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Review

Evaluating the Efficacy of Intelligent Methods for Maximum Power Point Tracking in Wind Energy Harvesting Systems

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Abstract: As wind energy is widely available, an increasing number of individuals, especially in off-grid rural areas, are adopting it as a dependable and sustainable energy source. The energy of the wind is harvested through a device known as a wind energy harvesting system (WEHS). These systems convert the kinetic energy of wind into electrical energy using wind turbines (WT) and electrical generators. However, the output power of a wind turbine is affected by various factors, such as wind speed, wind direction, and generator design. In order to optimize the performance of a WEHS, it is important to track the maximum power point (MPP) of the system. Various methods of tracking the MPP of the WEHS have been proposed by several research articles, which include traditional techniques such as direct power control (DPC) and indirect power control (IPC). These traditional methods in the standalone form are characterized by some drawbacks which render the method ineffective. The hybrid techniques comprising two different maximum power point tracking (MPPT) algorithms were further proposed to eliminate the shortages. Furtherly, Artificial Intelligence (AI)-based MPPT algorithms were proposed for the WEHS as either standalone or integrated with the traditional MPPT methods. Therefore, this research focused on the review of the AI-based MPPT and their performances as applied to WEHS. Traditional MPPT methods that are studied in the previous articles were discussed briefly. In addition, AI-based MPPT and different hybrid methods were also discussed in detail. Our study highlights the effectiveness of AI-based MPPT techniques in WEHS using an artificial neural network (ANN), fuzzy logic controller (FLC), and particle swarm optimization (PSO). These techniques were applied either as standalone methods or in various hybrid combinations, resulting in a significant increase in the system's power extraction performance. Our findings suggest that utilizing AI-based MPPT techniques can improve the efficiency and overall performance of WEHS, providing a promising solution for enhancing renewable energy systems.

Keywords: MPPT; wind energy harvesting system; artificial intelligence

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1. Introduction

Energy has played a critical role in driving industrial, commercial, and residential development. However, the increasing demand for energy has led to the need to explore additional resources to boost energy production. While fossil fuels are a common energy source, they also have negative environmental consequences such as air pollution and global warming. In contrast, renewable energy sources such as wind power are clean and do not have a greenhouse effect on the atmosphere, making them ideal for generating electricity without any environmental hazards. Wind power is a viable solution due to its abundance and non-depleting nature, making it an attractive option to address the growing concern for clean and green energy resources [1,2].

Electrical energy conversion from wind energy is achieved by WEHS, which mainly consists of a wind turbine (rotor hub and blades), a generator, and electric power converters [3]. In WEHS, the wind turbine converts the wind kinetic energy into mechanical energy, and the generator further transforms the mechanical energy into electrical energy [4–7].

The electrical power converter connected to the system converts the generated AC power to DC power which the DC load, such as battery charging, can use. For grid-connected WEHS, other devices such as boost converters, inverters, and transformers are required. The boost converter increases the DC output power before passing it to the inverter, which converts the DC power to AC. The step-up transformer boosts the AC power and connects it to the grid. The diagram of a typical grid-connected WEHS is shown in Figure 1.

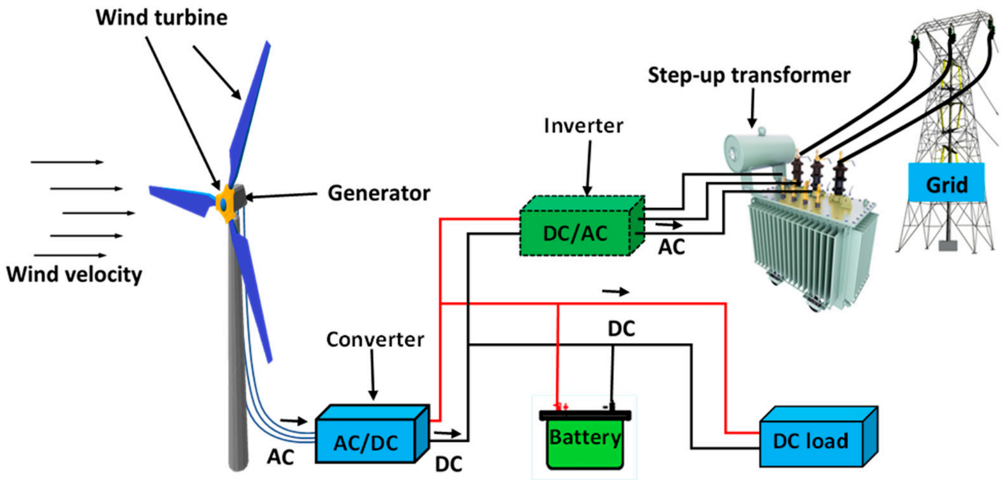

Figure 1. Grid-connected WEHS.

The MPPT controller is an essential component of modern wind energy systems, as it is necessary for optimizing energy conversion and maximizing power generation. Both Photovoltaic Systems (PVS) and WEHS face significant challenges in the implementation of MPPT techniques. These challenges include ensuring the efficiency and accuracy of MPPT, managing environmental factors, maintaining system stability, controlling costs, and overcoming the complexity of implementation.

Despite these challenges, MPPT remains a crucial component of modern energy generation systems. By effectively addressing these challenges, MPPT techniques can improve the overall efficiency and performance of renewable energy systems, making them more viable for widespread adoption and use. Therefore, researchers and engineers continue to work towards developing innovative solutions to overcome these challenges and enhance the implementation of MPPT techniques in both PVS and WEHS systems.

Hence, it is crucial to explore new MPPT techniques and evaluate their performance based on different factors. Recent studies have shown that the hybridization of MPPT techniques with advanced AI methods, such as deep learning, can significantly improve the efficiency and accuracy of MPPT systems. Thus, reviewing and comparing recent MPPT techniques that hybridize with AI methods in both wind and photovoltaic power generation can aid in the development of more efficient and reliable MPPT systems for renewable energy generation.

According to the most recent related reviews on MPPT techniques for the PVS and WEHS systems, as shown in Figure 2, it can be observed that fewer articles are reported on WEHS. Furthermore, a few AI-based MPPT algorithms were reported in only a limited number of review articles, as illustrated in Table 1, and a large number of studies on the MPPT techniques for WEHS focused mainly on the conventional methods, for example, in the studies carried out by Mousa et al. [8] and Pande et al. [9], various types of MPPT algorithm have reviewed, including few of the hybrid and AI-based algorithms. These papers have discussed in detail the application of perturb and observation (P&O) algorithms, followed by the improved version of P&O, such as modified perturb and observation (MPO).

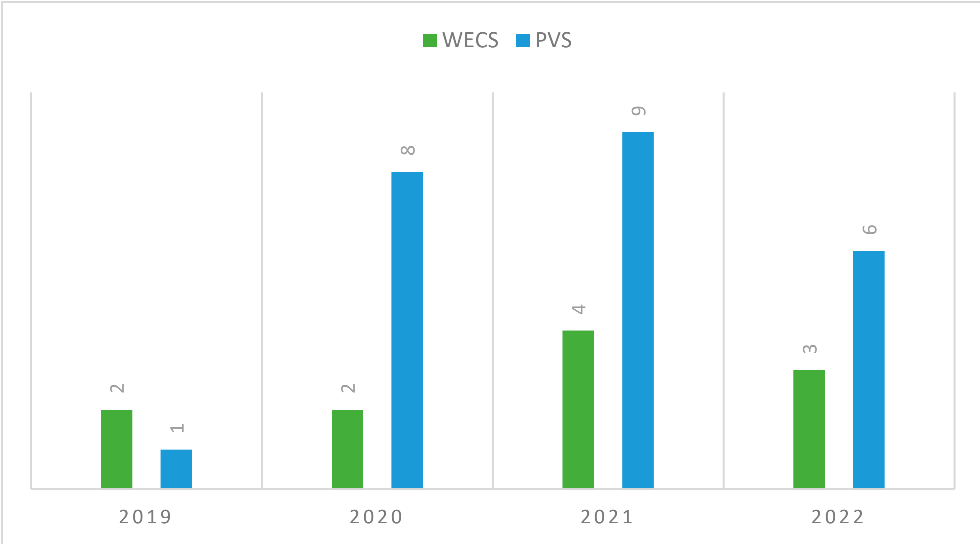

Figure 2. Recently published review articles on MPPT techniques for PVS and WECS.

Table 1. Summary of recent related studies of the MPPT method for WEHSS.

Ref.	Types and Numbers of MPPT Technique Covered				
	Conventional	**AI-Based**	**Hybrid (Conventional + Conventional)**	**Hybrid (AI + Conventional)**	**Hybrid (AI + AI)**
[8]	✓	FLC&NN	P&O+OTC, ORB, PSF	~	×
[9]	✓	FLC&NN	P&O+OTC, ORB, PSF	P&O+FLC, NN, PFS+NN, ORB+PSO	×
[10]	✓	FLC&NN	P&O+PSF	×	×
[11]	P&O, IC	RBN, PSO, ESN ~	RBF+PSF	P&O+FLC (Partially)	×
[12]	✓	ANN, PSO FLC, WOA, GWOA	/	×	×
[13]	✓	FLC&NN	×	PSF+FLC	×
[14]	✓	FLC, NN&GA	×	×	×
[6]	~	FLC, NN	P&O+PSF, OTC+P&O	×	×
[15]	✓	FLC, NN	×	×	×

Symbol: (✓) Covered; (×) Not covered; (~) Partially covered; (/) Not reported.

Table 1 provides an overview of the contemporary research on the efficacy of artificial intelligence based-MPPT techniques applied to wind energy conversion systems.

In summary, the reviews discussed the conventional, hybrid, and AI-based MPPT techniques in WEHS. However, the details provided are not covered enough, especially in standalone and hybrid AI-based MPPT algorithms. Therefore, this paper will focus on the MPPT techniques for WEHS with more emphasis on AI-based MPPT techniques and their performance on WEHS.

The remainder of this paper is organized as follows: Research background is presented in Section 2, modeling of WEHS is presented in Section 3, MPPT algorithms are presented in Section 4, and discussions, future directions and conclusions are presented in Sections 5–7, respectively.

2. Research Background

The operation of WEHS is described by the WT power curve shown in Figure 3. It consists of four main operating regions. In regions one and four, i.e., before cut-in speed and after cut-out speed, the turbine must be stopped and disconnected from the grid so that it is not driven by the generator. In region two, the controllers are used with the MPPT algorithm to track and extract the maximum possible power over the wind speed range. Region three is between the rated power and cut-out speed of the turbine. In this region, the operation of WT must be limited to the rated mechanical power to avoid damage to the electrical generator.

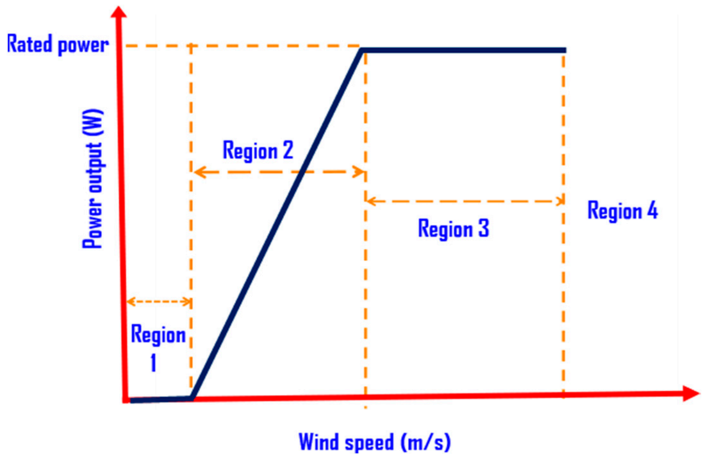

Figure 3. The power curve of the wind turbine.

Due to the intermittent nature of the wind, it is difficult for WEHS to harness the maximum power of the wind over a range of wind speeds. In this context, previous researchers have developed several algorithms to determine the maximum power output of WEHS, as presented by [6,9,16]. These algorithms include the tip speed ratio (TSR), optimal torque control (OTC), and power signal feedback (PSF), which tracks the mechanical power of the WT. Other algorithms, such as the P&O or hill-climb search (HCS) method, incremental conductance (INC), and optimal relation base (ORB), track the maximum converted electrical power from the generator. These traditional methods mentioned above have successfully tracked the MPP of WECS, but they have some drawbacks depending on the method. Therefore, developing an accurate MPPT algorithm to track the MPP is still a challenging task. To solve these problems, some researchers, such as [7,9,16–20], have modified the traditional methods. In [17–19], the TSR method in which the wind speed is measured by a mechanical sensor is replaced with the wind speed estimation method. The issue regarding generator stalling in the PSF method has been resolved in [7] by the concept of a modified PSF algorithm. The variable, adaptive, and hybrid step sizes concepts were proposed by [9,17] as the solution oscillation issue around the MPP by the P&O method. The authors of [16] proposed a method that eliminated the need for a sensor and look-up table as required in the ORB method. In [21], the INC algorithm has been modified for a better system with higher dynamic performance, precision, and fast convergence speed than P&O and the ordinary INC method. Other researchers, such as [22–26], have combined two or more traditional MPPT methods into a hybrid one so that one method could eliminate or reduce the drawback of the other. For instance, the limitation of ORB was addressed in reference [22] by integrating the P&O technique into the algorithm. Reference [23] utilizes a self-rotating P&O-based controller along with ORB to enhance the MPP tracking speed. On the other hand, reference [24] employs OTC in conjunction with P&O to minimize the perturbation step size of the P&O algorithm, thereby facilitating the attainment of MPP.

Recently, researchers have been focusing on implementing AI approaches in MPPT controllers. These approaches have been proposed either in standalone form, such as in references [3,27–33] or in hybrid forms, such as in references [20,34,35]. The use of an artificial neural network (ANN) has been employed in some of these approaches, such as in references [3,27,32,33], resulting in enhanced system performance, resilience, power response, and efficiency. Optimization algorithms such as particle swarm optimization (PSO), ant colony optimization (ACO), Archimedes optimization (AOA), and grasshopper optimization algorithm (GOA) have also been proposed, resulting in improved tracking speed, energy generation, dynamic performance, and global search capability to track the MPP, as demonstrated in references [28–31].

In reference [20], a hybrid AI MPPT algorithm was proposed by integrating radial basis function-neural networks (RBF-NN) and particle swarm optimization algorithms to replace the conventional controller. This hybrid algorithm achieved faster tracking of the MPP, increased system reliability, and a reduction in system losses, size, and cost. In addition, reference [34] proposed a controller that combined fuzzy logic control (FLC) and NN, resulting in improved power harvesting capability in a hybrid renewable energy system (HRES) and shorter simulation time to capture the MPP. Lastly, reference [35] proposed an adaptive neuro-fuzzy inference system (ANFIS) MPPT controller that combines NN and FL approaches, enabling the extraction of maximum power from the wind independently of wind speeds.

3. Modeling of WEHS

The wind power, as seen by the WT blades, is expressed by Equation (1). The WT blade captures the power of the wind and converts it to mechanical power (P_m) of the WT according to Equation (2). The output mechanical torque (T_m) and rotational speed (ω_m) of the WT, which are the inputs to the electrical generator, are given by Equations (3) and (4)

$$P_{wind} = \frac{\rho \pi R^2 V^3}{2} \quad (1)$$

$$P_m = \frac{\rho \pi R^2 C_p(\lambda, \beta) V^3}{2} \quad (2)$$

$$T_m = \frac{P_m}{\omega_m} \quad (3)$$

$$\omega_m = \frac{\lambda V}{R} \quad (4)$$

where $C_p(\lambda, \beta)$, λ, and R are the wind turbine blade efficiency, tip speed ratio, and radius, respectively. Furthermore, V, ρ and β are the wind speed, air density and blade pitch angle.

It is clear from Equation (2), $C_p(\lambda, \beta)$ is a function of λ and β given by Equation (5) [13].

$$C_p(\lambda, \beta) = k_1 \left(k_2 \frac{1}{\lambda_i} - k_{3\beta} - k_4 \beta^{k_5} - k_6 \right) Exp\left(-k_7 \frac{1}{\lambda_i} \right) \quad (5)$$

$$\text{and } \frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{1 + \beta^3}, \quad (6)$$

the values for $k_1 - k_7$, λ, and β depend on the wind turbine's type and characteristics.

The mechanical rotating speeds of the wind turbine are transformed into the electrical rotating speed of the generator using Equation (7)

$$\omega_e = \omega_m \times \frac{P}{2} \tag{7}$$

where P is the number of magnetic poles pairs.

And the frequency of rotation is calculated by Equation (8)

$$f = \omega_{rpm} \times \frac{P}{120} \tag{8}$$

where ω_{rpm} is the generator rational speed in revolution per minute.

Considering permanent magnet synchronous generator (PMSG), the dynamic equations for the voltages along the d and q axes are given by Equations (9) and (10)

$$u_d = -r_d i_d + \frac{d\psi_d}{dt} - \omega_e \psi_q \tag{9}$$

$$u_q = -r_q i_q + \frac{d\psi_q}{dt} - \omega_e \psi_d \tag{10}$$

where r_d and r_q represents the stator q and d axes resistance, respectively.

Going with the assumption that there is no rotor flux along the q-axis (i.e., it is only along the d-axis), Equations (11) and (12) are used to determine the currents along the d-axis and q-axis.

$$i_d = \frac{(\psi_{pm} - \psi_d)}{L_d} \tag{11}$$

$$i_q = -\frac{\psi_q}{L_q} \tag{12}$$

where L_d and L_q, ψ_d and ψ_q are the inductances and the flux linkages along the d and q axes, respectively.

The electromagnetic power produced by the PMSG is expressed by Equations (13) or (14)

$$P_e = \frac{3}{2}\left(\omega_e L_q i_q i_d - \omega_e L_d i_d i_q + \omega_e \psi_{PM} i_q\right) \tag{13}$$

$$P_e = \frac{3}{2}\omega_e \left[\psi_{PM} i_q - (L_d - L_q) i_d i_q\right] \tag{14}$$

where ψ_{PM} represent the magnetic flux linkage.

Finally, the electromagnetic torque developed by the PMSG is obtained by Equation (15)

$$T_e = \frac{P_e}{\omega_m} = \frac{3}{2}\,\mathrm{P}\left[\psi_{PM} i_q - (L_d - L_q) i_d i_q\right] \tag{15}$$

The dc current, voltage and electric power, which are the output of the rectifier, are expressed in Equation (16), Equation (17) and Equation (19), respectively.

$$I_{dc} = \frac{\pi I_{ph}}{\sqrt{6}} \tag{16}$$

$$V_{dc} = \frac{3V_{ph}\sqrt{6}}{\pi} \tag{17}$$

$$P_{dc} = V_{dc} I_{dc} \tag{18}$$

where I_{ph} and V_{ph} are the generator stator phase current and voltage of the generator.

The corresponding output current, voltage and power of the boost converter are given by Equations (19), (20) and (21) respectively.

$$I_{out} = \frac{V_{in XD}}{R_{load}} \tag{19}$$

$$V_{out} = \frac{3V_{in}}{1 - D} \tag{20}$$

$$P_{out} = V_{out} I_{out} \tag{21}$$

where V_{in} is the converter input voltage and D is the duty cycle which is given by Equation (22)

$$D = 1 - \frac{V_{in}}{V_{out}} \tag{22}$$

4. MPPT Methods for WEHS

The MPPT methods for WEHS can be categorized into traditional MPPT algorithms and intelligence-based MPPT algorithms. The traditional methods are further classified as indirect power control (IPC), which tracks the mechanical power of the WT, and direct power control (DPC), which tracks the maximum electrical power of the generator. The third class of this category of MPPT is the hybrid MPPT method which is the combination of different traditional MPPT algorithms. Smart or Intelligent MPPT algorithms include the MPPT controllers that employ AI algorithms to track the MPP of the WEHS. Therefore, the MPPT methods are broadly classified into four categories such as DPC, IPC), hybrid, and intelligent algorithms [8,9]. Considerable efforts have been dedicated toward the advancement of conventional MPPT controllers, with particular emphasis on enhancing their operational characteristics across various parameters and features. Notably, recent years have witnessed progress in improving the performance of conventional MPPT techniques through the integration or modification thereof alongside traditional and/or AI-based methods. In particular, the utilization of AI techniques in MPPT has garnered significant attention due to its inherent ability to effectively address prevalent issues inherent to these systems.

4.1. Traditional MPPT Methods for WEHS

Examples of IPCs MPPT are TSR, OTC, and PSF. TSR and the other two IPC methods require a mechanical sensor to measure wind speed, while OTC and PSF, in addition, require knowledge of the parameters of WT. In the TSR algorithm, the reference speed of the WT, which corresponds to the MPP, is estimated using Equation (23) and used to control the operation of the WT to the optimal TSR at which the maximum power coefficient is achieved. In OTC, Equation (24), the optimal torque reference relation is used to achieve the MPPT.

$$\omega^*_{ref} = \frac{\lambda_{opt} V_r}{R} \tag{23}$$

$$T^*_{opt} = 0.5\rho\pi R^5 \frac{C_{p\ max}}{\lambda^3_{opt}}\ \omega^2_{ref} \tag{24}$$

In the OTC method, the controller maintains a predefined relationship between the electromagnetic torque and rotational speed of the WT in accordance with the maximum power-rotor speed curve such that the rotational speed approaches the optimal value [6]. DPC methods are sensorless and use a precomputed system curve to find the MPP. The MPPT algorithm under DPC includes P&O, ORB, and IC. The P&O algorithm is based on discretizing (perturbing) a control variable, such as generator speed, and observing the resulting effect on generator output. The algorithm compares each successive generator output and adjusts the generator speed in the direction of the MPP [36]. In ORB control, the

MPP is tracked using a look-up table developed based on prior knowledge of the optimal relationship between the WT power and other parameters such as rotational speed, torque, rectifier DC voltage, or current [10]. Classification of the different MPPT algorithms is presented in Figure 4. The comparison between the different traditional methods of MPPT algorithms is summarized together with remarks in Table 2.

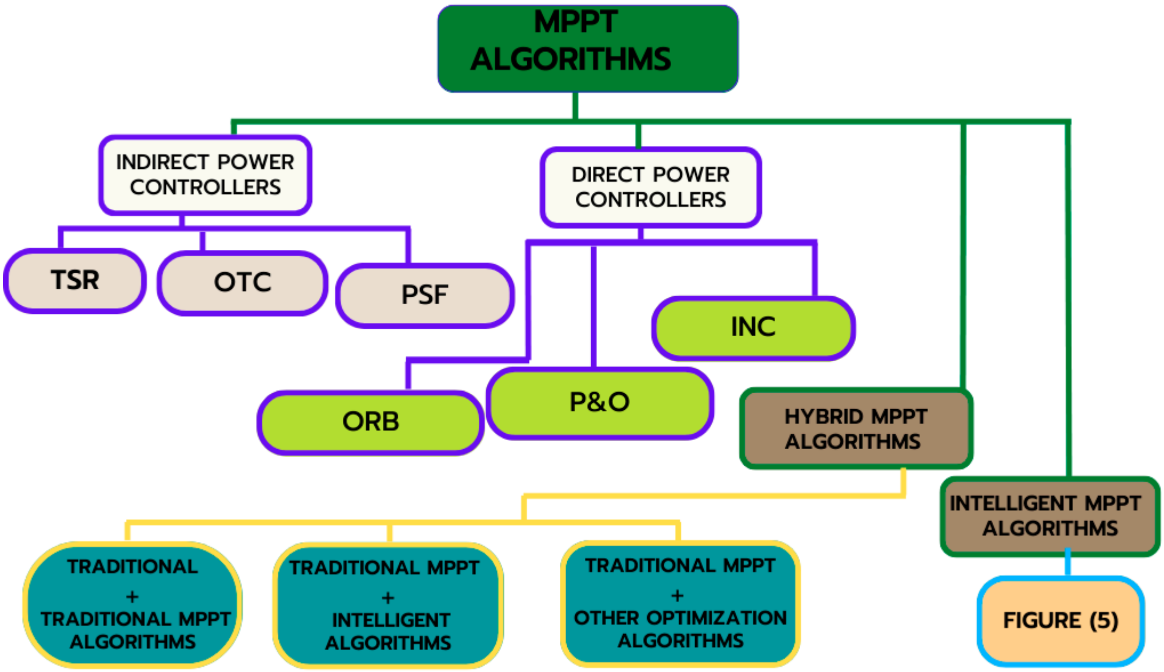

Figure 4. Classification of MPPT algorithms for WECS.

Table 2. Comparison between different type of Traditional method of MPPT algorithms.

MPPT Technique	Advantages	Major Drawbacks	Improvement
TSR	TSR is highly efficient, has high convergence speed, and quickly responds to wind speed changes [37]. Additionally, the TSR method is simple, and no memory is required for the process	The need for a mechanical sensor to measure wind speed results in inaccuracies, leading to increased costs for installation and maintenance.	A novel approach was developed to estimate wind speed, which removed inaccuracies associated with mechanical sensors. The algorithm's speed to track MPP was enhanced, and the technique was made simpler [18–20].
OTC	The OTC method is highly efficient and flexible, with stable torque regulation and easy application. It is also practical as it does not require real-time wind speed measurement, allowing for quick adjustments to changes in wind speed.	The mechanical sensor used for wind speed measurement and knowledge of wind turbine characteristics is necessary. In addition, the turbine's large inertia causes a sluggish response to torque commands, resulting in slow MPP tracking during sudden changes in wind speed. Moreover, measuring electromagnetic torque and turbine speed can increase the system cost and its dependency on generator parameters.	A quantum neural network (QNN) was introduced into the OTC method by [25] and efficiency improvement was recorded more than with conventional OTC and NN. Reference [26] proposed a fuzzy inference-based MPPT method to improve the OTC method. This method enhances the MPPT efficiency under fluctuating wind speeds while ensuring system stability.

Table 2. *Cont.*

MPPT Technique	Advantages	Major Drawbacks	Improvement
PSF	PSF has moderate performance under fluctuating wind speeds and high convergence speeds. The system cost is less compared to the TSR method.	The use of a mechanical sensor to measure wind speed introduces inaccuracies. Additionally, PSF is less efficient and more complex than the TSR and OTC methods. Moreover, it requires knowledge of wind turbine characteristics, and can cause the generator to stall when there are sudden changes in wind speed.	The modified PSF as reported by [7] has solved the issue of generator stalling but raises further issues, such as overshoot of the control variables and greater difficulty in tracking the MPP.
P&O	The proposed method eliminates the need for a mechanical sensor and requires less memory, making it simple to implement. Additionally, it does not require any prior knowledge of the system parameters and characteristics, resulting in lower overall system costs. Although its performance under intermittent wind speed is moderate, it is still a viable option.	Large step size causes oscillation around the maximum power point (MPP) while smaller step size leads to slower response. Both scenarios result in a loss of MPP tracking and reduced efficiency, particularly at varying wind speeds. In addition, the convergence speed is slow.	The drawbacks can be addressed by adopting the followings: Variable, Adaptive, and hybrid step sizes concept [9]. The step size was calculated using trapezoidal rule in [38] which successfully reduce computational complexity of the algorithms and eliminated power oscillation at the MPP.
INC	The benefit of this method is similar to P&O method but with better convergence speed, precision, and MPPT tracking efficiency.	Slow convergence speed. Oscillation at MPP	The INC method proposed by [21] addresses the trade-off between power and convergence speed in P&O methods. Moreover, the modified INC achieves a better system with higher dynamic performance, precision, and fast convergence speed compared to P&O.
ORB	No need for wind speed sensors and look-up tables [16]. Furthermore, high convergence speed than that of P&O and INC. In addition, oscillations around the MPPT are absent in ORB method	Required large memory for pre-obtained optimal relation curve. Required previous knowledge of the system.	Reference [22] improved the ORB method by using the P&O method as an initialization algorithm for online MPP search at local wind speeds. This eliminated the ORB method's drawback by extracting the necessary parameters for its operation.

4.2. Intelligent-Based MPPT Methods

Due to its ability to easily solve problems involving complex mathematical models, AI has proven attractive for applications in WEHS, particularly in the areas of design, modeling, and performance optimization. When applied as a standalone or integrated with the traditional MPPT controllers, AI-based algorithms have shown good results by improving the performance, such as the speed and efficiency of MPPT controllers. The following AI algorithms have been proposed by several researchers to improve the method of tracking the MPP of WEHS. This includes fuzzy logic control (FLC), artificial neural network (ANN), particle swarm optimization (PSO), ant colony algorithm (ACA), Archimedes optimization algorithm (AOA), Cuckoo search (CS), grasshopper optimization algorithm (GOA), multi-objective grasshopper optimization algorithm (MOGOA), electric charge particle optimization (ECPO) and enhanced atom search optimization (EASO) Technique. Figure 5 shows the list of recent AI algorithms that are applied in MPPT controllers for WEHS. Accordingly, refs. [3,27–33] applied the standalone AI-based method to track the MPP of WECS, while references [20,34,35] used the hybrid AI-based method.

The summary of the standalone AI-based (MPPT) algorithms and their contributions to enhancing MPPT tracking in WEHS are provided in Table 3.

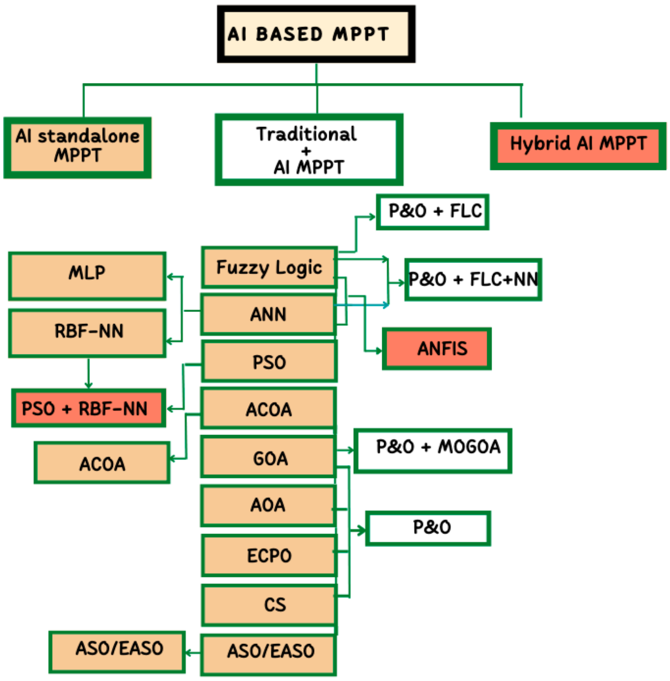

Figure 5. List of recent AI algorithms that are applied for MPPT controllers in WEHS.

Table 3. Role of standalone AI-Based MPPT Algorithms in Enhancing MPP Tracking for WEHS.

Intelligent MPPT Type	Remarks	Algorithm Performance	Reference
FLC	The FLC (fuzzy logic control) controller has demonstrated better power generation and faster response time when compared to other controllers such as P&O and ANN.	A power generation increase of approximately 20 W was achieved when compared to the P&O method.	[34]
ANN (MLP)	An Artificial neural network novel MPPT algorithm was developed Combining an intelligent modular multilayer perceptron (MLP) approach with a simplified model of WEHS.	The model in [3] has achieved an MPPT performance of 99.95% and error of 3% was recorded	[3]
NN (MLP)	Similar approached as in [3], The result obtained showed increased system robustness and fast power response and improved power coefficient.	The system achieved a power coefficient of 0.48 and a time response of 5 s.	[32]
ANN	The use of the ANN as an alternative MPPT algorithm resulted in improved MPP tracking and quicker response times compared to the P&O method.	Increase in power of approximately 30 W was achieved.	[34]
ANN (RBF-NN)	Radial basis function-neural networks (RBF-NN) was proposed to replace the need for measurement instruments, eliminate system errors, and minimize the size and cost of the system. Compared with other AI based methods such as backpropagation of NN and FLC, the proposed RBF-NN method showed better performance.	The response times for FLC, RBF-NN, and BP-NN were 0.47, 0.46, and 0.42, respectively. However, the BP-NN method had the highest ripple factor of 4%	[33]

Table 3. *Cont.*

Intelligent MPPT Type	Remarks	Algorithm Performance	Reference
RNN	A new control strategy for wind power systems was proposed using integral sliding mode control technique based on a recurrent neural network (RNN) where optimal control signals for maximum power extraction is estimated using the RNN. Simulations show that the proposed strategy outperforms existing control strategies in power generation, disturbance rejection, and robustness to parameter variations and uncertainties. The proposed approach can improve the performance and efficiency of wind power systems.	The root mean square error (RMSE) between the optimal power and the tracked power was calculated to be 0.153.	[27]

4.2.1. The Fuzzy Logic-Based MPPT Controllers

FLC is comprised of three main states process, fuzzification, inference, and defuzzification. Fuzzification involves the conversion of physical inputs variables into fuzzy sets (the error and the variation of the error) and the assigning of linguistic variables such as the Negative Big (NB), Negative Medium (NM), Negative Small (NS), Zero (Z), Positive Small (PS), Positive Medium (PM) and Positive Big (PB). The inference stage is the decision-making phase where membership rules are set and also logical relationships between the inputs and outputs variables are constructed, and finally, the fuzzy output is converted to an equivalent numeric value by defuzzification [39].

The concept of FLC based MPPT controller applied to WEHS is explained in Figure 6 and the equivalent MPPT controller circuit is depicted in Figure 7. It consists of two input variables that are fed to the fuzzy toolbox. The first variable is the error ($\epsilon(x)$) which represents the ratio of the current and voltage $\left(\frac{I(x)}{V(x)}\right)$ and their derivatives $\left(\frac{dI(x)}{dV(x)}\right)$, while the second input variable is the change in the error ($\Delta\,\epsilon(x)$), where $\Delta\,\epsilon(x) = \epsilon(x) - \epsilon(x-1)$. The fuzzy toolbox processed the inputs and produced the perturbation parameter, $\Delta\mathrm{D(x)}$ as its output which in turn is used by the P&O MPPT controller as its input variable. One of the advantages of integrating FLC in MPPT is that the controller can eliminate the oscillation around the MPP, especially in the P&O method. Furthermore, the method does not require the mathematical modeling of the WEHS since the variables of the controller can change in accordance with the dynamic changes of the system. Additionally, wind speed intermittency does not affect the performance of the method.

4.2.2. The Artificial Neural Networks (ANN) Based MPPT Controller

ANN is a numerical and symbolic-based learning technique that uses an arithmetic process rather than logic for pattern recognition, prediction, optimizations, control, system modeling and identification, signal processing, etc. [32,40]. ANN uses feedforward propagation and backpropagation for parameters training, and once the training is performed, the neural network produced almost the same output pattern for similar input data. This ability makes the NN suitable for their applications as intelligence controllers. The concept of ANN applied in the MPPT algorithm for WEHS, as proposed in [3,33], is depicted in Figures 8 and 9. It is an intelligent multilayer perceptron (MLP) structure that is constructed using Kolmogorov's theorem [41], which states that the number of neurons n_i for a hidden layer is obtained by the expression: $2n_i + 1$. Accordingly, the MLP structures contain two inputs, one hidden layer of K- neurons and one neuron output layer. The MLP is integrated into a simple WEHS structure. The MLP is a typical example of a feedforward artificial neural network.

The modular MPL in [3] is used to predict the mechanical rotational speed (ω_m) of the WT, which is used by the model to compute the optimal reference current for the rotor side converter. The MPP of the WEHS is tracked by the control mechanism at the rotor side converter using the optimal current as a reference. In each operation mode of the modular MLP and every dataset, ω_m is estimated as a targeted output variable using the DC current (i_{dc}) and DC voltage (v_{dc}) as input variables.

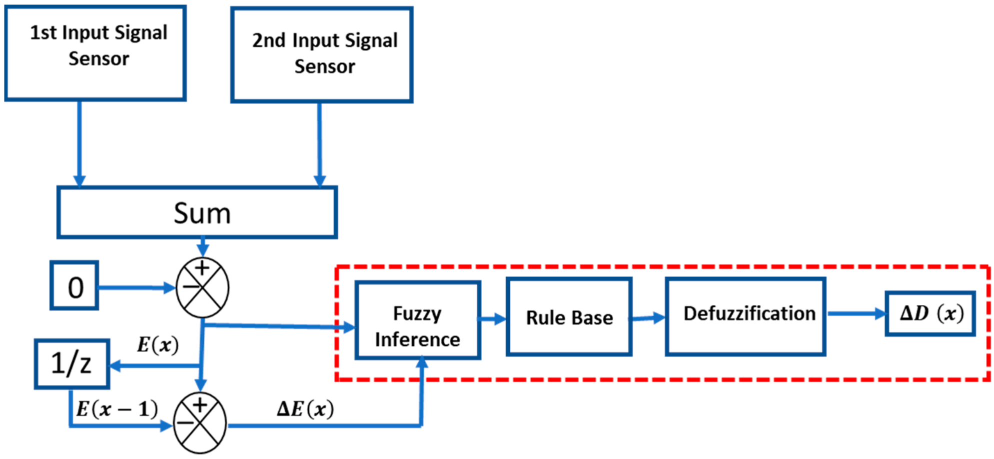

Figure 6. Concept of FLC-based MPPT controller applied to WEHS.

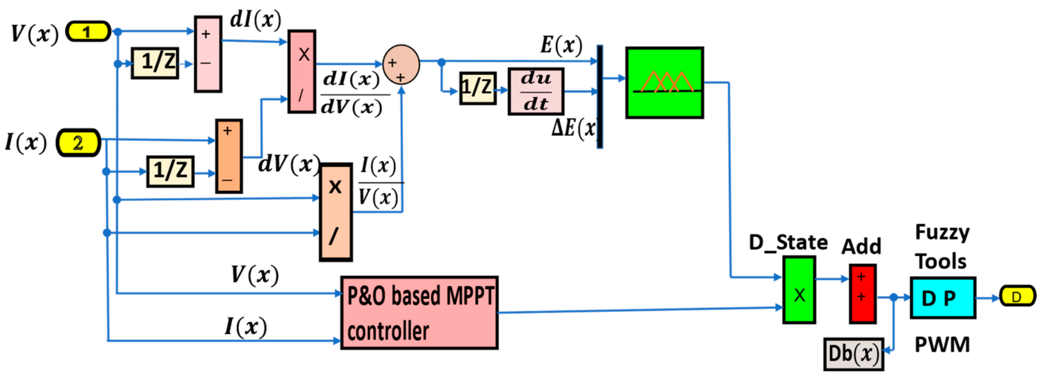

Figure 7. Equivalent circuit of FLC-based MPPT controller [42].

Each training dataset, which comprises the target function and the inputs to the MLP, was normalized according to Equations (25)–(27) using the mean and standard deviation of respective variables.

$$\omega_n^m = \frac{\omega_m - \mu_{\omega_m}}{\sigma_{\omega_m}} \tag{25}$$

$$i_{dc}^n = \frac{i_{dc} - \mu_{i_{dc}}}{\sigma_{i_{dc}}} \tag{26}$$

$$v_{dc}^n = \frac{v_{dc} - \mu_{v_{dc}}}{\sigma_{v_{dc}}} \tag{27}$$

And the final normalized output of the rotational speed of the MLP is calculated using Equations (28) and (29), the hidden layer activation function, and the corresponding linear function of the output neuron.

$$N_i = f_{sgm}(w_{in,1}\omega_n^m + w_{in,2}i_{dc} + w_{in,k}) \tag{28}$$

$$\omega_n^m = w_1N_1 + w_2N_2 + w_3N_3 + w_4N_4 + w_kN_k \ldots + w_{out} \tag{29}$$

where , $w_{\text{in},1} \ldots . w_{in,k}$ are weights connecting each successive inputs to the hidden layer neurons, w_1, w_2, $\ldots w_k$ are the weights connecting the output layer from the hidden layer neurons.

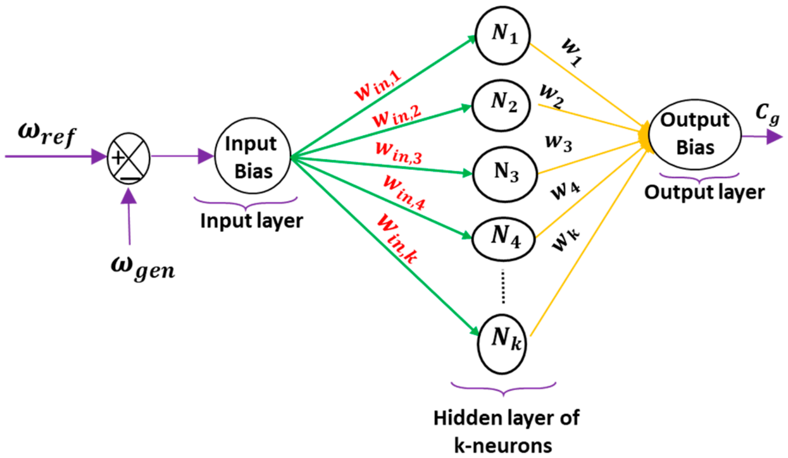

Figure 8. The concept of ANN applied in the MPPT algorithm for WEHS.

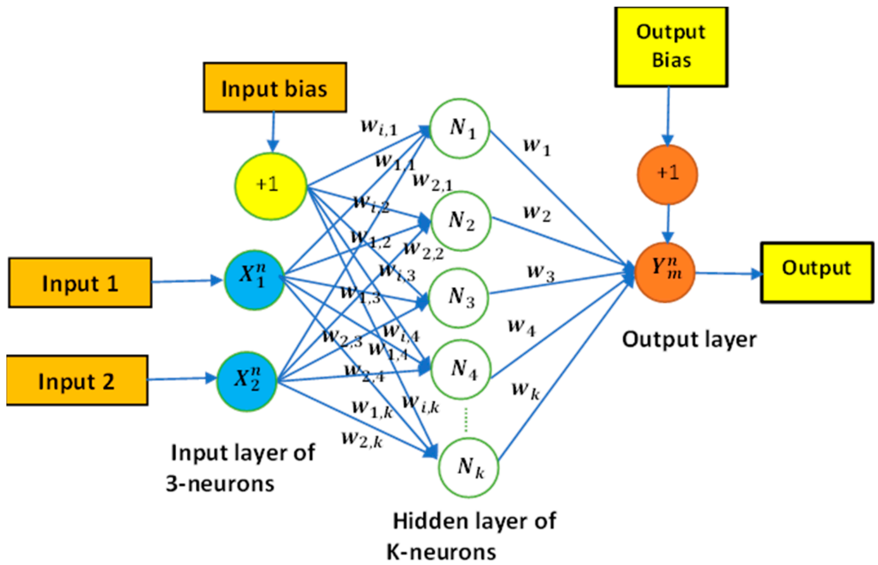

Figure 9. The concept of RBF-NN applied in the MPPT algorithm for WEHS.

4.2.3. MPPT Using PSO Algorithms

The PSO algorithms are a type of intelligent optimization algorithm which belongs to a class of optimization algorithms called metaheuristic algorithms. It is based on swarm intelligence that is inspired by the social behavior of animals (particles) such as fishes or birds (swarm) while searching for food in a physical space. The group of particles moves around in a search space and is guided toward better solutions by a set of rules. The goal of the algorithm is to find the global optimum (global best) of a given objective function by having the particles converge at the optimal solution. The movement of particles toward the optimal solution is influenced by the quality of their current position in the search space as well as the position of other particles in the group and random perturbations. PSO algorithms are often used to solve complex optimization problems that cannot be easily solved using traditional optimization techniques. A simple concept of the PSO algorithm is described in Figure 10.

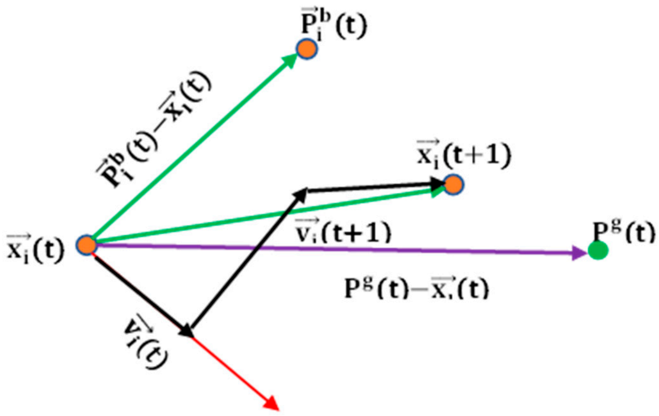

Figure 10. The simple concept of PSO Algorithm.

According to the figure, each particle in the swarm keeps track of its position $\vec{x_i}$(t) in the search space, which signifies the solution to the problem, and the velocity ($\vec{v_i}$(t+1) of each particle specifies its displacement in the searching space. Furthermore, i^{th} particle personal best position is denoted by P_i^b, and the global best position amongst all the particles is denoted by P^g. The general mathematical model of the PSO is described as follows:

x_i(t) is the current position of the particle, $i \leq 1 \leq p$, and p is the swarm population. The new position of each particle is updated using Equation (30)

$$x_i(t+1) \ = x_i(t) + \ v_i(t+1) \tag{30}$$

where $v_i(t + 1)$ is the particle new velocity which is given by Equation (31)

$$v_i\ (t+1) = wv_i\ (t) + c_1 r_1 \Big(P_i^b(t) - x_i\,(t)\big) + c_2 r_2 (P^g\ (t) - x_i(t)) \tag{31}$$

w, c_1, and c_2 are real values called inertia weight and acceleration coefficients, respectively, and, r_1 and r_2 are uniformly distributed random numbers between 0 to 1.

The above two equations are simple rules to be obeyed by all particles in the swarm for searching for the optimum solution to any given problem.

In a WEHS sense, the fitness function of each particle is calculated by Equation (32)

$$F_{FIT} = \frac{1}{0.1 + abs(\omega_r^* - \omega_r) * abs(P_m^* - p_m)} \tag{32}$$

where ω_r^* and P_m^* are the reference rotor speed and mechanical power of the WT, respectively, ω_r and p_m are the rotational speed and mechanical power of the WT at the wind speed speeds, v.

An effective control MPPT algorithm based on the PSO was proposed by [43] to maximize the efficiency of fixed-pitch wind turbines with double-fed induction generators (DFIGs) by compensating for the errors in the estimation of the circuit parameters of the generator. The MPPT algorithms provide the optimal reference speed that will maximize the mechanical power below the rated speed of the DFIG, while electrical losses of the DFIG are minimized by power management through the optimal rotor current, which is searched by the PSO algorithm. Compared to the results of the conventional methods, the proposed control algorithm has improved the energy generation of the system. Furthermore, in [20], the PSO algorithm was used for RBFNN learning rates and inertia weight adjustment to find their optimum values, as shown in Figure 11. Figure 12 depicts the steps of the PSO algorithm process.

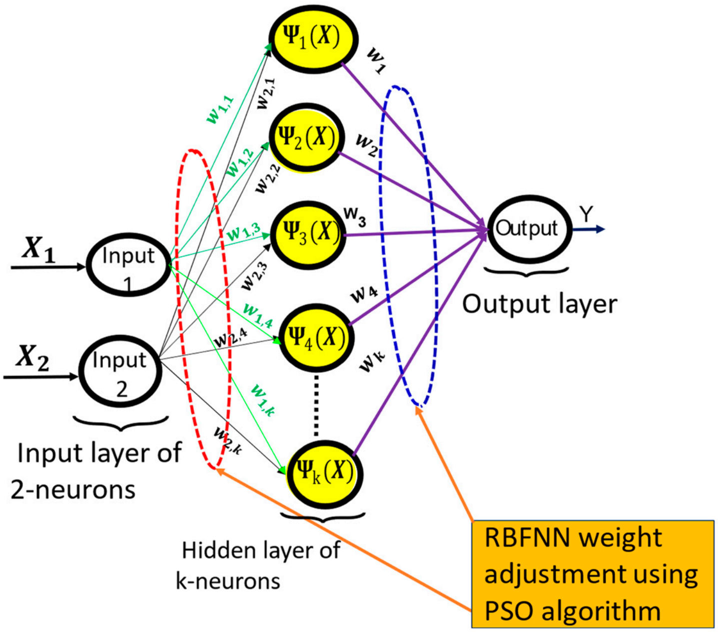

Figure 11. RBFNN-PSO MPPT Algorithm applied to WECS.

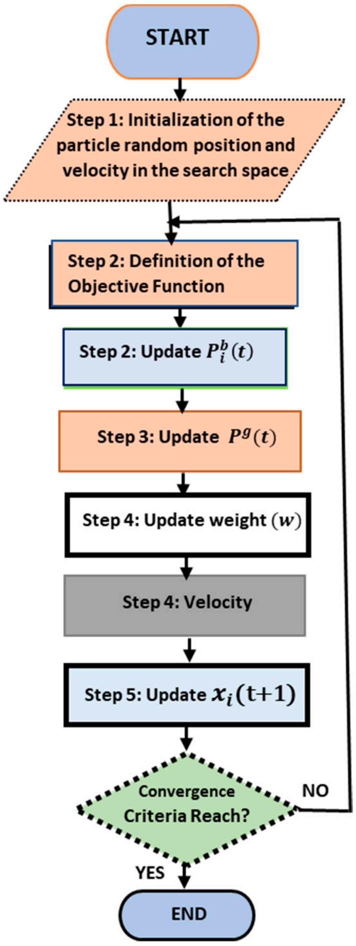

Figure 12. Flowchart for PSO algorithm.

4.2.4. MPPT Method Using Other Optimization Algorithms

Other metaheuristic algorithms such as ant colony optimization algorithm (ACOA), Archimedes optimization algorithm (AOA), Cuckoo search (CS), grasshopper optimization algorithm (GOA), multi-objective grasshopper optimization algorithm (MOGOA), electric charge particle optimization (ECPO), and enhanced atom search optimization (EASO) techniques have been used for MPPT algorithms in WEHS, and the results of their performance have shown very good improvement of the technique in terms of quick searching of the optimum operation point of the WEHS. The different optimization algorithms that are used for MPPT techniques for WEHS are summarized in Table 4.

Table 4. The summary of recent studies of various optimization algorithms used for MPPT in WEHS.

Intelligent MPPT Type	Description	Algorithm Performance Evaluation	Reference
PSO	An effective control MPPT algorithm based on the PSO was proposed to maximize the efficiency of fixed-pitch DFIG WT by compensating the errors in the estimation of the generator circuit parameters. Compared to the results of the conventional methods, the proposed control algorithm has improved the energy generation of the system.	More energy of 1.28% was generated	[43]
ACOA	ACOA was developed and used to tune the PI controller to determine its optimal parameters for speed control. This approach increased the power coefficient and overall performance of the WEHS.	The system achieved a Cp of 0.453, which is slightly higher than the 0.4518 achieved using a PI controller. Additionally, an increase in power output of 150 W was obtained.	[28]
AOA, GOA, CSOA, ECPO,	The shortcomings of the HCS method in terms of MPP tracking speed and efficiency were successfully overcome using the AOA. Compared with other optimization methods such as CSOA, GOA, and ECPO, better performance was obtained with AOA.	The system power generation has increased to 102.20 W, 101.19 W, 78.30 W and 63.52 W respectively with AOA, GOA, ECPO and CSOA algorithm.	[29]
GOA and MOGOA	Fractional order sliding mode controller (FOSMC) based on the traditional P&O method was modified to incorporate the MOGOA. The successful implementation of the MOGOA significantly improved the system's robustness as well as its dynamic performance.	The proposed algorithm achieved an integral of time multiple of absolute error (ITAE) value of 4.18 and 1.48 s for power overshoot and settling time, while the conventional and sliding mode control approaches achieved values of 5.63 and 1.64 s.	[30]
EASO	An optimal solution of high quality and fast system response was achieved using an EASO technique developed for PMSG-based WEHS. According to [30], the technique has a powerful global search capability to track the MPP.	The proposed method achieved an integral absolute error (IAE) control benchmark of 0.1481, which is lower than the values recorded for the PSO and GA algorithms, which were 0.182 and 0.213, respectively.	[31]

4.3. The Hybrid MPPT Techniques

This method involves the combination of different kinds of traditional MPPT techniques or involving AI-based algorithms in the MPPT method for tracking the maximum power point of the WEHS. Accordingly, the hybrid MPPT methods are presented as hybrid-traditional MPPT techniques, hybrid-traditional-AI MPPT techniques, or hybrid-AI MPPT techniques. Various hybrid MPPT algorithms that were developed in recent years to improve the performance of the traditional MPPT methods are discussed below.

4.3.1. The Hybrid-Traditional MPPT

Hybrid traditional MPPT algorithms combine various traditional MPPT techniques to track the maximum power point; it is more robust than the other algorithms in their standalone form and can provide a better overall performance of the system. Table 5 provides a summary of hybrid MPPT algorithms based on the traditional MPPT techniques that have been investigated and used in WEHS.

Table 5. Summary of Hybrid-Traditional MPPT Algorithms for WEHS.

Type of MPPT Algorithms	Remarks	Reference
P&O+PSF	Improvement in power efficiency tracking was achieved with the hybrid MPPT	[44]
ORB+P&O	Combines ORB with a self-rotating P&O-based controller that improves the tracking speed of the hybrid MPPT.	[23]
P&O+OTC	The OTC was employed to detect power peak point and reduce the perturbation step size of the P&O algorithm to reach MPP.	[24]

4.3.2. Hybrid Methods (Traditional and Intelligent)

Due to its intelligent ability to solve complex problems, AI-based methods are developed and integrated with the traditional MPPT methods, as presented in Table 6. This will make the technique more robust and less dependent on the machine's characteristics. According to the literature, the combinations have successfully eliminated the drawback of the traditional method and further enhanced the method's reliability and efficiency. Furthermore, the method's tracking speed was improved, and its accuracy was increased.

Table 6. Summary of hybrid methods (traditional MPPT and intelligent) for WEHS.

Hybrid MPPT Name	Description	Algorithm Performance Evaluation	Reference
P&O+FLC	Fuzzy logic controller (FLC) has been integrated into the adaptive P&O MPPT method which increased the computational speed of the MPPT controller. Furtherly, the new hybrid method successfully eliminated the drawbacks of both the standalone conventional adaptive P&O MPPT and the FLC.	The proposed controller yielded a power increase of 37.93% compared to the P&O method and 17.65% compared to the FLC controller. Additionally, 110 W more power was generated with the proposed controller than with the P&O method and 60 W more than the FLC controller [45]. Moreover, 36.38% of energy yield was recorded with the new controller in [46].	[42,45,46]
P&O+ANN	By integrating ANN into the traditional P&O algorithm, an increase in accuracy was achieved.	The new approach effectively monitored the power coefficient at the optimal level of 0.35 and the nominal power generation of 3 MW.	[47]
ORB+ PSO	PSO was used in the ORB algorithm to search for the maximum power coefficient. The resulting hybrid algorithm provided high efficiency	The PSO-ORBMPPT algorithm has a tracking efficiency of up to 99.4%, which is higher than that of conventional OTC and ORB MPPT algorithms. Additionally, the PSO-ORBMPPT algorithm harvests 1.9% more electrical energy than the conventional algorithms.	[48]

4.3.3. Hybrid Methods (Intelligent and Intelligent)

Hybrid intelligent methods, which combine different artificial intelligence techniques, have been used in MPPT control in WEHS to improve the performance of the control system.

More studies were conducted to further enhance the MPPT algorithms' performance by combining several AI algorithms, the results of which are summarized in Table 7.

Table 7. Summary of hybrid methods (intelligent and intelligent) for WEHS.

Types of Intelligent MPPT Algorithm	Description	Performance Metrics and Results	Reference
FLC, NN	The controller in [34] which combined FLC and NN has improved power harvesting capability in a hybrid renewable energy system (HRES) and shorter simulation time to catch the MPP as compared to other standalone methods such as P&O, FLC, and ANN.	Compared to the standalone P&O, FLC, and ANN methods, the hybrid method achieved an increase in power generation of 35 W, 15 W, and 5 W, respectively, in the WEHS.	[34]
ANFIS	An Adaptive Neuro-Fuzzy inference system (ANFIS) (MPPT) controller for grid-connected WEHS was proposed. The method described can extract the MP from the wind by tracking the MPP independently of the wind speeds.	The ANFIS controller resulted in a 37% smaller voltage overshoot compared to the PI controller. Additionally, a power increase of approximately 7.64% was achieved.	[35]
RBF-NN, MPSO	RBF-NN and modified PSO were integrated into MPPT controller in [20], to replace the conventional MPPT controller. The hybrid combination was able to track the MPP of the WEHS in addition to estimating both the effective wind speed and the rotational speed of the WT. Increased in system reliability, and reduced converters loss, size, and system cost were also achieved.	The proposed hybrid method resulted in a 40% reduction in converter size and produced highest power coefficient of 0.498, whereas other methods, such as ENN+PSO, RBNN-GA, and RBFNN, achieved lower power coefficients of 0.475, 0.47, and 0.43, respectively.	[20]

One of the hybrid intelligent methods used in MPPT control is the combination of a neural network and a fuzzy logic controller. In this method, the neural network is used to predict the wind turbine's power output, while the fuzzy logic controller adjusts the rotor speed to ensure that the turbine operates at the maximum power point. The neural network can learn from past wind speed and power output data and use this information to predict the turbine's power output for a given wind speed. The fuzzy logic controller can then adjust the rotor speed based on the predicted power output to ensure that the turbine operates at its maximum power point.

5. Discussions

This section discusses the challenges of hybrid MPPT methods; the main challenges posed by hybrid MPPT are the design and optimization of the hybrid algorithm. In addition, the integration of different techniques can increase system complexity, which can have an impact on the system's reliability and stability. Furtherly, hybrid MPPT algorithm design and optimization necessitate careful consideration of the system's complexity, reliability, and stability, as well as proper validation of the algorithm's robustness and adaptability. The following subsections discuss the different hybrids methods in detail.

5.1. Intelligent-Based MPPT Models

Recent advances in AI have resulted in the development of intelligent-based MPPT algorithms with improved performance. Intelligent-based MPPT models, such as fuzzy logic, neural networks, and genetic algorithms, on the other hand, provide better accuracy and efficiency. These techniques can adapt quickly to changing environmental conditions such as wind speed, temperature, etc., resulting in increased power tracking accuracy and energy conversion efficiency. Furthermore, intelligent-based MPPT models can optimize WEHS control parameters in real-time, resulting in improved system performance under varying wind conditions.

Moreover, intelligent-based MPPT models can overcome traditional MPPT method limitations such as wind speed measurement dependency and system parameter uncertainties. Fuzzy logic-based MPPT methods, for example, can effectively handle uncertainties and nonlinearity, both of which are common challenges in wind energy systems. Similarly, MPPT algorithms based on neural networks can adapt to changing environmental conditions, resulting in improved system performance and increased energy conversion efficiency. Furthermore, the intelligent-based MPPT method using optimization techniques such as PSO and other metaheuristic algorithms such as ACOA, AOA, CS, GOA, MOGOA, ECPO, and EASO techniques have been used for the MPPT in WEHS, and the results of their performance have shown a very good improvement of the technique in terms of quick searching of the WEHS's optimum operation point [28–31,43]. Therefore, in terms of accuracy, efficiency, and adaptability, intelligent-based MPPT methods outperform traditional MPPT techniques, resulting in optimal energy extraction from the wind source. Thus, intelligent-based MPPT techniques are promising approaches for improving WEHS application performance.

5.2. Hybrid Methods (Traditional and Intelligent-Based MPPT)

The traditional MPPT methods, such as P&O and INC techniques, are widely used. Traditional MPPT methods have several performance limitations that can lead to decreased efficiency and energy loss. The sensitivity of traditional MPPT techniques to system parameters and wind speed measurement is one of their primary limitations. Wind turbulence affects the smooth functions of the anemometers, resulting in inaccurate measurement of actual wind speed striking the wind turbine. As a result, traditional MPPT techniques may result in inefficient operation and energy waste.

For improving WEHS performance, MPPT methods that combine traditional and intelligent-based techniques have been proposed. These hybrid approaches seek to overcome the shortcomings of traditional MPPT techniques while retaining their benefits.

For instance, hybrid MPPT methods can optimize WEHS control parameters in real-time by allowing the tracking algorithm to be adjusted based on changing wind speed and direction, resulting in improved system performance and maximum energy extraction from the source under the rapid change in wind conditions.

The hybrid methods proposed by [42,45,46], which combine P&O and FL-based techniques, can adapt to changes in wind speed and direction, resulting in improved tracking accuracy and energy conversion efficiency. Similarly, hybrid MPPT methods that combine P&O and neural network-based techniques yielded a hybrid system that successfully tracked the System MPPT [47]. Therefore, resulting in improved system performance, such as tracking accuracy and increased energy conversion efficiency.

5.3. Hybrid Methods (Intelligent and Intelligent)

Hybrid intelligent MPPT methods combine two or more intelligent techniques to improve the MPPT algorithm's performance. A hybrid approach, for example, that combines FL and ANN-based techniques can overcome the limitations of each technique while retaining their benefits. FL can handle uncertainty in system parameter values, whereas ANN can adapt to changing environmental conditions and provide accurate predictions of wind turbine power output. Similarly, the ANN is used to predict the wind turbine's power output, as in [34], while the FL controller adjusts the rotor speed to ensure that the turbine operates at the maximum power point. The ANN can learn from past wind speed and power output data and use this information to predict the turbine's power output for a given wind speed. The FL controller can then adjust the rotor speed based on the predicted power output to ensure that the WEHS operates at its maximum power point. When compared to other MPPT methods such as P&O, FLC, and ANN in their standalone form, the hybrid method in [34] that combined FLC and ANN achieved improved system power harvesting capability as well as a shorter simulation time to capture the MPP.

Also, the method reported in [35], which utilized the MPPT strategy for grid-connected WEHS based on the ANFIS, was capable of extracting the MP from the wind by tracking the MPP regardless of wind speeds.

Furthermore, in [20], the hybrid combination of RBF-NN and MPSO was able to track the MPP in addition to estimating the effective wind speed and the rotational speed of the WEHS. Additionally, improving system reliability was achieved, and converter size, loss, and cost were all decreased.

Overall, hybrid intelligent methods of MPPT in WEHS can improve the control system's performance and increase the system's energy harvesting efficiency. These methods can learn from past data and use optimization techniques to find the optimal solution for maximizing power output, ensuring that the WEHS operates at their maximum potential.

6. Future Directions

Advancements in AI-based MPPT techniques for wind energy harvesting systems have led to significant improvements in efficiency, accuracy, and overall system performance. However, further research and development are still necessary to explore and implement more advanced AI algorithms, such as reinforcement learning and other metaheuristic optimization techniques, which can improve MPPT techniques even further. Developing real-time MPPT systems that can adapt to rapidly changing environmental conditions such as wind speed and direction can lead to more efficient and reliable wind energy harvesting systems. While simulations are crucial for testing and validating AI-based MPPT techniques, implementing these algorithms in real-world hardware systems can provide valuable insights into their practical feasibility and performance under actual operating conditions.

7. Conclusions

The optimization of wind energy harvesting systems' power output using MPPT has received considerable attention in the research community. Various methods have been proposed for tracking MPPT in WEHS. While traditional techniques have been explored, such as direct and indirect power control, they have certain drawbacks, such as a large convergence speed, the need for system parameter information, the need for wind speed measurement, and low power tracking efficiency. Even though traditional hybrid methods showed an improvement in the WEHS performance, they suffer from other drawbacks, such as the convergence speed of the algorithm, the need for wind speed measurement, and system parameters dependency. AI-based techniques have the ability to swiftly adjust to changes in environmental factors such as wind speed and temperature. Various intelligent-based MPPT techniques, including fuzzy logic-based methods and those based on neural networks, have been developed to improve energy conversion efficiency in wind energy systems. Additionally, optimization techniques such as PSO and metaheuristic algorithms such as ACOA, AOA, CS, GOA, MOGOA, ECPO, and EASO have been utilized, resulting in significant improvements in quickly tracking the optimum operation point of the system. Consequently, results in greater precision in MP tracking and an increase in the efficiency of energy conversion. Hybrid MPPT algorithms comprising the traditional methods and AI-based MPPT algorithms have been proposed. More improvement in system performance has been achieved with the traditional-AI hybrid method by removing the algorithm's dependency on system parameters and the need for wind speed measurement. Furtherly, AI-AI hybrid methods such as FL-ANN, where ANN is used to predict the wind turbine's power output while the FL controller adjusts the rotor speed to its optimal operating point, has proved to be the most efficient method. The AI-based hybrid, in addition to successfully removing the MPPT drawbacks, has also improved the algorithms' robustness and performance. This study focused on the review of AI-based MPPT methods, and their performance was discussed briefly.

The findings revealed that AI-based methods, such as FLC-ANN, have the highest performance in terms of efficiency and accuracy by combining the handling of uncertainty and robustness of FLC with the learning and adaptability of ANN, this hybrid approach benefits from the strengths of both techniques. This synergy enables the FLC-ANN method to better adapt to dynamic and non-linear environments, such as those presented by varying wind speeds and directions, while also demonstrating robustness in the face of uncertainties and system disturbances.

Therefore, it is encouraging to explore and evaluate new MPPT techniques that hybridize with AI methods in wind power generation to improve the efficiency and reliability of renewable energy generation systems.

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References

1. Roga, S.; Bardhan, S.; Kumar, Y.; Dubey, S.K. Recent technology and challenges of wind energy generation: A review. *Sustain. Energy Technol. Assess.* **2022**, *52*, 102239. [CrossRef]
2. Famoso, F.; Brusca, S.; D'Urso, D.; Galvagno, A.; Chiacchio, F. A novel hybrid model for the estimation of energy conversion in a wind farm combining wake effects and stochastic dependability. *Appl. Energy* **2020**, *280*, 115967. [CrossRef]
3. Lopez-Flores, D.R.; Duran-Gomez, J.L.; Chacon-Murguia, M.I. A Mechanical Sensorless MPPT Algorithm for a Wind Energy Conversion System based on a Modular Multilayer Perceptron and a Processor-in-the-Loop Approach. *Electr. Power Syst. Res.* **2020**, *186*, 106409. [CrossRef]
4. Tan, J.D.; Chang, C.C.W.; Bhuiyan, M.A.S.; Minhad, K.N.; Ali, K. Advancements of wind energy conversion systems for low-wind urban environments: A review. *Energy Rep.* **2022**, *8*, 3406–3414. [CrossRef]
5. Umar, D.A.; Yaw, C.T.; Koh, S.P.; Tiong, S.K.; Alkahtani, A.A.; Yusaf, T. Design and Optimization of a Small-Scale Horizontal Axis Wind Turbine Blade for Energy Harvesting at Low Wind Profile Areas. *Energies* **2022**, *15*, 3033. [CrossRef]
6. Zhang, X.; Jia, J.; Zheng, L.; Yi, W.; Zhang, Z. Maximum power point tracking algorithms for wind power generation system: Review, comparison and analysis. *Energy Sci. Eng.* **2022**, *11*, 430–444. [CrossRef]
7. Kazmi, S.M.R.; Goto, H.; Guo, H.J.; Ichinokura, O. Review and critical analysis of the research papers published till date on maximum power point tracking in wind energy conversion system. In Proceedings of the 2010 IEEE Energy Conversion Congress and Exposition, Atlanta, GA, USA, 12–16 September 2010; pp. 4075–4082. [CrossRef]
8. Mousa, H.H.H.; Youssef, A.R.; Mohamed, E.E.M. State of the art perturb and observe MPPT algorithms based wind energy conversion systems: A technology review. *Int. J. Electr. Power Energy Syst.* **2021**, *126*, 106598. [CrossRef]
9. Pande, J.; Nasikkar, P.; Kotecha, K.; Varadarajan, V. A review of maximum power point tracking algorithms for wind energy conversion systems. *J. Mar. Sci. Eng.* **2021**, *9*, 1187. [CrossRef]
10. Khan, M.J. Review of Recent Trends in Optimization Techniques for Hybrid Renewable Energy System. *Arch. Comput. Methods Eng.* **2021**, *28*, 1459–1469. [CrossRef]
11. Khan, M.J.; Mathew, L. Comparative Study of Optimization Techniques for Renewable Energy System. *Arch. Comput. Methods Eng.* **2020**, *27*, 351–360. [CrossRef]
12. Kumari, B.; Aggarwal, M. A Comprehensive Review of Traditional and Smart MPPT Techniques in PMSG based Wind Energy Conversion System. In Proceedings of the 2019 International Conference on Power Electronics, Control and Automation (ICPECA), New Delhi, India, 16–17 November 2019; Volume 2019. [CrossRef]
13. Malik, M.Z.; Baloch, M.H.; Gul, M.; Kaloi, G.S.; Chauhdary, S.T.; Memon, A.A. A research on conventional and modern algorithms for maximum power extraction from wind energy conversion system: A review. *Environ. Sci. Pollut. Res.* **2021**, *28*, 5020–5035. [CrossRef]

14. Apata, O.; Oyedokun, D.T.O. An overview of control techniques for wind turbine systems. *Sci. Afr.* **2020**, *10*, e00566. [CrossRef]
15. Xiao, Y.; Li, S.; Xu, M.; Feng, R. Research on the economy of implementing the MPPT for wind-solar hybrid power generation system: A review. In Proceedings of the 2022 41st Chinese Control Conference (CCC), Hefei, China, 25–27 July 2022; Volume 2022, pp. 5339–5344. [CrossRef]
16. Kumar, D.; Chatterjee, K. A review of conventional and advanced MPPT algorithms for wind energy systems. *Renew. Sustain. Energy Rev.* **2016**, *55*, 957–970. [CrossRef]
17. Jia, Y.; Yang, Z.; Cao, B. A new maximum power point tracking control scheme for wind generation. In Proceedings of the International Conference on Power System Technology, Kunming, China, 13–17 October 2002; Volume 1, pp. 144–148. [CrossRef]
18. Wu, S.; Wang, Y.; Cheng, S. Extreme learning machine based wind speed estimation and sensorless control for wind turbine power generation system. *Neurocomputing* **2013**, *102*, 163–175. [CrossRef]
19. Asghar, B.; Liu, X. Adaptive neuro-fuzzy algorithm to estimate effective wind speed and optimal rotor speed for variable-speed wind turbine. *Neurocomputing* **2018**, *272*, 495–504. [CrossRef]
20. Sitharthan, R.; Karthikeyan, M.; Sundar, D.S.; Rajasekaran, S. Adaptive hybrid intelligent MPPT controller to approximate effectual wind speed and optimal rotor speed of variable speed wind turbine. *ISA Trans.* **2020**, *96*, 479–489. [CrossRef] [PubMed]
21. Yang, B.; Zhu, T.; Wang, J.; Shu, H.; Yu, T.; Zhang, X.; Yao, W.; Sun, L. Comprehensive overview of maximum power point tracking algorithms of PV systems under partial shading condition. *J. Clean. Prod.* **2020**, *268*, 121983. [CrossRef]
22. Abdullah, M.A.; Yatim, A.H.M.; Tan, C.W. An online Optimum-Relation-Based Maximum Power Point Tracking Algorithm for Wind Energy Conversion System. In Proceedings of the 2014 Australasian universities power engineering conference (AUPEC), Perth, Australia, 28 September–1 October 2014.
23. Ahmed, S.; Rashid, M.A.; Mohamed, S.B.; Yaakob, S.B. A novel maximum power point tracking algorithm for wind energy conversion system. *Eng. Lett.* **2019**, *27*, 822–830.
24. Kazmi, S.M.R.; Goto, H.; Guo, H.J.; Ichinokura, O. A novel algorithm for fast and efficient speed-sensorless maximum power point tracking in wind energy conversion systems. *IEEE Trans. Ind. Electron.* **2011**, *58*, 29–36. [CrossRef]
25. Ganjefar, S.; Ghassemi, A.A.; Ahmadi, M.M. Improving efficiency of two-type maximum power point tracking methods of tip-speed ratio and optimum torque in wind turbine system using a quantum neural network. *Energy* **2014**, *67*, 444–453. [CrossRef]
26. Liu, J.; Meng, H.; Hu, Y.; Lin, Z.; Wang, W. A novel MPPT method for enhancing energy conversion efficiency taking power smoothing into account. *Energy Convers. Manag.* **2015**, *101*, 738–748. [CrossRef]
27. Yin, X.; Jiang, Z.; Pan, L. Recurrent neural network based adaptive integral sliding mode power maximization control for wind power systems. *Renew. Energy* **2020**, *145*, 1149–1157. [CrossRef]
28. Mokhtari, Y.; Rekioua, D. High performance of Maximum Power Point Tracking Using Ant Colony algorithm in wind turbine. *Renew. Energy* **2018**, *126*, 1055–1063. [CrossRef]
29. Fathy, A.; Alharbi, A.G.; Alshammari, S.; Hasanien, H.M. Archimedes optimization algorithm based maximum power point tracker for wind energy generation system. *Ain Shams Eng. J.* **2022**, *13*, 101548. [CrossRef]
30. Falehi, D. An innovative optimal RPO-FOSMC based on multi-objective grasshopper optimization algorithm for DFIG-based wind turbine to augment MPPT and FRT capabilities. *Chaos Solitons Fractals* **2020**, *130*, 109407. [CrossRef]
31. He, X.; Wei, P.; Gong, X.; Meng, X.; Shan, D.; Zhu, J. Enhanced Atom Search Optimization Based Optimal Control Parameter Tunning of PMSG for MPPT. *Energy Eng. J. Assoc. Energy Eng.* **2022**, *119*, 145–161. [CrossRef]
32. Yaichi, I.; Semmah, A.; Wira, P. Control of doubly fed induction generator with maximum power point tracking for variable speed wind energy conversion systems. *Period. Polytech. Electr. Eng. Comput. Sci.* **2020**, *64*, 87–96. [CrossRef]
33. Kumar, R.; Agrawal, H.P.; Shah, A.; Bansal, H.O. Maximum power point tracking in wind energy conversion system using radial basis function based neural network control strategy. *Sustain. Energy Technol. Assess.* **2019**, *36*, 100533. [CrossRef]
34. Khan, M.J.; Kumar, D.; Narayan, Y.; Malik, H.; Márquez, F.P.G.; Muñoz, C.Q.G. A Novel Artificial Intelligence Maximum Power Point Tracking Technique for Integrated PV-WT-FC Frameworks. *Energies* **2022**, *15*, 3352. [CrossRef]
35. Chhipa, A.A.; Kumar, V.; Joshi, R.R.; Chakrabarti, P.; Jasinski, M.; Burgio, A.; Leonowicz, Z.; Jasinska, E.; Soni, R.; Chakrabarti, T. Adaptive neuro-fuzzy inference system-based maximum power tracking controller for variable speed wecs. *Energies* **2021**, *14*, 6275. [CrossRef]
36. Abdullah, M.A.; Yatim, A.H.M.; Tan, C.W.; Saidur, R. A review of maximum power point tracking algorithms for wind energy systems. *Renew. Sustain. Energy Rev.* **2012**, *16*, 3220–3227. [CrossRef]
37. Abdelqawee, M.; Yousef, A.Y.; Hasaneen, K.M.; Nashed, M.N.F.; Hamed, H.G. Standalone wind energy conversion system control using new maximum power point tracking technique. *Int. J. Emerg. Technol. Adv. Eng. Certif. J.* **2019**, *9*, 95–100.
38. Pande, J.; Nasikkar, P. A Maximum Power Point Tracking Technique for a Wind Power System Based on the Trapezoidal Rule. *Energies* **2023**, *16*, 2799. [CrossRef]
39. Malobe, P.A.; Djondine, P.; Eloundou, P.N.; Ndongo, H.A. A Novel Hybrid MPPT for Wind Energy Conversion Systems Operating under Low Variations in Wind Speed. *Energy Power Eng.* **2020**, *12*, 716–728. [CrossRef]
40. Abdalla, A.; Zakaria, M.N.; Sulaiman, S.; Ahmad, W.F.W. A comparison of feed-forward back-propagation and radial basis artificial neural networks: A Monte Carlo study. In Proceedings of the 2010 International Symposium on Information Technology, Kuala Lumpur, Malaysia, 15–17 June 2010; Volume 2, pp. 994–998. [CrossRef]
41. Kůrková, V. Kolmogorov's theorem and multilayer neural networks. *Neural Netw.* **1992**, *5*, 501–506. [CrossRef]

42. Khan, M.J. An AIAPO MPPT controller based real time adaptive maximum power point tracking technique for wind turbine system. *ISA Trans.* **2022**, *123*, 492–504. [CrossRef] [PubMed]
43. Sompracha, C.; Jayaweera, D.; Tricoli, P. Particle swarm optimisation technique to improve energy efficiency of doubly-fed induction generators for wind turbines. *J. Eng.* **2019**, *2019*, 4890–4895. [CrossRef]
44. Chen, J.; Lin, T.; Wen, C.; Song, Y. Design of a Unified Power Controller for Variable-Speed Fixed-Pitch Wind Energy Conversion System. *IEEE Trans. Ind. Electron.* **2016**, *63*, 4899–4908. [CrossRef]
45. Chaicharoenaudomrung, K.; Areerak, K.; Areerak, K.; Bozhko, S.; Hill, C.I. Maximum Power Point Tracking for Stand-Alone Wind Energy Conversion System Using FLC-P&O Method. *IEEJ Trans. Electr. Electron. Eng.* **2020**, *15*, 1723–1733. [CrossRef]
46. Khan, J.; Mathew, L.; Alotaibi, M.A.; Malik, H.; Nassar, M.E. Fuzzy-Logic-Based Comparative Analysis of Different Maximum Power Point Tracking Controllers for Hybrid Renewal Energy Systems. *Mathematics* **2022**, *10*, 529. [CrossRef]
47. Azzouz, S.; Messalti, S.; Harrag, A. A Novel Hybrid MPPT Controller Using (P&O)-neural Networks for Variable Speed Wind Turbine Based on DFIG. *Model. Meas. Control A* **2019**, *92*, 23–29. [CrossRef]
48. Abdullah, A.; Al-Hadhrami, T.; Tan, C.W.; Yatim, A.H. Towards green energy for smart cities: Particle swarm optimization based MPPT approach. *IEEE Access* **2018**, *6*, 58427–58438. [CrossRef]