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Power Energy Management for a Hybrid Renewable System Using Artificial and Computational Intelligence †

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Abstract

There are significant difficulties with power quality and stability as a result of active cooperation between renewable energy sources and load demand. To maintain power stability between renewable energy supplies and the microgrid/utility grid, novel solutions must be implemented. By using an artificial and computational intelligence controller to schedule power from multiple sources (photovoltaic, wind, grid, and battery) under a set of constraints, such as weather, load-shedding hours, and peak pricing hours, this paper introduces a novel approach for power management in grid-connected hybrid renewable systems with PV–wind and energy storage systems. The approach involves using an artificial neural network (ANN) to process all of the inputs and creating an ANN rule set from a modelled hybrid renewable system. A rule-based power scheduler is developed, and simulations are run for a full day. The suggested fuzzy control approach can detect ongoing variations in grid load-shedding patterns, PV–wind power generation, load demands, and battery state-of-charge to enable prompt and accurate decision-making. The proposed ANN rule-based scheduler can handle nonlinearity by integrating metaheuristics into computer-assisted decision-making and can function effectively with imprecise inputs, negating the need for an exact numerical model. The MATLAB/Simulink R2023a software was used for simulation, and the system operated as efficiently as possible. The simulation results suggested that an ANN offers a foundation for extension to handle numerous particular scenarios.

Keywords: power energy management; renewable energy; artificial intelligence; power system; computational intelligence

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1. Introduction

Renewable energy sources have increasingly become an essential component of energy production as fossil fuel reserves are nearing depletion. Solar energy is regarded as the most desirable renewable energy source. Although these resources are improving in many ways, their irregularity and rising capital costs remain the main obstacles to their use. A hybrid energy power system with a storage battery can improve the system's operational efficiency, reliability, and power quality and availability. To solve optimization problems approximatively, find optimal solutions in a fair amount of time, and make good use of artificial computational resources, heuristic and metaheuristic algorithms are included

in the category of methods. These algorithms, meanwhile, do not promise to identify the ideal answers the first time. This stems from how these algorithms use stochastic search. A number of factors have contributed to the growing popularity of metaheuristics in engineering applications [1]. To begin with, their notions are straightforward and simple to execute. They perform better than local search algorithms, too. Thirdly, there are a variety of uses for them. Information about the derivative function is also not required. By mimicking physical or biological events, nature-inspired metaheuristic algorithms resolve optimization issues. The energy industry is embracing generative AI due to a number of factors. Renewable Energy Optimization: To maximize energy yield and grid stability, generative AI examines weather patterns, grid data, and energy use to optimize the output and performance of renewable energy sources like solar and wind. Smart Grid Management: Predictive maintenance, demand forecasting, and load balancing are made possible by generative AI algorithms in smart grids, which optimize energy distribution, lower losses, and increase overall grid resilience. Asset Performance Optimization: Using real-time data monitoring and analysis, generative AI maximizes asset lifespan and performance by forecasting failures, finding inefficiencies, and optimizing maintenance schedules in power plants and transmission infrastructure. Energy Efficiency in Buildings: By simulating building energy usage, generative AI models optimize lighting, insulation, HVAC systems, and other aspects of buildings to save energy consumption and operational costs in both residential and commercial spaces. Decarbonization Strategies: To help with the shift to a low-carbon energy future, generative AI discovers emissions hotspots, optimizes the energy mix, and assesses the effect of integrating renewable energy. Microgrids can run on either direct current (DC) or both. Figure 1 shows a hybrid renewable system arrangement.

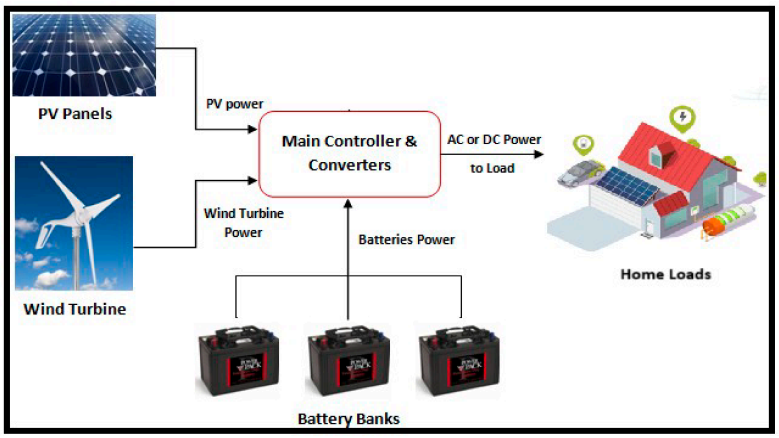


Figure 1. Hybrid renewable system.

The islanded operating mode is undoubtedly a useful capability to have in case the power grid fails. Different AC or DC microgrid setups are needed for different scenarios. However, due to their reduced conversion losses and fewer power conversion stages, lack of synchronization problems, and independence from power quality issues that occur on AC grids, DC microgrids in particular are drawing a lot of study attention. This paper aims to perform power energy management using artificial and computational intelligence in a hybrid renewable system.

2. Literature Review

The authors in [2] introduced a particle swarm optimization (PSO) technique directly to a power-electronic-switch-level microgrid simulation model for optimization, as opposed to employing small-signal models. Optimization was conducted under diverse operating situations to address the system's nonlinearity, yielding good results. Because

the control parameters were changed collectively, regardless of controller types or levels, it was difficult to analyze how particular control parameters affected overall performance. This study suggests gradual parameter improving and the division of the controller design process into modular components. According to reference [3], microgrid control uses three control modes: high-, medium-, and low-frequency modes. The study of distributed control theory has been divided into three fundamental approaches [4]: cooperative control, which is predicated on the consensus theory, both distributed optimization, also referred to as a component of decomposition-based techniques, and (intelligent) agent control, which is composed of autonomous local agents that carry out control actions based on local goals and information from neighbors and the environment, typically using machine learning techniques [4], facilitating the sharing of information among units to address localized optimization challenges [5]. In [6], a summary of current studies on distributed control systems utilized with DC-MGs is included. Specifically, the authors discuss finite-time and asymptotic consensus processes. Communication issues and solutions are also covered. Distributed control methods are barely discussed in [7], which does not examine stability, in order to achieve cost-effective electrical energy dispatch in MGs. A review of control methods for hybrid AC/DCMGs is provided in [8]. Distributed control techniques are not taken into consideration in this article, and secondary control is outside the control of the authors in [9]. However, the authors in [9] only talk about the power management techniques for this type of MG. The authors in [10] present a summary of synchronous reference-frame-based small-signal stability techniques for the AC distribution grid and employ impedance-based models. Analyses and comparisons are made between various temporal stability techniques. On the same theme, a review of MG small-signal stability is looked at in [10]. A global priority now is integrating renewable energy into the energy system.

3. Hybrid Renewable System and Proposed Artificial and Computational Intelligence Technique

The capacity of microgrids to interface with the grid and function entirely independently and autonomously in an islanded mode is a compelling feature. Simulation on AC-side inverter output in a MATLAB/Simulink artificial neural network (ANN) is a highly used computational model. The computation weight and bias occur in feed-forward propagation and back-propagation in the ANN. Back-propagation lowers the discrepancy between the estimated and actual results, while feed-forward propagation provides an accurate estimate. The input layer processes the dataset used by the neural network. Additionally, Figure 2 shows the basic architecture of the ANN, which presents the data supplied The input data is multiplied by weights and added to the bias in each hidden layer of the ANN. The more hidden layers there are, the more accurate the ANN-derived forecast is. The output layer generates the necessary outcome for the program under consideration.

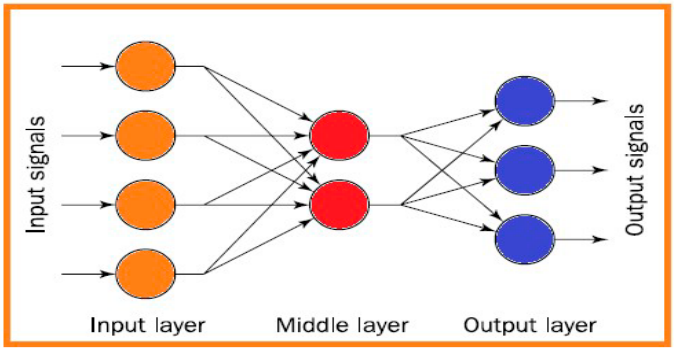


Figure 2. Basic architecture of ANN.

Mathematical Modelling for ANN in Hybrid System

Gradient descent: The optimization technique known as gradient descent is used to find a local minimum of a differentiable function that significantly lowers a cost function. A gradient calculates the variance in the output and modifies the weights when the inputs are slightly changed. In order to reduce the difference between the ideal and anticipated outcomes, (1) is used, which outlines the cost function,

$$f(w,b) = \frac{1}{N}\sum_{i=1}^{n}(y_i - (wx_i + b))^2 \quad (1)$$

Therefore, (1) is used to find the gradient of the cost function in (2),

$$f'(w,b) = \begin{pmatrix} \frac{df}{dw} \\ \frac{df}{db} \end{pmatrix} = \begin{pmatrix} \frac{1}{N}\sum -2x_i(y_i - (wx_i + b)) \\ \frac{1}{N}\sum -2(y_i - (wx_i + b)) \end{pmatrix} \quad (2)$$

Iterating over the input datasets yields the updated weights (w) and biases (b) for the hidden layer. The partial derivatives are then calculated in order to solve the gradient function. This new gradient, which also displays the slope of our cost function at our current point (the current parameter values), indicates the direction in which we can shift our parameters to minimize the cost function.

4. Simulation Results and Discussion

Power Energy Management During Fault Outbreaks

In order to obtain the most power from the wind-and-PV array, the "perturb and observe" technique is used to alter the voltage between the terminals. In a DC microgrid, the consumer's side will be severely impacted by DC line-to-ground faults that happen on the load side. Figure 3 shows the harmonic distortion ITHD measure ratio. The output is very small, initially ranging at 0.2 pu peak-to-peak between 0 s and 0.5 s. In the second stage, it increases 2 pu peak-to-peak, and lastly it increases to 4.2 pu peak-to-peak between 1 s to 1.5 s.

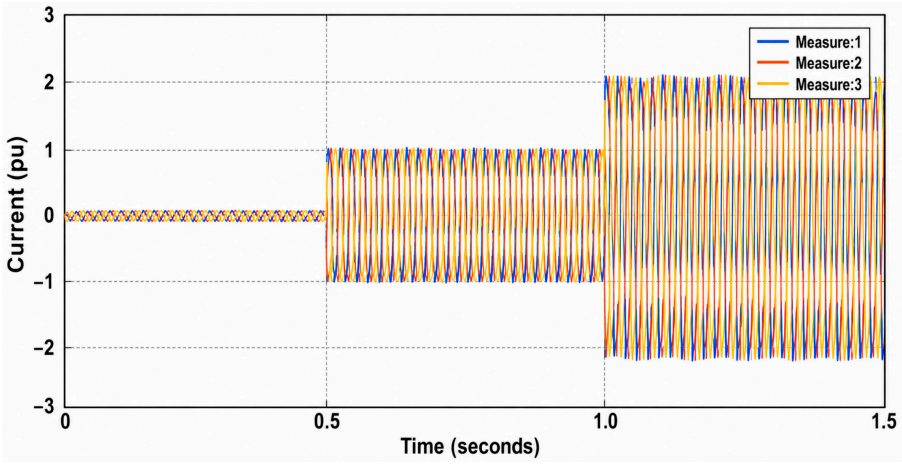


Figure 3. Harmonic distortion ITHD measure.

A discrete harmonic distortion THD3 is depicted in Figure 4. There are significant waves on the voltage and consumer side due to faults, resulting in fluctuating and blown voltage in each unit. The fault causes the voltage to fluctuate between 0.18 pu to 0.5 pu in the period between 0 s and 0.5 s, even though it initially reaches the maximum output voltage of 1.1 pu. Since there is a fault, the rated value of this condition delays the return

to stable. At t = 0.501 s, the output is stable at 0.1 pu until t = 1 s, where a slight impact is noted, but the system eventually returns back to normal.

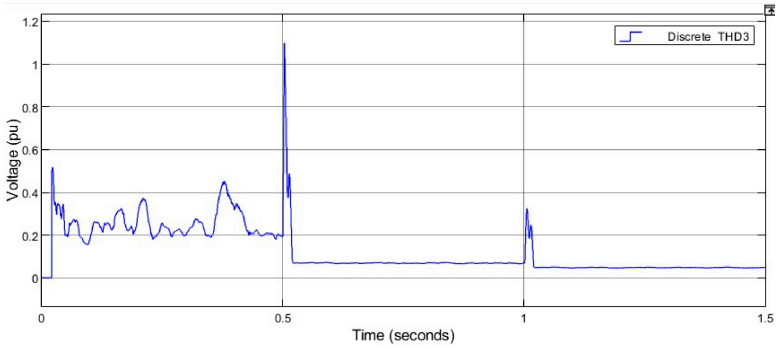


Figure 4. Discrete THD3 phase-to-line fault circuit.

In Figure 5, wind generation/Te and wind generation/Tm in the average state are displayed without a storage component. When the base wind speed is approximately 12 m/s, wind turbines generate electricity. The wind generation has a variance in speed. A value of 0.8 pu of the nominal mechanical power is the maximum power at the base wind speed. There is no output power stability during fault conditions. Wind generation/Te is more than 150 kW, while wind generation/Tm is lowered to 120 kW initially. In the first 0.25 s, the system experiences fluctuation, and from 0.25 s, the system approaches steadiness, with 75 kW and 25 kW.

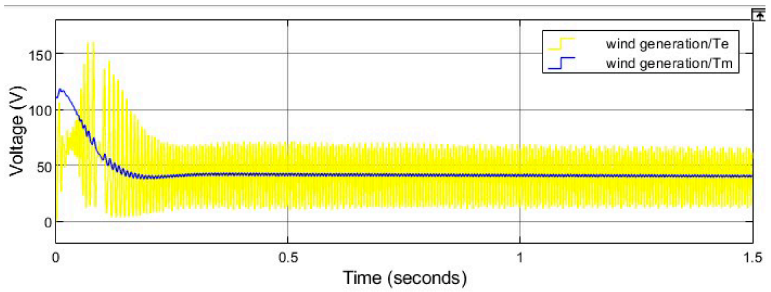


Figure 5. Wind generation/Te and wind generation/Tm.

On the generation side, the simulation results of wind generation/Tm and wind MPPT/1 during the L-L fault are displayed in Figure 6. Due to the fault that occurred, the wind energy generation is shifted greatly when compared to that under normal conditions. A significant shift in wind MPPT/1 and wind generation is observed on the waveform during the fault. It produces an output that is unstable and not in balance. The wind MPPT/1 increases to 65 kW at t = 0.625 s. The wind generation/Tm starts very high at 120 kW and drastically drops to 40 kW. At t = 0.25 s, the wind generation/Tm and wind MPPT/1 are equal, with a 40 kW output, and remain at equilibrium throughout.

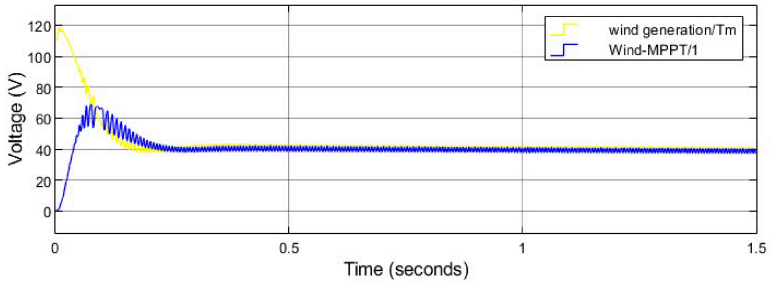


Figure 6. Wind generation/Tm and wind MPPT/1.

The battery phase voltage under fault conditions is depicted in Figure 7. The voltage overshoots to 333 V and then drops to 327 V. As the system continues, it displays reliability, as its fluctuation drops during the first 0.5 s, where it varies around 325 V; again, between t = 0 s and t = 0.5 s, the system shows no stability; after t = 0.5 s, the output is stable and nearly identical, with an average voltage of 327 V, which is stable at this point.

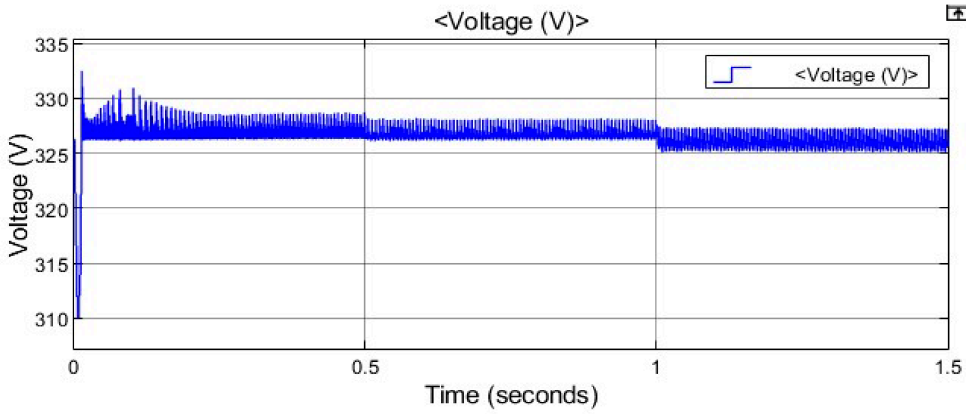


Figure 7. Equivalent DC phase-to-line fault circuit.

The overall performance of the study is shown in Table 1. display the power flow results summary for PV model voltages. Table 2 displays the power flow results summary for wind generation.

Table 1. Power flow results summary for PV model voltages.

PV Model Voltages	
Condition	**Outputs**
DC grid voltage at full load	Vdc_1 = 666.5 V
DC grid voltage without battery storage connected	Vdc_1 = 665 V
DC voltage during normal operation	Vdc_1 = 700 V

Table 2. Power flow results summary for wind generation.

Wind Generation	
Conditions	**Outputs**
Wind generation/Tm with wind MPPT/1 without battery storage	Tm = 43.5 kW MPPT/1 = 42.5 kW
Wind generation with wind MPPT/3 and discrete first-order filter	MPPT/3 = 13.5 kW First order = 12 kW
Wind generation/Te and wind generation/Tm output during normal conditions	Te = 160 kW Tm = 120 kW
Wind generation/Tm and wind MPPT/1 output during normal conditions	Tm = 120 kW, MPPT/1 = 70 kW Equilibrium = 40 kW
Wind generation/Te and wind generation/Tm without battery storage	Te = 75 kW Tm = 44 kW

Figure 8 shows a summary of the battery and wind system performance, and Figure 9 Shows a summary of the inverter output performance.

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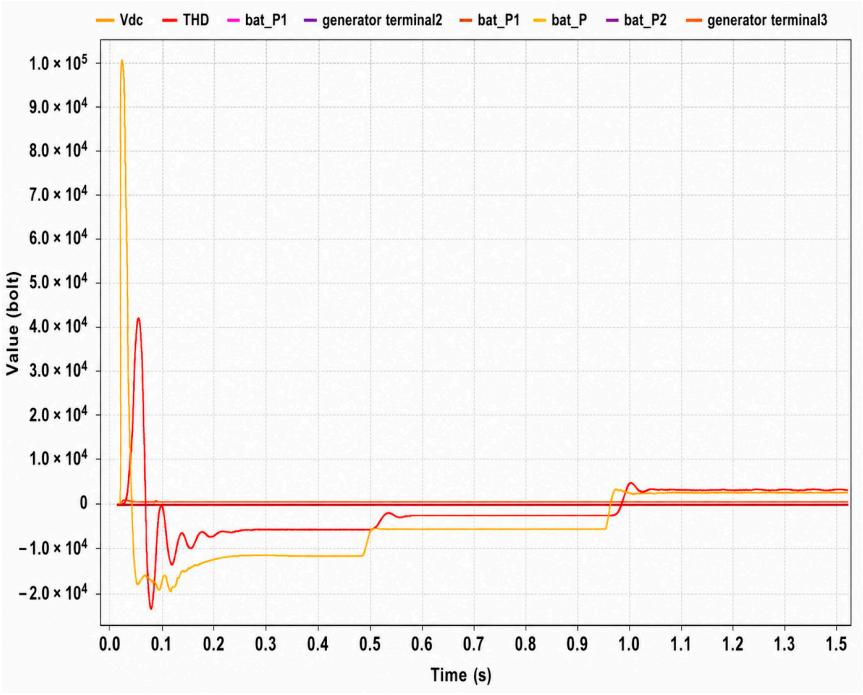


Figure 8. Battery and wind system performance.

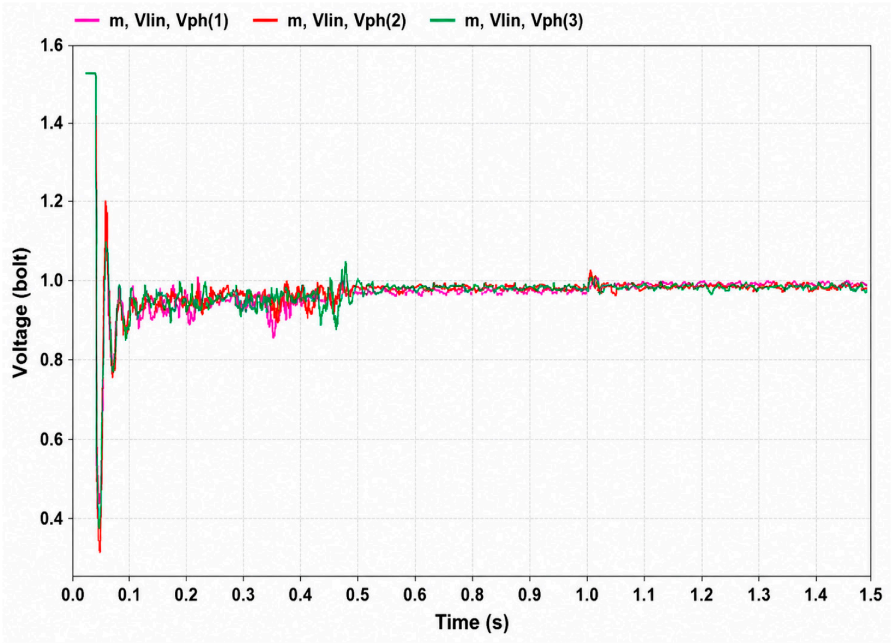


Figure 9. Inverter output performance.

5. Conclusions

The utilization of microgrid systems with PV–wind energy-producing units has advanced, and this study focuses on these advancements, paying particular attention to the pertinent microgrid control systems, techniques, and concepts. A practical solution to the control problems of PV–wind hybrid generation microgrid systems is using an ANN in the microgrid, which integrates suitable artificial intelligence algorithms. Due to its strong performance, there is a growing interest in using FL practically. This work suggests using a rule ANN scheduler to manage power under a set of constraints. Its advantages include the ability to handle nonlinearity, the ability to function with imprecise inputs, and the lack of a precise mathematical or numerical model. Additionally, it integrates human heuristics with

computer-assisted decision-making. In order to make accurate and timely judgments, the rule-based control approach can detect constant variations in PV–wind power generation, load demands, and battery state-of-charge. By including more specific requirements for maximizing availability and lowering the cost of electricity usage, the existing model can be readily expanded.

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