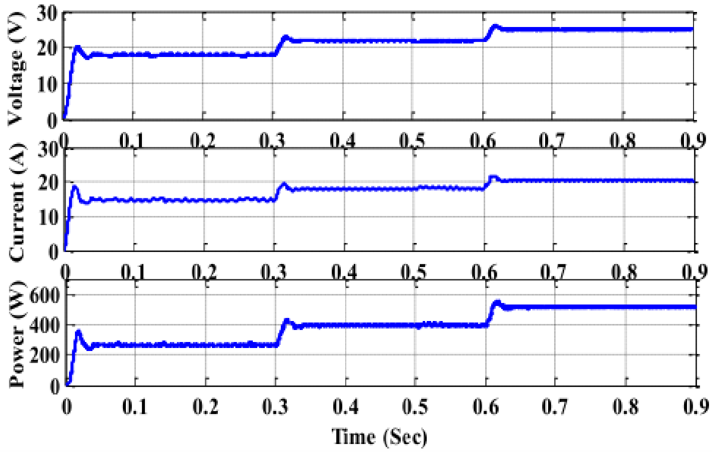

Figure 8. WECS output

When calculating the solar irradiation availability for the suggested system, the following factors are considered: As seen in Fig. 9, computations are performed under the assumptions that shade will affect solar irradiation by 40%, 20%, and 0%, respectively. For time intervals of 0 to 0.3 seconds, 800 W/m2 for 0.3 to 0.6 seconds, and 1000 W/m2 for 0.6 to 0.9 seconds, the findings are as follows. When the available solar irradiation is taken into consideration, the output voltage, current, and power waveforms of a photovoltaic panel are displayed in Figure 10.. When 600 W/m of solar radiation is accessible, 324 W is produced for a duration of 0 to 0.3 seconds; similarly, the availability of solar irradiations determines the values of 436.8 W and 554.4 W for durations of 0.3 to 0.6 seconds and 0.6 to 0.9 seconds, respectively.

The wind velocity data availability is taken into account for system development in the following ways: for a period of 0 to 0.3 sec as 8 m/s, 0.3 to 0.6 sec as 10 m/s, and for the time considering available input data from each source. An average DC link power of 587 W from 0 to 0.3 sec, 721 W from 0.3 to 0.6 sec, and 858.8 W from 0.6 to 0.9 sec is provided by the developed hybrid system with a single MPPT.

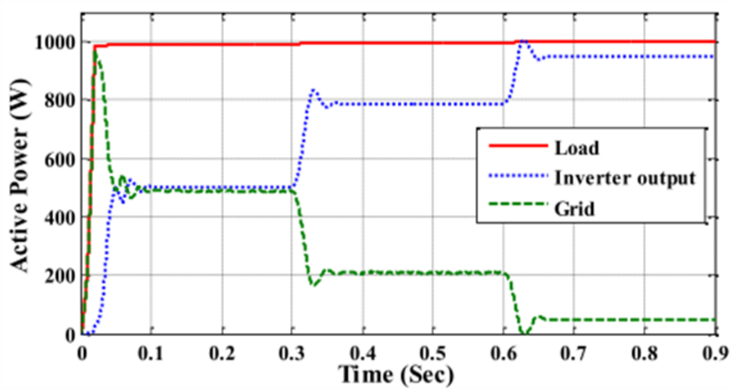

Figure 9. Active power in system

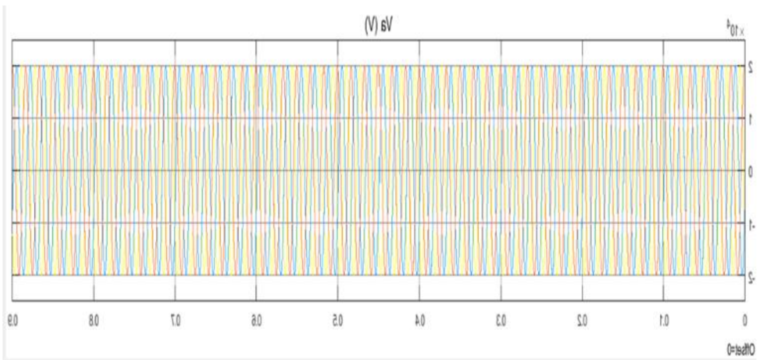

Figure 10. Grid voltage

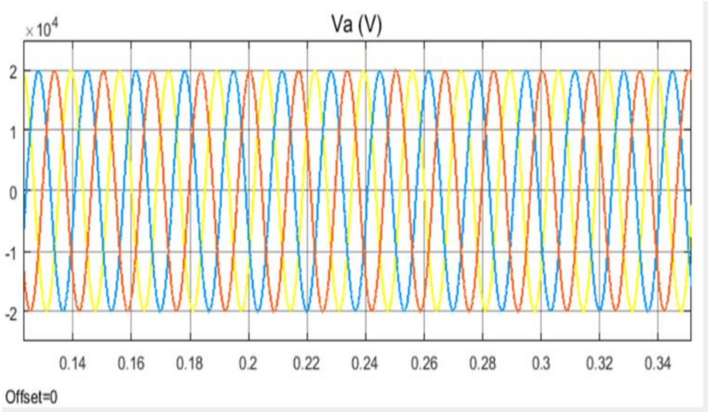

Figure 11. Three phase grid voltage

VII. CONCLUSION

The electric load has increased in the last ten years. An advantageous substitute for lessening the burden on the main power networks is a solar power plant. In this paper, the application of a hybrid boost converter and an ANN-based MPPT for load control is investigated. With its hybrid converter and ANN-based MPPT controller, there are few fluctuations and fast tracking. The literature-available MPPT methods for obtaining the most power possible from a hybrid system are discussed. The technique is capable for standalone function. Also this is compatible for the wind speed and solar irradiation data across time

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